MANAGEMENT DECISION MAKING IN THE AGE OF BIG DATA: AN EXPLORATION OF THE ROLES OF ANALYTICS AND HUMAN JUDGMENT

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ABSTRACT

This thesis explores the effects of data analytics and human judgment on management decision making in an increasingly data-driven environment. In recent years, the topics of big data and advanced analytics have gained traction and wide-spread interest among practitioners and academics. Today, big data is considered a buzzword by some and an essential prerequisite for future business success by others. Recent research highlights the potential of big data analytics for decision making, but also points out critical challenges and risks.

The aim of this research is to take an in-depth look at management decision making by using qualitative case studies and critical incidents to carefully examine managers' decision-making processes. This exploration evolves around the two main research questions:

i) How do managers perceive the role of advanced analytics and big data in the decision-making process?

ii) How do managers perceive the alignment of advanced analytics and big data with more traditional decision-making approaches such as human judgment?

The content and thematic analyses of data from 25 semi-structured interviews with managers, executives, and business analysts from nine organizations provided several key insights. Managers were found to rely on data and human judgment in their decision making to varying extents and in different roles. The processes followed by the decision makers depended on the decisions at hand, the managers’ characteristics and preferences, as well as environmental factors.

The findings empirically support the development of an ecological systems framework, which provides a holistic picture of managerial decision making in the age of big data. The study contributes by applying the dual process theory to the context of data-driven decision making. Practical implications for organizations are derived from the findings and identify organizational considerations and prerequisites. The influence of the managers’ environments on decision making emphasizes the organizations’ need to utilize a holistic approach when adopting a data-driven decision-making culture.

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GLOSSARY

BI = Business Intelligence

CIT = Critical Incident Technique

(R)DBMS = (Relational) Database Management System

DIKW = Data Information Knowledge Wisdom

DM = Decision Making

DSS = Decision Support System

EDW = Enterprise Data Warehouse

ERP System = Enterprise Resource Planning System

ETL = Extract, Transform, Load

IP = Internet Protocol

IS = Information Systems

IT = Information Technology

KMS = Knowledge Management System

RFID = Radio-Frequency Identification

CHAPTER 1: INTRODUCTION

1.1. Research Background and Significance

Can big data be considered a game changer? In Carr's famous article, "IT Doesn't Matter", he labeled information technology as a mere commodity that has lost its potential for competitive advantage since becoming ubiquitous (Carr, 2003). The comparatively new phenomenon of big data, however, promises unique advantages to innovative companies that are willing and able to exploit its capabilities. With an estimated 40 trillion gigabytes of data created, replicated, and consumed in 2020, the 'digital universe' is expected to steadily continue growing and creating more information that can be used for business purposes (Kune, Konugurthi, Agarwal, Chillarige, & Buyya, 2016). Organizations also have access to increasing volumes of organizational data–up to tens or even hundreds of petabytes (Grover, Chiang, Liang, & Zhang, 2018). Astute businesses and managers are thus increasingly embracing the unique opportunities to capitalize on this big data to gain a competitive advantage.

This is reflected in the spending trends on big data and business analytics, according to the Worldwide Semiannual Big Data and Analytics Spending Guide created by the IDC (Goepfert & Shirer, 2019, p. 1): "Worldwide revenues for big data and business analytics (BDA) solutions are forecast to reach $189.1 billion this year, an increase of 12.0% over 2018". This revenue growth is furthermore expected to remain stable, leading to an expected BDA revenue of $274.3 billion in 2022. Both professional sectors and academia show a growing interest in the topic, resulting in a wide range of research on big data and steadily expanding the level of knowledge (Mishra, Luo, Jiang, Papadopoulos, & Dubey, 2017). A search in the Web of Science shows 28 published articles/editorials in the year of 2011 with “Big Data” in their title or topic, with the number rising to 657 in 2013, 2,896 in 2015, and 6,999 in 2018, respectively. This exceptional increase demonstrates the growing interest of researchers in the topic and reflects the rapidly increasing awareness of big data across organizations and industries globally.

The worldwide significance of big data can also be seen in New Zealand, where this research took place, and where it is thus focused. The New Zealand Data Future Forum in 2014 took stock of the state of big data, discussing its potential, risks, and opportunities (Kirk, 2014). The Ministry of Education was one of the early adopters employing traffic, geospatial and population data and information for use in predictive analytics. The Forum concluded that the available data and technology could potentially transform New Zealand government institutions and the general economy; however, most of this potential remained untapped. In 2016, the New Zealand Herald reported an estimated value of $4.5 billion in big data and sophisticated analytics across New Zealand businesses, with government and banking spearheading the maximizing of its potential (Ryan, 2016).

Most recently, in 2019, ZDNet reported on the All Blacks’ use of performance analytics (Barbaschow, 2019). NZ Rugby adopted SAS Visual Analytics in 2013, and has since been using competitor, player, and team data, focusing on match performance data. The data is visualized to align with game strategy, to gather specific insights, or to generally fill knowledge gaps. While the technology provides significant advantages, the rugby players are still considered to be in charge of the game. Data analytics is therefore seen as a supportive tool in the background, used to inform decisions and provide context (Barbaschow, 2019).

NZ Rugby is not alone, as more and more companies and institutions show interest in adopting data-driven decision making, particularly due to their ever-increasing access to data. Big data is the result of this increase and can be differentiated from traditional datasets by several characteristics, primarily its volume, variety, and velocity–often referred to as the 3 Vs (Laney, 2001). Essentially, big data is seen as a large amount of data from various sources and in diverse formats that is generated–and ideally processed–in (near) real-time. Due to this growing complexity, analytics needs to adapt and evolve to incorporate these characteristics. Generally defined as the use of hardware and software to extract meaning and patterns from data, analytics is also becoming more advanced: offering the potential to not only descriptively analyze past data, but also in a predictive manner to plan and foresee events and developments, and even in a prescriptive capacity, advising for best actions (Kaisler, Armour, Espinosa, & Money, 2013).

As beneficial as its use can be, recognizing the limitations of data analytics is an important consideration for business applications. Data itself cannot lead companies to guaranteed success; human factors, such as experience, knowledge and wisdom, are also of vital importance. As Silver (2012, p. 9) warns, "It is when we deny our role in the process that the odds of failure rise. Before we demand more of our data, we need to demand more of ourselves." Managers therefore need to reflect upon their current decision making and use the reflection period to determine the best ways to incorporate big data into their decision processes.

Due to its increasing volume, variety and velocity, big data has the potential to significantly improve decision making (Bumblauskas, Nold, Bumblauskas, & Igou, 2017; Davenport, Barth, & Bean, 2013; McAfee & Brynjolfsson, 2012). In fact, it can be considered critical for the management level of an organization, especially since "a significant, perhaps the distinctive, task of the manager is making decisions" (James, 1975, p. 22). Managerial decision making is the key to good managerial performance. Indeed, an empirical study by Köse (2016) confirmed "a statistically significant relationship between the decision-making competence of the managers and managerial performance." Simon (1960, p.1) actually equates 'managing' to 'decision making'. Managers need to identify decision situations, develop and evaluate potential solutions, and make an informed choice for the best way forward.

Successfully using data in this process requires certain managerial characteristics and preparedness. New challenges and the extended requirements of big data demand a certain way of thinking and decision making from managers, as, for example, S. Shah et al. (2012) suggest. Not all senior managers showed the necessary aptitude for this thinking, which the study assessed by looking at the managers' ability to allocate and utilize relevant information for their decision-making process. Only 50% of surveyed senior managers had sufficient analytical skills, considered colleagues' perspectives, and found a balance between their own judgment and analytical output. This combination of analytics and judgment components was found to be connected to increased productivity and effectiveness (S. Shah, Horne, & Capellá, 2012).

But how can big data change decision making so significantly that managers require an advanced skill set to take advantage of it and stay competitive? Whereas big data can be seen as the next step in the evolution of data and analytics (Intezari & Gressel, 2017), what sets it apart is the rapid generation of new and unstructured data, as well as leaps in machine learning, which both offer new opportunities (Agarwal 2014). The difference between the more traditional structured and the newer semi-structured and unstructured data is defined by Russom (2011). Structured data can be found in spreadsheets and relational databases and can easily be captured and queried.

In contrast, forms of unstructured data, such as images, audio, video, etc., pose difficulties for analysis, due to their ill-defined nature. This unstructured data constitutes almost 95 percent of the currently available big data (Grover et al., 2018). In between structured and unstructured data exists semi-structured data, which is increasingly used for analytics (Russom, 2011). Semi-structured data is often simply unstructured data that has been enriched with metadata, which makes it searchable and organizable. Some examples of metadata are time and location tags for photos and emails. Semi-structured data itself still lacks structure, but these identifiable features support its analysis.

Decision making can profit from a combination of these newly acquired data sources with traditionally structured data, which together help compose a more thorough overall picture (McAfee & Brynjolfsson, 2012). According to McAfee and Brynjolfsson (2012), companies that rely on data-driven decision making exceed their competition by 5% in productivity and by 6% in profit. This creates a link between the use of big data and improved performance, emphasizing the benefits of big data for predictive analysis.

Due to the variety of these new data sources, big data also shows various applications for modern organizations. For example, big data and analytics have been shown to play a large role within organizations by providing timelier and more accurate information about factors such as product demand, integrated supply chain networks, operational processes, and improved collaboration with partnering organizations (Gunasekaran, Yusuf, Adeleye, & Papadopoulos, 2018). It also enables better inventory control, improved transportation, job scheduling, and quality control at the operational level. This is particularly achieved by an improved understanding of the customer experience, which facilitates the customization of recommendations, the identification and prediction of root causes for failures, the catalyst for quality and innovation, and the improvement of complaint management and operational procedures (Grover et al., 2018). Industries where opportunities for big data and analytics have been identified include manufacturing (Gunasekaran et al., 2018), farming (Wolfert, Ge, Verdouw, & Bogaardt, 2017), the public sector (Kim, Trimi, & Chung, 2014), and many more.

Big data and analytics, when applied successfully, have the ability to improve productivity, efficiency, and offer several valuable opportunities (Melé, 2010). Big data can enable organizations to automate various processes, and therefore minimize the required personal input from management (McAfee & Brynjolfsson, 2012). Here, the necessity of case-by-case judgment diminishes, and intuition and practical wisdom fade into the background (Bhidé, 2010). However, in their implementation of big data analytics, some organizations intentionally leave room for intuition, judgment and wisdom, since they see equally clear benefits in the use of expertise, experience and values (Jimenez, Araneta, & Tan, 2012). Intuition is thereby understood as an emotional and unconscious process, that involves rapidly formed holistic associations and experiences (Dane & Pratt, 2007; Khatri & Ng, 2000). Particularly experienced managers benefit from their knowledge, i.e. years of application and personalization of information (Alavi & Leidner, 2001), when making intuitive judgments.

Not all organizations have discovered the potential of big data analytics and therefore cannot yet realize its value opportunities. First-movers and creative analysts are gaining a competitive edge from utilizing big data, thus creating the need for all other businesses to follow suit (Davenport, 2006; Huber, 1990; McAfee & Brynjolfsson, 2012). But for big data to be successfully employed, several environmental components need to be put in place. Organizational culture is critical for this success (Diaz et al., 2018). Companies must also consider privacy and security (Raguseo, 2018). On top of this, big data initiatives also require employees that are different from conventional analysts (Davenport, 2014a). A growing number of organizations are expected to make use of big data, which raises the question if all of them will use it wisely.

Whereas certain research streams have encouraged organizations to compete on analytics and big data (Davenport, 2006; McAfee & Brynjolfsson, 2012), others call for more caution, and emphasize prudence and wisdom (Bhidé, 2010; Rooney, Mandeville, & Kastelle, 2013). But while the predictive power and precision of information systems may lead to an increasing trust in analytics, this reliance on abstract data and knowledge may lead to the neglect of judgment, experience and wisdom (Bhidé, 2010). So this begs the question: is there a middle ground? "Unfortunately, while many provocative ideas about the interplay between rational and intuitive decision making have been suggested, empirical research in this area, particularly in the field of management, remains insufficient" (Dane and Pratt, 2007, p.48). This research, therefore, aims at further exploring the interaction between human judgment and analytics in managerial decision making, a thread of exploration which is further discussed in the next section.

1.2. Research Problem and Research Questions

Current practitioner literature and academic research on big data and advanced analytics is primarily focused on the technological challenges, new analytics tools and capabilities, and the implementation and organizational effects of those advanced technologies (Sivarajah, Kamal, Irani, & Weerakkody, 2017; Wamba et al., 2017;

Wang, Kung, & Byrd, 2018). Most literature stops at the point of successful implementation or resumes at the point of evaluating the impact of big data technologies. Additionally, most research in this area is focused on high-level effects, such as big data's potential to improve firm performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Kung, Kung, Jones-Farmer, & Wang, 2015), and to significantly improve decision making (Wamba et al., 2017). However, the 'how' of these effects has not been addressed extensively, and the actual application of big data in the decision-making process has not been sufficiently explored.

Once organizations adopt big data technologies, managers are still not necessarily aware of how to access or use this new information, how they can balance it with their extant decision-making methods, and even if that information is trustworthy. Therefore, even though this topic seems to invite further exploration, research in this field is still lacking, possibly due to the novelty of big data and its rather recent application in organizations. Extant literature on data-driven decision making is limited to the context of traditional analytics, which mostly does not account for more complex applications of data. This literature tends to emphasize the advantages of analytics and mostly supports reliance on analytics over intuition or other human factors (Davenport, 2006, 2013; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013). Literature in favor of intuition, judgment and wisdom in decision making, on the other hand, is often of an exclusively theoretical and conceptual nature (Bhidé, 2010; Bonabeau, 2003; Melé, 2010), or based in the area of psychology (Gilhooly & Murphy, 2005; Kounios & Beeman, 2009; McCrea, 2010).

The research objective of this study is thus to address this gap in the extant literature and to explore management decision making in the age of big data. Its aim is to explore how and if managers are in fact using big data in their decision-making processes, and how they perceive its effects, which will lead to a holistic view of decision making in the age of big data. This study therefore ultimately set out to form a rich understanding of the actual use of big data in various organizations across different industries.

An important aspect in this context is whether managers can trust their own judgment in this new and unprecedented field of big data. Furthermore, factors that influence this decision-making approach also need to be addressed. As the relation between data-driven and judgment-based decision making is not sufficiently answered by current research efforts, this thesis addresses this gap via its two main research questions:

1. How do managers perceive the role of advanced analytics and big data in the decision-making process?
2. How do managers perceive the alignment of advanced analytics and big data with more traditional decision-making approaches such as human judgment?

The following section outlines the specific research design that was used to explore these research questions.

1.3. Research Design

This research followed a multi-step process, which is outlined Figure 1. As a first step, a comprehensive literature review was conducted in order to closely examine the field of big data and determine gaps in extant research efforts. This review provided an overview of the current definitions and understanding of big data and advanced analytics. The chapter also identified a shortcoming in the extant literature specifically regarding the application of big data analytics in managerial decision making. This led to a further exploration of decision-making theory, and consequently literature on human judgment and data use in managerial decision making. Lastly, as the extant literature highlighted various challenges managers encounter when employing big data, the literature review therefore identified several organizational prerequisites for successful big data programs.

The literature showed a strong focus on applications of big data and technological use cases, as well as challenges. Furthermore, the effects on organizational performance and competition were frequently emphasized. However, the literature lacked an exploration of ways to incorporate big data into the managerial decision-making process. This led to the formulation of the two research questions, on which this thesis focused: exploring decision makers' understanding of big data and advanced analytics, as well as their perception of incorporating it into their decision-making processes.

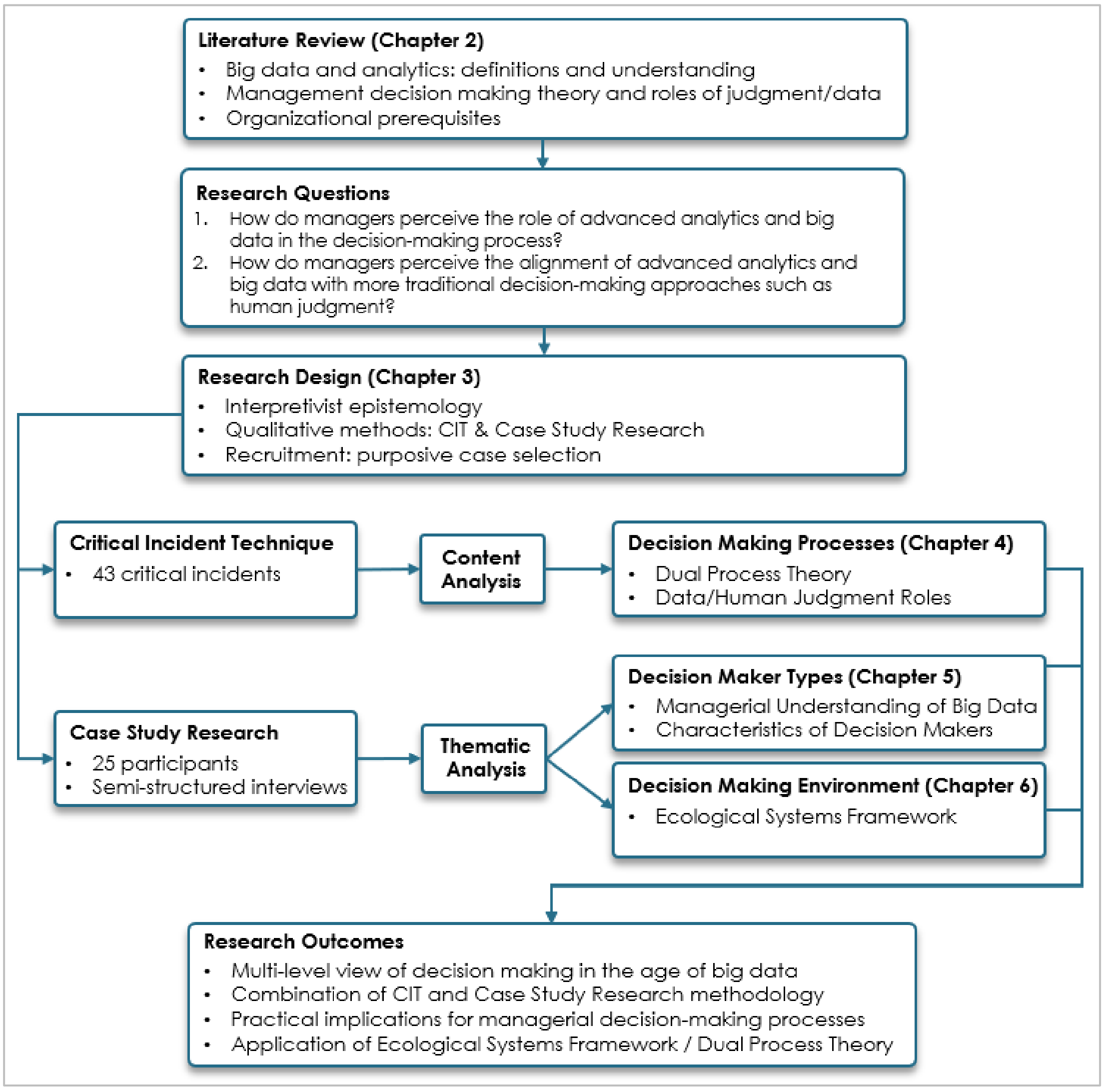

Figure 1. *Research Process*

These research questions informed the used methodology of this study and led to the next step of the research process, which is the research design. The nature of the questions demanded an interpretivist approach, as they explore the subjective assessment and experiences of managers regarding big data in decision making in their individual context (Creswell, 2012). A qualitative approach was then selected in order to collect the rich data that was required to reach the in-depth insights the research questions required (Carson, Gilmore, Perry, & Gronhaug, 2001). As decision making is at the core of this thesis, the used methodology was chosen for its ability to collect data about actual decision-making processes, as well as reflections on and general perceptions of the topic of data-driven decision making.

A combination of the Critical Incident Technique (CIT) (Flanagan, 1954) and case study research methodology (Yin, 2014) was ultimately chosen, as it promised rich and diverse insights. Both methodologies, case study research (Cavaye, 1996; Popovič, Hackney, Tassabehji, & Castelli, 2018; Walsham, 1995), and CIT (Coetzer, Redmond, & Sharafizad, 2012; Trönnberg & Hemlin, 2014), have previously been used for qualitative decision-making studies that focused on human judgment and/or analytics. Combining these two methods provided insights into actual decision-making processes and circumstances, and furthermore captured contextual factors such as personal characteristics and environmental factors.

Case studies of the main unit of analysis, i.e. the decision makers, were conducted using semi-structured interviews. The embedded unit of analysis in the cases were critical incidents describing memorable decisions based on (big) data. This combination enabled the capture of the managers' perceptions of the topic, but also their actions in actual decision-making situations. Twenty-five managers and business analysts were interviewed in total.

For the CIT portion of the interview, a rigorous set of questions was asked, which led to the managers' recollection of 43 usable incidents. The data collected with this methodology was primarily content analyzed, and later thematically analyzed in line with the case studies. The case study portion of the interview addressed general impressions around data-driven decision making, environmental influences, specific characteristics of the managers, and their reflection on past decisions. This provided rich context for the managers' decisions, and often highlighted contrasts between actual and ideal decision making. The case study piece of the interview was solely thematically analyzed.

A multi-level analysis approach was then employed to enable a full examination of individual decision making, including contextual factors (Andersson, Forsgren, & Holm, 2001; Kidwell, Mossholder, & Bennett, 1997). Abductive reasoning led to a spiral process of matching findings to theories that had been identified during the literature review, exploring new theories, and exploring propositions put forward in recent publications, which then led to a thorough and holistic multi-level picture of managerial decision making (Blaikie, 2007). While the original setup of the study mainly accounted for managerial decision-making processes, the findings soon showed the significance of differentiation between different manager types and their contexts. Abductive reasoning facilitated the emerging of these additional themes and layers.

Recruitment followed purposive case selection, which was based on replication logic, ensuring the cases had theoretical value (Miles, Huberman, & Saldana, 2014; Stake, 2006). Attention was therefore paid to diversity in respect to the organization's use of analytics, the organizational size and culture, the industry, and the manager's department, position, and experience. The participants of this study included heads of departments, (general) managers, C-level positions, but also analysts. All participants were involved in managerial decisions and provided various views on the issue. For the sake of simplification, the different types of participants were all nevertheless referred to as managers, as they were involved in managerial decision making, i.e. preparing the decision and recommendation, designing the process, etc.

The analysis efforts led to various insights, and several groups of themes were identified. Three findings and discussion chapters were then developed, which correspond to the multi-level analysis approach. Chapter 4 reports on the embedded unit of analysis findings. Dual process theory was applied to the different decision-making processes, covering the different types of decisions. The various roles of analytics and human judgment were identified and their importance for the different processes was determined. This chapter was mainly informed by the content analysis with minor inputs from the thematic analysis. Chapter 5 covers the main unit of analysis, the individual manager, with the findings exploring different types of managers and the influences of their characteristics on the decision-making processes they followed. The context was explored as the last level of analysis in Chapter 6, identifying environmental factors that significantly impact individual managers and their decision making. Chapters 5 and 6 were primarily informed by the thematic analysis, with minor insights gained from the content analysis.

The multi-level analysis approach led to several relevant research outcomes. These outcomes are further discussed in the next section.

1.4. Research Contributions

The study contributes to the extant literature by presenting a multi-level view of managerial decision making in the age of big data. This multi-level view led to several theoretical implications, as well as methodological and practical contributions.

Applying seminal decision-making process work (e.g. Mintzberg, Raisinghani, & Theoret, 1976; Simon, 1960) to the context of data-driven decision making to assess their validity in the age of big data led to the first of four key theoretical implications. Decision-making processes were found to still consist of three main stages: identification, development, and selection. Four main triggers for the identification of a decision situation could be differentiated, and analytics was found to be one of these four initiators of the decision-making process. The development stage was found to be extended by the additional insights of analytics, which allowed for a more thorough development and evaluation of alternatives. The selection stage particularly benefited from the use of data-driven decision making, as it allowed managers to objectively justify their choices to other stakeholders.

A second theoretical implication resulted from the use of the dual process theory (Bazerman & Moore, 2013; Dane & Pratt, 2007): The two-system view enabled a thorough identification and differentiation of the roles that analytics and human judgment take on in the decision-making process, in which stages, and to what extent. As a result of this thesis, the classic decision-making processes (e.g. Mintzberg et al., 1976; Simon, 1960) were extended to account for these different roles of data analytics and human judgment, furthering current understanding for the use of both.

The third theoretical implication is the expansion of extant decision categories (Ackoff, 1990; Snowden & Boone, 2007) by developing decision types that reflect decision-making processes in the age of big data. These three decision types, namely balanced, high-data, and high-judgment decisions are distinguished by the manager's extent of data and human judgment use. Furthermore, it was examined which decision situations would benefit of which decision type, providing insights on when data and judgment are most appropriate to use.

Going beyond the decision-making processes, Bronfenbrenner's ecological systems framework (1977, 1979) was used as a lens to evaluate the cases and to craft a managerial decision-making environment. This led to the fourth theoretical contribution by enabling the incorporation of the concept of analytics maturity, which had heretofore been criticized for a lack of theoretical footing (Lahrmann, Marx, Winter, & Wortmann, 2011). Further factors that were identified as part of this environment were: the individual managers themselves; their team-level influences such as the access to business analysts for support with data-driven decisions; organizational-level aspects such as the prevalent organizational decision-making culture, traditional or data-driven; and industry-level influences such as the access and exposure to data.

The methodology underlying this research contributes by offering a combination of CIT and case study research, which, to the researcher's knowledge, has never before been employed in such depth. The combination of both methodologies facilitated a data collection and analysis approach that allowed for the collection of rich, in-depth data that connected real-life experiences with general perceptions. The approach provided a contrast between managers' actual decisions and their views on general decision-making processes. This gave participants the opportunity to reflect on their own decision-making behavior.

Besides the opportunity for reflection, the study incurred several practical contributions, for one the upcoming textbook 'Management Decision-Making, Big Data and Analytics' by Gressel, Pauleen, and Taskin (2020) guiding managers on their journey to becoming apt decision makers in the age of big data. Furthermore, the definition of different decision-making processes in this thesis can assist managers in finding ways of balancing data and judgment use and adjusting the extent of this use, depending on decision-specific factors. Organizations on their journey to more data-driven decision making will also benefit from the findings of this research. The managerial decision-making environment highlights how organizational factors and other influences impact managers in their decision making. This can assist organizations in creating a beneficial environment for their employees. The component of analytics maturity can furthermore assist with understanding and reaching the next stages of the journey to data-driven decision making. Lastly, the differentiation of distinct types of managerial decision makers also identified their differing needs, which companies can now consider with more insight and care when transforming into a data-driven organization.

1.5. Thesis Outline

This study begins with an overview of the extant literature on big data and advanced analytics, which covers the evolution of data and analytics over recent years and highlights current understanding of the concepts. This is followed by an overview of the decision-making literature, which emphasizes the need for further exploration of analytics and judgment use and their contribution to the managerial decision-making process in the age of big data. The last part of the literature review presents organizational prerequisites that are expected to support managers in their data-driven decision making.

The next chapter (Chapter 3) provides an outline of the methodology of this study, beginning with the research rationale, which informed the actual research design. This design is a combination of CIT and case study research, which was aimed at thoroughly exploring the two research questions. This is followed by the data collection, which reports on the specifics of purposive case selection as well as the structure, questions, and piloting of the interviews. The chapter concludes with a section on coding the data and the multi-level thematic and content analyses that were employed.

Chapters 4 to 6 each contain the findings and discussions for one of the three levels of analysis, starting with Chapter 4 on the embedded unit of analysis. After outlining the data analysis for this chapter, the data-driven decision-making process steps are outlined, distinct roles of human judgment and data are differentiated, and the contrast between actual and ideal decision making is presented. The findings are then discussed in the context of extant literature. The findings and discussion on the main unit of analysis, the decision maker, are covered in Chapter 5. The managers' understanding of big data and analytics is addressed first, followed by a categorization of distinct types of managerial decision makers, highlighting their varying preferences, experiences, etc. The last findings and discussion chapter (Chapter 6) reports on the context of the case studies as a function of the managerial decision-making environment, a concept that was created using the ecological systems framework as a lens. These external factors contain team-, organization-, and industry-level influences, as well as the component of analytics maturity.

The study is rounded off with a conclusion chapter (Chapter 7) that highlights theoretical implications, as well as methodological and practical contributions. The limitations of this research are also discussed, and lead to suggestions for future research. A list of references and appendices is provided after the study's conclusion.

CHAPTER 2: LITERATURE REVIEW

This literature review serves the purpose of providing a broad background in terms of the context of this study and introduces theoretical concepts from which the study then draws. First, the historical background of data management and analytics is reviewed to highlight big data's evolution and distinctiveness. Since this is a management information systems study, the topic of analytics and its adjacent concepts are covered first, given that all following areas and topics refer to these concepts. Second is a discussion of a body of literature on decision making. This includes the principles of the dual systems theory, exploring further the concepts of human judgment as well as the role of information systems (IS) in the managerial decision-making process. Third, the prerequisites of managerial decision making with analytics are explored, including managerial, as well as organizational, industrial, and technological challenges.

2.1. (Advanced) Analytics and Big Data

Advanced analytics as well as big data (analytics) are often perceived and marketed as a new phenomenon, disregarding the fact that these concepts are built upon and affiliated to established technologies such as data warehouses and database management systems (DBMS) (Bumblauskas et al., 2017; H. Chen, Chiang, & Storey, 2012; Intezari & Gressel, 2017; Watson & Marjanovic, 2013). In fact, early forms of data management and analytics, which facilitated the storing and processing of data, have been used since the 1950s to support decisions and business processes (Bumblauskas et al., 2017; Davenport, 2013; Petter, DeLone, & McLean, 2012).

Going back even further in time, Bumblauskas et al. (2017) refer to Taylor's scientific management techniques in the early 1900s as the initial catalyst for storing and analyzing data, albeit to a limited degree, methods being constrained by the technological capabilities of that time. From the 1930s, digital computers were introduced and eventually led to the data processing era, in which managers of financial and military institutions relied on information systems to complete subtasks and automate processes in the 1950s to 1960s (Bumblauskas et al., 2017; Petter et al., 2012). The increasing use of information systems from the 1960s to 1980s enabled managers to use data for routine decision making in the management reporting and decision support era (Petter et al., 2012; Watson & Marjanovic, 2013). Managers, however, struggled with the vast quantities of collected data and the resulting information overload (Bumblauskas et al., 2017; Petter et al., 2012), which prompted many to adapt their processes and develop new decision tools and techniques. The challenges of information overload and the need to adapt the ways of decision making in this era are often echoed in big data literature (Davenport, 2013; Niesen, Houy, Fettke, & Loos, 2016; Prescott, 2016; S. Shah et al., 2012; Watson, 2016).

In the 1980s and 1990s, organizations recognized the value of IS use also for their strategic goals, which led to a further increase in the use of IS and to the development of more user-friendly interfaces in the strategic and personal computing era (Petter et al., 2012). The challenge of improving user interfaces, and hereby addressing information overload concerns, is also reflected in big data literature on visual tools for improved management decision making (LaValle et al., 2011; Miller & Mork, 2013; Moore, 2017).

At the beginning of the 1990s, the dawn of the enterprise system and networking era, enterprise resource planning (ERP) systems made data available across organizations, leading to data sharing between managers and applications, and furthermore enabling group decision support systems (Bumblauskas et al., 2017; Petter et al., 2012). In the mid-1990s, the internet allowed the capabilities of information sharing to expand beyond organizational borders, and made information accessible instantaneously across the world (Bumblauskas et al., 2017). This also marked the beginning of the customer-focused era (2000 and beyond), as organizations began collecting IP-specific information about their customers through cookies and server logs, which enabled a customized experience for individuals (Bumblauskas et al., 2017; H. Chen et al., 2012). Pioneering efforts of such sophisticated IS include, for example, Amazon's recommendation engine, as well as Google's search algorithm (Petter et al., 2012).

As can be seen from this brief history, the difficulties encountered by organizations and managers throughout the early years of 20th century data gathering are to some extent comparable to the ones that organizations are now facing with big data: "Seen in the context of earlier information systems and types of data, big data is just a further step in the evolution of data and their applications" (Intezari & Gressel, 2017, p. 74). Big data can be seen as an extension of traditional data, and big data solutions as an extension of traditional data warehouses and analytics, not as an "either/or" decision that companies have to make (Watson & Marjanovic, 2013). Organizations, therefore, are given a wide spectrum of sophisticated analytics techniques and tools to choose from, many of which are rooted in the field of data management (H. Chen et al., 2012).

To further develop an understanding of how managers can best employ these tools for decision making, this section looks at the importance of converting mere data into knowledge for decision making; compares categorizations of analytics capabilities; explores a working definition of big data and advanced analytics; and finally, presents the most common challenges and opportunities that managers face when working with big data.

2.1.1. Data, Information, Knowledge, and Wisdom: The DIKW Pyramid

The evolution of big data provides managers with a significant increase in available data. However, raw data alone, regardless of volume, cannot assist in improving managerial decision making. In order to gain insights from it, the data must be processed and put into a form that is useful for users in a timely manner (Bumblauskas et al., 2017). It is therefore required that the sophistication of analytics tools improves alongside the evolution of data to better allow managers the possibility of gaining information, knowledge and wisdom from vast amounts of data. Big data analytics is in turn expected to improve managerial decision making (Bumblauskas et al., 2017; Wamba et al., 2017).

The distinction between these key terms, namely data, information, knowledge, and wisdom, is vital to understanding the key role analytics tools play in managerial decision making (Bumblauskas et al., 2017). This particular order of the terms is often graphically represented in the form of the DIKW pyramid, which can be seen in Figure 2. This depiction suggests that there is an upward movement, starting out from the broad base of data, which gets transformed into information, then knowledge, and is finally synthesized into wisdom through understanding (Ackoff, 1989).

Data is seen as “a set of discrete, objective facts about events” (Davenport & Prusak, 1998, p. 2), and is therefore simply a “unprocessed raw representation[s] of reality” (Faucher, Everett, & Lawson, 2008, p. 6). Information is then perceived as data that has been processed to be useful and meaningful for the receiver of the information (Ackoff, 1989; Davenport & Prusak, 1998). Knowledge is the application and personalization of that information, possessed by individuals (Alavi & Leidner, 2001). "Wisdom," at the top of the pyramid, "is the critical ability to use knowledge in a constructive way. Equally, wisdom has in it the critical ability to discern ways in which new ideas can be created" (Matthews, 1997, p. 209).

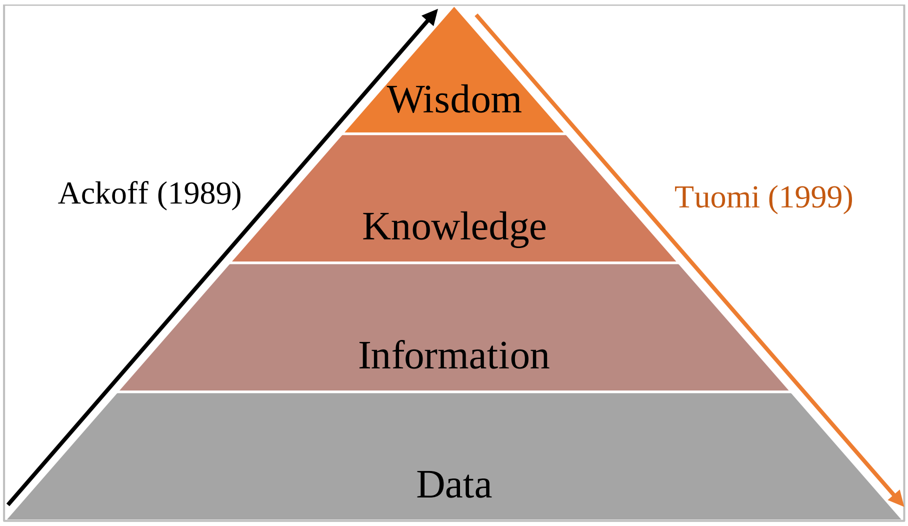

Figure 2. *DIKW Pyramid*

The DIKW pyramid is not without its critics. In a contrasting view of the pyramid presented by Tuomi (1999), the sharing of a knowledge base is also crucial for an individual to arrive at the same conclusions from stored data or information as others. It is also argued that the pyramid is indeed inverse, and that no data can be classified as raw, since knowledge is required for the data identification and collection (Tuomi, 1999). While Ackoff (1989) theorized that an organization will only gain wisdom from big data when knowledge can be created, accessed and applied, Tuomi's reversed framework (1999) concludes that wisdom and knowledge are absolute prerequisites for the collection and exploitation of big data.

Other researchers have chosen to adapt the idea of the DIKW pyramid, often omitting the concept of wisdom. Moore (2017) focuses on the first three levels–data, information and knowledge–of the pyramid in her study, incorporating them as steps in a data-driven decision-making process. This process begins with the gathering of data, then the inferring of meaning by setting the data into a context, therefore receiving information. Knowledge is eventually created by synthesizing or combining information, which might involve experience-based judgment calls, for example.

In their highly-cited book, ‘Working Knowledge: How Organizations Manage What They Know’, Davenport and Prusak (1998) also limit themselves to the three base levels of the pyramid, reasoning that the distinction between those three concepts is already sufficiently difficult for organizations and that for their purposes, the concept of wisdom is incorporated into knowledge. Building on Davenport and Prusak (1998), Bumblauskas et al. (2017) add the additional level ‘actionable knowledge’ to the pyramid after knowledge: “… decision makers must be able to derive meaning from data or information driving decision-making that can translate into specific action and communication to others” (Bumblauskas et al., 2017, p. 12f.). This actionable knowledge is theorized required for making effective and timely decisions in the age of big data. Prescott (2016) also focuses on the first three levels of the pyramid when incorporating them into a framework known as the ‘knowledge staircase’, which refers to the process of developing employee competencies.

The different applications of the DIK(W) pyramid show that the distinction of data, information, and knowledge is significant and widely spread across different research areas. Research on big data and advanced analytics particularly benefits from a clear understanding of those myriad concepts. Big data will only deliver insights and create value if there is a process in place to tailor it to the user so it can eventually be turned into knowledge and wisdom. Information technology can assist with the transformation from data into information (Davenport & Prusak, 1998).

2.1.2. Evolution of Data and Analytics

Whereas small amounts of data could be grasped without the help of sophisticated tools, the variety and amount of data that managers have available nowadays requires advanced tools to gain insights. The following section presents three key frameworks classifying the evolution and capabilities of analytics, which are additionally summarized in Table 1. Comprehending the evolution of big data and advanced analytics from its origin in early data management generations fosters a deeper understanding of the status quo (Watson & Marjanovic, 2013). Furthermore, these frameworks provide an overview of the applications and tools managers currently have available for their decision making.

Chen et al. (2012) is the most widely cited framework incorporating BI and analytics capabilities. According to the IT research and advisory firm Gartner, "business intelligence (BI) is an umbrella term that includes the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance" (Business Intelligence, n.d.). Since 1990, BI has evolved from a mere IT resource into "an organizational capability of strategic importance" (Lahrmann et al., 2011, p. 1). Data analytics is generally understood as the use of hardware and software to extract meaning and patterns from data. Gartner defines it as a "catch-all term for a variety of different business intelligence (BI)- and application-related initiatives […] Increasingly, "analytics" is used to describe statistical and mathematical data analysis that clusters, segments, scores and predicts what scenarios are most likely to happen" (Analytics, n.d.). In the three evolutionary steps that Chen et al. (2012) differentiate, BI&A is used as a unified term.

The first step, BI&A 1.0, has its foundation in warehousing and data management, the collected data being mostly structured and stored in relational database management systems (RDBMS) (H. Chen et al., 2012). Managers commonly rely on database queries and reporting tools. Graphics and visualizations are used for exploration and performance metrics. Furthermore, predictive modeling, data segmentation and clustering, and regression analyses are well adopted options in BI&A 1.0. In BI&A 2.0, the collected data is web-based and unstructured. The use of data shifts from mere business reporting functions to the analysis of customer online behavior, optimization of web presences and product recommendations. Organizations can gain a better understanding of their customers' needs when tracking their online activities by using cookies, IP addresses, and server logs. Text and web mining techniques are also applied to unstructured, user-generated content from social networking and multimedia sites, which eventually must be integrated with organizations' RDBMS. In BI&A 3.0, mobile and internet/sensor-enabled devices enable operations and transactions that are targeted toward individuals and are adapted to a specific context or location. The techniques for capturing and analyzing mobile and sensor data are still in a developmental stage (H. Chen et al., 2012; Mazzei & Noble, 2017) with early adopters enjoying first gains (H.-M. Chen, Schütz, Kazman, & Matthes, 2017).

Davenport (2013) depicts the evolution of big data with a focus on analytics. The framework suggests that there are three eras of analytics, each era being characterized by "new priorities and technical possibilities" (Davenport, 2013, p. 65). Analytics 1.0 is established as the first era of analytics, the era of BI. The era is marked by the discovery of the use of data for business applications, as well as the utilization of data on customers and production primarily to optimize and support decision making. Analytics is limited to descriptive capabilities, and the process of collection and analysis is time-consuming. It is the era of data warehousing and business intelligence software, which focuses on queries and reporting. This depiction concurs with Chen et al.'s (2012) first evolutionary step, BI&A 1.0.

Davenport's Analytics 2.0 is the era of big data, with external data now being available from the internet, sensors, audio and video (Davenport, 2013). To analyze these additional data sources, new tools are required such as Hadoop, which is an open source software that allows faster data processing using parallel servers. DBMS cannot manage the amount and unstructured nature of the data, so companies explore NOSQL options. However, these new possibilities are limited to industry innovators, i.e. organizations that are internet-based or in the social networking business. Analytics 2.0 widely coincides with BI&A 2.0, but also incorporates the competencies of BI&A 3.0 as depicted by Chen et al. (2012). According to Davenport (2013), the final era is Analytics 3.0: the era of data-enriched offerings. This era marks the transition from big data being used mainly by Silicon Valley "information firms and online companies" to it being employed by virtually all industries and companies ranging from start-ups to multinational conglomerates (Davenport, 2013, p. 67).

Watson and Marjanovic (2013) focus on the grounding of big data in the field of data management. They depict big data as the fourth generation of data management, therefore also rooting big data in the database management field, in concurrence with Chen et al. (2012) and Davenport (2013). However, Watson and Marjanovic (2013) add more distinctions in the pre-big data era: Decision Support Systems (DSS), which are not specifically addressed in the prior two frameworks, are introduced as the first generation of their framework. This generation is characterized by a single decision maker relying on a DSS that is populated by only one or a small number of internal, structured data sources; its use was additionally limited to strategic and tactical decisions.

The following generation of enterprise data warehouses (EDW) is led by an increase in reporting needs, which results in a larger number of systems providing data, leading to increased use that extends beyond organizational boundaries. Real-time data warehousing is considered the third generation. Again, mostly structured data is being captured in real time, enabling managers to extend their use of data to operational decision making as well, leading to another increase in users. This distinction between the second and third generation is not made by the prior frameworks. Each combine them into one evolutionary step, namely Analytics 1.0 and BI&A 1.0 (H. Chen et al., 2012; Davenport, 2013).

Lastly, the current big data generation offers new data sources that exceed the capabilities of RDBMS because of big data's key characteristics of volume, variety, and velocity (Watson & Marjanovic, 2013). New technologies enable the use of big data to create more context for improved decision making, particularly when combined with traditional data. In this last framework, mobile and sensor data are not specifically addressed.

Table 1. *Evolution of Data and Analytics*

Evolutionary Step	Chen et al., 2012	Davenport, 2013	Watson & Marjanovic, 2013
DSS			*First Generation (of Data Management): The DSS* - a single decision maker using data and analytical aids to support decision making. Data sources are single or just a few operational systems.
EDW	*BI&A 1.0* - Data is mostly structured, collected by various legacy systems in RDBMS. Data is mostly used for business reporting functions, statistical analyses and data mining.	*Analytics 1.0: era of business intelligence* - the era of the enterprise data warehouse. Data is prepared, stored, queried and reported. Analyses are time-consuming. No explanations or predictions are offered.	*Second Generation: EDW* - data-focused approach to data management. Data is structured and updated in batch mode from several systems.
DBMS and data ware-housing			*Third Generation: Real-Time Data Warehousing* - Operational decisions and processes are supported by real-time data. Data volume is increased, but data is still mostly structured.
Big Data for first movers		*Analytics 2.0: era of big data* - mostly used by internet-based firms, changing the role of data and analytics. Use of internal, external and unstructured data. Rise of Hadoop, NoSQL and cloud computing.	
Big Data for all organizations	*BI&A 2.0* - Data is web-based and unstructured. Data is used to analyze customer online behavior, optimize web presences and product recommendations. User-generated content provides feedback and opinions.	*Analytics 3.0: era of data-enriched offerings* - other large organizations from various industries follow the trends of Analytics 2.0.	*Big Data Generation* - new ways of using data, such as deeper understanding, better predictions, or greater context. Relatively new data sources are utilized.
Mobile & Sensor Data	*BI&A 3.0* - Data is mobile and sensor-based. Data supports highly mobile, location-aware, person-centered, and context-relevant operations and transactions.		

The stages of these frameworks differ in terms of both emphasis and detail: while Davenport (2013) focuses solely on analytics capabilities, Chen et al. (2012) combine analytics and BI developments, and Watson and Marjanovic (2014) emphasize big data's data management roots. Nonetheless, the general tendencies and overall developments correspond in all three frameworks, showing a gradual evolution of big data and advanced analytics. The most recent and evolved stage is presented as a wide range of organizations utilizing big data for various purposes, incorporating unstructured and diverse data sources into their decision making (H. Chen et al., 2012; Davenport, 2013; Watson & Marjanovic, 2013).

2.1.3. Definition of Big Data and Advanced Analytics

The age of big data and advanced analytics offers new opportunities for managerial decision making, but also entails diverse challenges because of its technological novelty and managers' inexperience in this new area. Especially regarding the term big data, not all practitioners are consistently informed. Particularly when it comes to management, knowledge gaps can be identified (Davenport, 2013; Gandomi & Haider, 2015; Wang et al., 2018; Watson & Marjanovic, 2013). This leads to a misunderstanding of big data's opportunities, limitations and challenges (Davenport, 2014a). To comprehend all aspects of big data decision making, it is essential not only to understand the evolution of big data and advanced analytics, but also what is currently understood about these terms. Since both topics are relatively new to industry and academia, a consensus has not yet been reached. Therefore, the following section explores the respective current literature and derives a working definition for this thesis.

First used in a publication on the visualization of large datasets by Cox and Ellsworth in 1997, the term 'big data' has since been increasingly explored and shaped. In 2001, big data received a characterization distinguishing it from traditional data. Gartner's Doug Laney established three defining dimensions which are now commonly known as the "3 V's" (Laney, 2001): *volume*, *velocity*, and *variety* (McAfee & Brynjolfsson, 2012; O'Leary, 2013; Wang et al., 2018; Watson & Marjanovic, 2013). Since then, a fourth and fifth dimension have been added by several sources: *veracity* (Abbasi, Sarker, & Chiang, 2016; Jagadish et al., 2014; Sathi, 2012; Sivarajah et al., 2017), and *value* (Bumblauskas et al., 2017; Colombo & Ferrari, 2015; Mishra et al., 2017; Wamba et al., 2017). An overview of these dimensions can be seen in Table 2.

Table 2. *Big Data Dimensions*

Dimension	Description	References
Volume	Datasets exceed the capacity of DBMS and traditional analytics tools.	McAfee & Brynjolfsson, 2012; O'Leary, 2013; Sivarajah et al., 2017; Wamba et al., 2017; Wang et al., 2018; Watson & Marjanovic, 2013
Velocity	Data is processed in (near) real-time. Data collection, analysis, and interpretation are continuous processes.	McAfee & Brynjolfsson, 2012; O'Leary, 2013; Sivarajah et al., 2017; Wamba et al., 2017; Wang et al., 2018; Watson & Marjanovic, 2013
Variety	Diverse data sources – often unstructured – from social media, sensors, audio or video files pose problems for the data analysis.	McAfee & Brynjolfsson, 2012; O'Leary, 2013; Sivarajah et al., 2017; Wamba et al., 2017; Wang et al., 2018; Watson & Marjanovic, 2013
Veracity	Data sources must be credible and suitable for the organization to provide reliable results.	Abbasi, Sarker, & Chiang, 2016; Jagadish et al., 2014; Sathi, 2012; Sivarajah et al., 2017; Wamba et al., 2017
Value	Economic benefits are derived from the use of big data.	Bumblauskas et al., 2017; Colombo & Ferrari, 2015; Mishra et al., 2017; Wamba et al., 2017

The *volume* of big data far exceeds the size of traditional datasets, creating challenges for DBMS and data warehouses (Kaisler et al., 2013; Katal, Wazid, & Goudar, 2013; Provost & Fawcett, 2013; Sivarajah et al., 2017; Wang et al., 2018; Watson & Marjanovic, 2013). However, the volume of data that determines what qualifies as big data is hard to pinpoint to a specific number, generally ranging from terabytes to petabytes or even exabytes (Abbasi et al., 2016; Mishra et al., 2017). This results from the continuous growth of data that is produced every second over the internet, sensors, customer transactions, and so forth (McAfee & Brynjolfsson, 2012; Phillips-Wren, Iyer, Kulkarni, & Ariyachandra, 2015; Pospiech & Felden, 2016; Watson & Marjanovic, 2013).

Furthermore, the technological capabilities are increasing, offering more data storage capacity to companies for lower costs and enabling them to store increasing amounts of customer and production data. The growing market of cloud computing (Gantz & Reinsel, 2012), for example, offers organizations of all sizes tailored solutions and capacities for their data storage (H. Chen et al., 2012; Delen & Demirkan, 2013). Organizations pay for the used capacity, and in exchange are provided with rapid elasticity and ubiquitous network access. A further aspect of cloud computing is the possibility of analytics-as-a-service. Users do not only have the ability to access their data and information from remote devices, but can also use the necessary analytic tools on demand (Delen & Demirkan, 2013; Hazen, Boone, Ezell, & Jones-Farmer, 2014). This service assists especially with attaining the other two components of big data, namely velocity and variety.

The *velocity* of big data is characterized by the speed of data generation (Phillips-Wren et al., 2015; Wang et al., 2018). Regarding velocity, a dataset can only be classified as big data if the data is processed in (near) real-time (Hazen et al., 2014; McAfee & Brynjolfsson, 2012). Data is not analyzed in hindsight, but in ‘continuous flows and processes’ (Davenport et al., 2013, p. 23), providing and demanding more flexibility and faster actions (Abbasi et al., 2016; Mishra et al., 2017). The velocity of data is especially crucial for decision making, since certain decisions can influence data that is simultaneously being gathered and analyzed. Changes and alterations that result from decision making therefore have to be immediately implemented and updated in the ongoing data stream (Bumblauskas et al., 2017; O'Leary, 2013). The speed of data creation is at the heart of the expansion of big data and advanced analytics. However, techniques that enable the analysis of this vast stream of data remain underutilized in organizations (Bumblauskas et al., 2017; H. Chen et al., 2012).

The *variety* dimension of big data can be seen in the different forms of internal and external data sources and various kinds of information that are stored (Davenport, 2013; Hazen et al., 2014; McAfee & Brynjolfsson, 2012; Phillips-Wren et al., 2015; Pospiech & Felden, 2016; Wang et al., 2018). Data is no longer limited to structured, numerical data, which is typically displayed in spreadsheets and merely represents 5% of all available data (Mishra et al., 2017). The variety of big data allows unstructured forms of data to be collected from social networks, texts, audio or video files, sensor data, GPS signals, click-streams and so on (Abbasi et al., 2016; Mishra et al., 2017; O'Leary, 2013; Phillips-Wren et al., 2015). This variety of data offers a new spectrum of possibilities, as well as challenges that exceed the capabilities of traditional DBMS (McAfee & Brynjolfsson, 2012).

An often used extension of these original 3 Vs can be found represented in the dimension *veracity*, a descriptor often suggested in more recent literature (Abbasi et al., 2016; Jagadish et al., 2014; Sathi, 2012; Sivarajah et al., 2017; Wamba et al., 2017). Veracity reflects how credible a data source is and how well the data suits the organization's audience. In order to benefit from decision making and analytics in general, the data sources have to be credible enough to ensure data fidelity, truthfulness, correctness and accuracy (Phillips-Wren et al., 2015; Sathi, 2012). Veracity is therefore a useful data quality measure for the varying reliability of big data sources, which are often affected by spam, noise, and biases (Abbasi et al., 2016; Mishra et al., 2017; Phillips-Wren et al., 2015; Sivarajah et al., 2017). The first step to ensuring veracity is "creating an inventory of available data sources and the metadata that describes the quality of those sources in terms of completeness, validity, consistency, timeliness, and accuracy" (Miller & Mork, 2013, p. 57).

Value refers to economic benefits that result from the use of big data, and is considered by some sources as its fifth dimension (Bumblauskas et al., 2017; Colombo & Ferrari, 2015; Mishra et al., 2017; Wamba et al., 2017). It is a concept that originates from practitioner reports on big data by Oracle and market research firm Forrester. It reflects the necessity to identify value-adding sources of information that are meaningful (Dijcks, 2012; Gogia et al., 2012).

This thesis refers to big data using a definition based on the original 3 Vs, as this characterization is the most common denominator in academic and practitioner literature. Veracity, rather, is considered an inherent challenge for organizations that results from the other three dimensions. Value is also not considered a dimension, but the general aim of utilizing big data. In the context of this thesis, big data is defined as a vast amount of structured and unstructured data from various sources that are constantly generated and processed.

For big data to be converted into information and eventually knowledge, advanced analytics tools that are capable of handling the 3 Vs of big data must be applied (Intezari & Gressel, 2017). Advanced analytics, in contrast to traditional analytics, can be considered a collection of sophisticated tools that primarily serve the discovery and exploration of large and detailed datasets (Russom, 2011). Therefore, advanced analytics is frequently applied in the context of big data: “We define advanced analytics to be the application of multiple analytic methods that address the diversity of big data – structured or unstructured – to provide estimative results and to yield actionable descriptive, predictive and prescriptive results” (Kaisler et al., 2013, p. 729). Tools and techniques that are considered part of advanced analytics are, for example, complex SQL queries, data mining and statistical analysis, as well as data visualization (Russom, 2011).

While equipped for big data sets, these techniques can also be employed for the exploration of traditional datasets, as Bose (2009) defines advanced analytics as “a general term which simply means applying various advanced analytic techniques to data to answer questions or solve problems” (p.156). Managers mainly employ them for predictive and prescriptive purposes to predict and optimize outcomes (Barton, 2012; Gartner, 2014), but the techniques can also benefit descriptive analytics. These three types of analytics, namely descriptive, predictive, and prescriptive, are characterized by their purpose and utilized tools, as described below.

Descriptive analytics serves the purpose of determining well-defined past and present opportunities or potential problems (Delen & Demirkan, 2013; Sivarajah et al., 2017). The information gained from business reporting tools such as scorecards and data warehousing enables organizations to alter or adapt their future behaviors (Davenport, 2013; Delen & Demirkan, 2013). Big data can be advantageous in the provision of more extensive and real-time data, offering further insight into business situations and customers (LaValle et al., 2011; Watson & Marjanovic, 2013).

Predictive analytics enables managers to make more prudent and forward-looking decisions, since the constructed models are designed to predict future conditions (Davenport, 2013; Shmueli & Koppius, 2011; Sivarajah et al., 2017). Predictive analytics utilizes qualitative and quantitative techniques to go beyond the prediction of the future and analyze various scenarios, such as how past observations would have been altered if the given conditions had been different (Waller & Fawcett, 2013). "Predictive analytics uses data and mathematical techniques to discover explanatory and predictive patterns […] representing the inherent relationships between data inputs and outputs" (Delen & Demirkan, 2013, p. 361). Big data offers increased accuracy for predictions, benefiting various business scenarios from different industries. McAfee et al. (2012) look at an airline case that improved its prediction of arrival times of airplanes at the airport by using various data sources beyond the pilots reporting. Using additional sensor, weather and flight schedule data led to a more rigorous predictive model and therefore improved the airline's decision making (McAfee & Brynjolfsson, 2012).

Prescriptive analytics provides the decision maker with sufficient information about optimal behaviors to clearly determine the best course of action (Davenport, 2013; Delen & Demirkan, 2013). This form of analytics is widely based on optimization and randomized testing (Sivarajah et al., 2017). When analytics is embedded into operational processes, the input of big data will automatically evoke a result, change or decision, and therefore increase the efficiency of day-to-day business activities (Davenport, 2013; Provost & Fawcett, 2013). Empirical evidence from a study on optimized allocation of an organization's sales force suggests that revenue can be increased marginally if prescriptive analytics are embedded (Kawas, Squillante, Subramanian, & Varshney, 2013).

This thesis assumes the term advanced analytics to mean a set of advanced tools and techniques that is applied to several or vast data sets, and therefore exceeds the use and outcome of traditional analytics.

2.1.4. A Critical Look at Big Data: Opportunities and Challenges

The rapid generation of vast and often unstructured amounts of data presents new opportunities for organizations. However, the use of big data is tied to several challenges that organizations need to overcome, as well as to certain controversies among customers, practitioners and academics surrounding legal and privacy aspects. This section provides a concise overview of the inherent opportunities of big data, which appeal to organizations because of their potential to create value. Some of the key challenges of big data are also discussed in a concise manner to point out the key areas to consider when organizations are planning to implement big data technologies. Factors regarding the organizational prerequisites for optimized big data implementation and use are discussed further in section 2.3.

2.1.4.1. Opportunities and Use Cases

With big data gaining traction, first-movers were expected to gain a significant advantage from using big data (Davenport, 2013). This accelerated the development and availability of a wide range of applications. By now, value added from big data is visible in various industries and business areas such as finance, marketing and sales, production and manufacturing, as well as supply chain and logistics (Kaisler et al., 2013; Manyika et al., 2011; Mishra et al., 2017; Watson & Marjanovic, 2013). Research of various disciplines, for example health care, also benefits from the extended possibilities of big data (Agarwal & Dhar, 2014; Mishra et al., 2017). With the medical field gaining access to a large amount of patient information, big data increases the potential to research diseases such as Alzheimer's or diabetes, while taking geographical information, habits and other influencing factors into consideration (Agarwal & Dhar, 2014).

One of the reasons for those opportunities is the increase in transparency, a movement away from closed-off and siloed databases. Within organizations, this transparency is created through the integration of multiple systems and data from multiple departments–sometimes even with input from external companies. The result are openly available datasets that assist with functional and business analysis (Brown, Chui, & Manyika, 2011; Kaisler et al., 2013; Motamarri, Akter, & Yanamandram, 2017). However, the accessibility of information across sectors cannot only be considered an opportunity for organizations: "It can threaten companies that have relied on proprietary data as a competitive asset" (Brown et al., 2011, par.11). Brown et al. (2011) refer to the real estate industry as an example of this, because it relies on asymmetry of information availability between buyers and sellers. The transparency of this information allows a bypassing of real estate agents, therefore challenging their ability to create profit.

Another reason for big data opportunities lies in the variety of data sources, specifically in the availability of sensor data. The areas of production, manufacturing and maintenance particularly benefit from employing sensors, as can be seen in computer-assisted innovation enabled by embedded product sensors (Kaisler et al., 2013). Big data can, for example, assist in predicting the failure of machine parts, offering the opportunity to exchange these parts before actual damage or production delays happen (Watson & Marjanovic, 2013). One of the companies taking advantage of this opportunity is Etihad. By equipping its airplanes with hundreds of sensors, Etihad is able to collect a significant amount of digital data about its fleet, which can then be analyzed and applied for predictive maintenance (Alharthi, Krotov, & Bowman, 2017). This generates substantial savings for the company by preempting problems and storing location information on their fleet in real time. A similar use case is Tesco PLC, which saves on energy costs by analyzing 70 million data points from their refrigerator units to closely monitor performance and predict maintenance, as well as servicing needs (Laskowski, 2013).

Besides the use for manufacturing and production, sensor data also unlocks a new layer of understanding for customers. This gives rise to additional marketing and sales opportunities, such as experimental analysis testing approaches and decisions, as well as improved market segmentation and sentiment analyses (Kaisler et al., 2013; Watson & Marjanovic, 2013). A sophisticated example is Disney parks' MagicBands, which are bracelets with integrated radio-frequency identification (RFID) sensors (Alharthi et al., 2017). The bracelets function as entry passes to the park and offer the benefit of pre-booking and line-cutting to the visitors. Most importantly for the company, the RFID chips allow Disney to collect digital information on the bracelet wearers' movements and interactions with the park. The analysis of this data provides Disney with insights into customer behavior, enabling them to improve customer experience by relying on data about waiting times, purchasing history and customer preferences. In addition to the revenue gains realized by the targeted marketing opportunities and improved customer experience, operational efficiency is also improved (Kuang, 2015).

The pre-booking feature, for example, allows for increased crowd control and optimized staffing at rides and restaurants.

2.1.4.2. Challenges and Considerations

While this synopsis of different use cases and opportunities demonstrates big data's potential and appeal, organizations are also confronted with a range of challenges that must be considered before and while employing big data solutions. One of the main obstacles recognized in big data literature are the technological challenges, such as handling the complexity of the data, as well as providing the right infrastructure. The complexity results from the rapid rate of data growth, as well as the multiple sources and formats of the data, which increase the challenge of analyzing it (Alharthi et al., 2017). Data from these different sources needs to be acquired, recorded, integrated, cleaned and reduced down to meaningful information (Lodha, Jain, & Kurup, 2014).

In terms of underlying infrastructure, organizations need to invest in new technologies that exceed the capabilities of traditionally used software and hardware (Alharthi et al., 2017). The real-time analysis of vast amounts of records requires extended capabilities and is essential for organizations to gain up-to-date insights. While the data can be stored in database systems, its analysis requires the use of analytics packages for statistical analyses and data mining (Lodha et al., 2014). A strong infrastructure requires coordination between the DBMS and analytics packages.

Organizations' investments in new technology to explore big data have been immense for years (Goepfert & Shirer, 2019; Ross, Beath, & Quaadgras, 2013). Many, however, do not see the expected results. This is because what the data is telling them is not always easily transferred into action and often requires major changes in the organization and its processes. As Ross et al. (2013) point out, a lot of companies struggle with the information they already have for reasons of poor information management, lack of analysis skills and failure to act on insights. Advanced technology such as big data is therefore not necessarily the right solution for all organizations. Some businesses might benefit from traditional options that are often falsely considered as inferior (Huber, 1990).

Corporate culture is an important aspect to consider in this context. As research shows large, data driven and competitive corporations are in a better position to benefit from the increase in analytical competencies (Davenport, 2006; Huber, 1990; McAfee & Brynjolfsson, 2012). In this type of environment, analytical and technical reports are often used as key justifications in the decision-making process (McAfee & Brynjolfsson, 2012; Nicolas, 2004).

For the adoption of big data technologies, Human Resources (HR) concerns must be considered as well. A major challenge that organizations face is the lack of analytics skills in existing employees, as well as a shortage of specialized analytics talent, such as data scientists, on the market (Alharthi et al., 2017; H.-M. Chen et al., 2017). In order to plan ahead accordingly, Watson and Marjanovic (2013) suggest a skills assessment of current employees to address existing gaps with training or external hires. Otherwise, a “lack of data analytics skills among existing employees may increase data entry errors that could result in placing information in the wrong record, losing valuable information, and limiting the value a business can derive from the data that it captures” (Alharthi et al., 2017, p. 288).

While the involvement of business, IT, and HR departments seem to be straightforward for the strategic deployment of big data, legal and Public Relations (PR) divisions should also be involved in the planning and preparation process. One of the most publicly discussed challenges of big data is the concern about legal, ethics and privacy risks of big data use. At the center of this debate is the insecurity of users when assessing which of their data might be collected and who might process it (Matzner, 2014). In his work on big data ethics, Zwitter (2014) refers to this lack of awareness about the collection and use of data as an "ethical disadvantage qua knowledge and free will" (p.3) for the user.

Big data is considered a particular threat to the user's privacy because of its variety dimension, enabling the integration of datasets from multiple sources (Lodha et al., 2014). Anonymized datasets in their original context might not pose any privacy threats for users, but through the combination with other datasets for various purposes, they might reveal the user's identity or other private information (Alharthi et al., 2017; Matzner, 2014; Nunan & Di Domenico, 2013). An example of this is provided by Boyd and Crawford (2012) in their critical piece on big data. Harvard researchers had released anonymized social media data from students to the public, which was then partially deanonymized by other researchers exploring the dataset. This privacy breach affected the students, who had no knowledge of their data being collected.

Social media data is a particularly interesting part of the privacy debate, with public posts marking a new territory for ethical considerations, as Boyd and Crawford (2012) point out:

> Very little is understood about the ethical implications underpinning the Big Data phenomenon. […] What if someone's 'public' blog post is taken out of context and analyzed in a way that the author never imagined? What does it mean for someone to be spotlighted or to be analyzed without knowing it? Who is responsible for making certain

> that individuals and communities are not hurt by the research process? What does informed consent look like? (p.672)

Social media organizations themselves, such as Twitter or Whatsapp, are often under scrutiny, as their privacy policies do not clearly specify the current and future use of the data shared on their platforms as well as other collected data about the user (Alharthi et al., 2017). From an ethical point of view, researchers–and generally all analysts–should carefully consider the use of social media data, even though posts might be publicly accessible (Boyd & Crawford, 2012). This ethical challenge also extends beyond the case of social media to other forms of big data. The field of health research, for example, demands caution from its researchers to maintain a privacy-preserving research environment under the guidelines from ethics review boards (H. Chen et al., 2012).

From a legal perspective, most organizations processing user data rely on "notice and consent" models, outlining the purpose of the collected data and the limitation of its use (Mantelero & Vaciago, 2015, p. 105). However, big data challenges this legal framework, as the main purpose of its analysis is to discover insights through correlations and integrations of different sources. This makes it nearly impossible for organizations to disclose all potential uses at the point of data collection. Nunan and Di Domenico (2013) therefore ask the question: "How can consumers trust an organisation (sic) with information when the organisation (sic) does not yet know how the information might be used in the future?" (p.5).

Mantelero and Vaciago (2015) further point out that users often consent to the collection of their data despite not understanding or ignoring the legal wording of privacy agreements to use certain services. In the aftermath, users are often startled by the use of their data, and given a better understanding of the consequences they might not have given their consent to (Matzner, 2014). The effort and level of knowledge required to fully grasp and gain access to the privacy terms and conditions might put some users at a disadvantage, as referred to by Zwitter (2014).

When planning for the collection and use of big data, organizations need to account for those ethical and legal challenges in their strategy to avoid controversies and financial repercussions (Motamarri et al., 2017). As Kemp (2014) concludes in his work on the legal aspects of managing big data:

> A sound analytical legal model for understanding the rights and duties that arise in relation to Big Data in order to manage risk, and the development of a structured approach to legally compliant and software enhanced Big Data input, processing and output will be essential factors for successful Big Data projects and their governance and management. (p. 491)

Besides establishing a legal model and ensuring ethical conduct, there are security aspects which must be considered from a technical perspective (Lodha et al., 2014). Secure data protection requires privacy awareness access control features, which exceed the often prevalent basic forms of access control in big data platforms, and support privacy policies (Colombo & Ferrari, 2015).

As can be seen, big data is a complex concept that offers value creating opportunities for organizations that comprehend its challenging nature and are willing to holistically prepare for its use. Big data affects most organizational functions to some degree and requires sometimes significant adjustments throughout the organization. Its use also opens the organization up to criticism and legal battles, if the security of collected data is compromised. Nevertheless, big data has the potential to significantly enrich the decision making of managers by providing in-depth insights and predictions, enabling fact-based judgments.

2.2. Management Decision Making

The importance of decision making for managers can be seen in Herbert Simon's introduction of his renowned lectures on 'The New Science of Management Decision' in 1960: "What part does decision making play in managing? I shall find it convenient to take mild liberties with the English language by using "decision making" as though it were synonymous with "managing"" (Simon, 1960, p. 1). Decision making is considered a key aspect of management, and proficiency in it distinguishes an effective manager from an ineffective one (Harrison, 1995). While the field of decision making has experienced (often quantitative) research interest for years (Harrison, 1995), big data promises to significantly affect managerial decision making (Davenport et al., 2013; Prescott, 2016; S. Shah et al., 2012). Exploring the effects of big data and advanced analytics on this crucial management function is therefore a promising research endeavor.

The following section introduces extant literature on management decision making focusing on the process of decision making and the roles of analytics and human judgment. First, the dual process theory is introduced. This theory is used as a lens for this study to explore the effects of big data's arrival on the decision-making process. Then, two streams of influencing factors are discussed. On the one hand, the influence of technology such as analytics, DSS, and KMS is assessed. On the other hand, the influence of human judgment, which in this study serves as an umbrella term for factors such as intuition, experience, insight, and wisdom, is considered. This approach provides an overview of current views on the use of human judgment as well as managers' reliance on data and technology in decision making.

2.2.1. Decision Making: Dual Process Theory

A decision is defined as a "moment, in an ongoing process of evaluating alternatives for meeting an objective, at which expectations about a particular course of action impel the decision maker to select that course of action most likely to result in attaining the objective" (Harrison, 1995, p. 5). Arriving at this moment, and therefore a decision, can be achieved through one of two ways, according to dual process theory (Dane & Pratt, 2007; Gilhooly & Murphy, 2005). This perspective of dual processing enjoys popularity among researchers of decision-making theory, particularly in the field of psychology (Dane & Pratt, 2007; Evans, 2003). While there are different variations of the dual process theory in cognitive and social psychology (Dane & Pratt, 2007; Evans, 2003; Stanovich & West, 2000), this thesis follows the two-system view that has found an application in the field of managerial decision making (Bazerman & Moore, 2013; Dane & Pratt, 2007; Kaufmann, Wagner, & Carter, 2017; Wray, 2017).

The two-system view postulates that there are two distinct cognitive processes that can result in a decision, distinguishing intuition from reasoning (Kahneman, 2003). While the two modes of thought have been labeled under different terms in past publications (Stanovich & West, 2000), considerable commonalities exist between the two (Kahneman, 2003). The generic terms for these two systems are System 1 and System 2, respectively (Evans, 2003; Kahneman, 2003). These terms are also applied in managerial decision making (Bazerman & Moore, 2013). The two systems are briefly introduced in the following paragraphs, then discussed in further detail in the next sections.

The labeling of these two systems eventuates from an exploration of individual differences of reasoning by Stanovich and West (2000). Their work accumulates the various properties of these two systems as outlined by previous publications and characterizes the systems accordingly. System 1 is therefore conceptualized as “automatic, largely unconscious, and relatively undemanding of computational capacity,” while System 2 “encompasses the processes of analytic intelligence” (p. 658). A decision maker interpreting a problem via System 1 will automatically contextualize this problem, invoking an intuitive, often biased judgment. This system generally finds application in a familiar setting, when the decision maker works under time constraints and can confidently rely on his intuition (Bazerman & Moore, 2013).

System 2, on the other hand, is more regulated, enabling the decision maker to decontextualize the problem (Stanovich & West, 2000). Rules and principles can therefore be applied in a more controlled fashion in this system, leading to a depersonalization and a more objective judgment. This system informs the decision maker’s most important decisions, which require a logical and conscious process (Bazerman & Moore, 2013).

While these systems can act separately, they are often found to work in tandem (Bazerman & Moore, 2013). System 1 processes provide support for System 2 in the form of shortcuts to “stop the combinatorial explosion of possibilities that would occur if an intelligent system tried to calculate the utility of all possible future outcomes,” (Stanovich & West, 2000, p. 710). Furthermore, as System 1 processes can lead to biased results if used uncorrected, one of System 2’s tasks is to monitor these processes (Evans, 2003; Gilhooly & Murphy, 2005; Kahneman, 2003; Wray, 2017). The monitoring of System 1 by System 2 leads to a more controlled process, which is often related to the concept of rationality in decision making (Evans, 2003).

While this monitoring function of System 2 can be useful for avoiding oversimplifications caused by heuristics, it is not without its limitations, as Kahneman (2003) points out. Particularly the availability or representativeness heuristics were shown to be problematic for System 2. For one, there is the risk of overcorrection, leading managers to judge a situation incorrectly in the opposite direction than the heuristic would have led them. Another consideration is System 2's dependency on triggers and the framing of decisions: if managers are not reminded of specific training or knowledge they possess, they likely rely on heuristics like someone who does not have the knowledge in the first place (Kahneman, 2003).

In this research, dual process theory in form of the two-system view is chosen as a lens instead of the often applied concept of rationality in management decision-making research (Harrison, 1995; Intezari, 2013). Rational decision making assumes the strict following of a clearly structured process that consists of the clarification of objectives, assessment of alternatives and potential consequences, and a selection of the alternative best suited for obtaining the objectives (Harrison, 1995). Non-rationality consequently is considered a failure to act rationally due to narrow-mindedness or biases attributed to a set of beliefs or prior experience. While System 1 can in parts be compared to non-rational decision making, and System 2 to more rational decision making (Evans, 2003), the underlying assumption differentiates the two concepts, as the two-system view recognizes the cooperation and value of both systems.

The assumptions of rationality in decision making have been criticized in the past. Simon (1987) does not concur with the idea of a strictly rational decision maker:

"intuition is not a process that operates independently of analysis; rather, the two processes are essential complementary components" (p. 61). He also introduces the concept of bounded rationality, which outlines the decision maker's limitations as their rationality is bounded by the complexity of problems and insufficient mental capacity to process all available information and alternatives (Simon, 1957). Other limitations of bounded rationality are the lack of information, cost and time constraints, failures of communication, precedents and the decision maker's perception (Harrison, 1995). Kahneman and Tversky further explore which factors cause decision makers to act against the assumptions of rational decision making. Their work identifies diverse heuristics and biases that influence management decision making, which are further discussed in the following section (Tversky & Kahneman, 1973, 1975, 1992).

In the context of this thesis, the dual process theory is expected to be a valuable lens to explore the management decision-making process, as well as the roles of human judgment and analytics in it. Since System 1 processes are prone to biases, the increasing availability of data and analytics outcomes are expected to support System 2 processes in countering these biases. On the other hand, the lack of management's familiarity with big data is expected to impact System 1's capability to eliminate alternatives for System 2. The age of big data's influence on the challenges of balancing System 1 and 2 is therefore further explored in this thesis.

2.2.1.1. System 1 – Intuitive Judgments

From an evolutionary perspective, System 1 is considered the older of two systems depicted in the dual process theory, as the system's processes are shared between humans and animals (Evans, 2003). The system is shaped by habits and experiences, making any adjustments to or control of its processes challenging (Kahneman, 2003).

Various other characteristics of this system are identified in the literature on the two-system view, as can be seen in Table 3. It is most commonly referred to as fast, automatic, and effortless. This enables System 1 processes to generate “intuitive, immediate responses” (Gilhooly & Murphy, 2005, p. 282), with consciousness only being able to grasp the final product (Evans, 2003; Gilhooly & Murphy, 2005).

Table 3. *System 1 Characteristics*

Characteristic	Sources
Relatively fast	Bazerman & Moore, 2013; Dane & Pratt, 2007; Evans, 2003; Gilhooly & Murphy, 2005; Kahneman, 2003; Stanovich & West, 2000; McCrea, 2010
Automatic	Bazerman & Moore, 2013; Betsch & Glöckner, 2010; Dane & Pratt, 2007; Evans, 2003; Gilhooly & Murphy, 2005; Kahneman, 2003; Stanovich & West, 2000
Effortless	Bazerman & Moore, 2013; Dane & Pratt, 2007; Evans, 2003; Kahneman, 2003; Stanovich & West, 2000
Acquisition by biology, exposure, and personal experience	Dane & Pratt, 2007; Evans, 2003; Kahneman, 2003; Stanovich & West, 2000
Implicit (not available to introspection)	Bazerman & Moore, 2013; Betsch & Glöckner, 2010; Gilhooly & Murphy, 2005; Kahneman, 2003
Associative	Dane & Pratt, 2007; Kahneman, 2003; Stanovich & West, 2000
Emotional	Bazerman & Moore, 2013; Kahneman, 2003; McCrea, 2010
Unconscious	Betsch & Glöckner, 2010; Dane & Pratt, 2007; Stanovich & West, 2000
Holistic	Betsch & Glöckner, 2010; Dane & Pratt, 2007; Stanovich & West, 2000

In the context of management decision making, System 1 is often referred to as intuition, which is described as a holistic, time-efficient, emotional, but unconscious process that relies on learning from experience (Dane & Pratt, 2007; McCrea, 2010). The outcome of this intuitive process is referred to as an intuitive judgment (Dane & Pratt, 2007; Kahneman, 2003). A key part of intuition is holistic associations, which is the process of matching stimuli to known patterns and fitting “isolated bits of data and experiences into an integrated picture” (Khatri & Ng, 2000, p. 60). In this process, the stimuli are matched to either simple cognitive structures, known as heuristics, or more complex cognitive structures, which are referred to as expert decision-making perspectives (Dane & Pratt, 2007).

Expert decision-making perspectives are often described as superior or complementary to analytical structures; especially in the case of unstructured problems, since there are no accepted decision rules in place: “One could argue that the rapid change that characterizes current organizational environments makes intuitive decision making more necessary today than it has been in the past" (Dane & Pratt, 2007, p. 49). Experts are often found to make competent intuitive judgments without being able to give valid reasons or describe the process leading to their judgment (Simon, 1987). Indeed, the decision itself would be disrupted and drawn out by an attempt to analyze those reasons (Dane & Pratt, 2007; Dijkstra, Pligt, & Kleef, 2013).

The rapid arrival of experts at a decision can be explained through a “recognition and retrieval process” (p. 61) evoked by a set of premises that leads them to the right conclusion (Simon, 1987): “only the final product of such processes is available to consciousness” (Gilhooly & Murphy, 2005, p. 282). The basis for this retrieval process is a large stock of previously acquired knowledge and experiences that are anchored in the manager’s memory and are accessed during the decision-making process (Betsch & Glöckner, 2010; Khatri & Ng, 2000; Simon, 1987). This knowledge and experience are skills that managers acquire through decision-making practice, enabling them to make accurate, intuitive judgments rapidly and effortlessly (Kahneman, 2003). Individual differences in managers’ decision-making capabilities are therefore relevant for the outcome of intuitive judgments (Stanovich & West, 2000).

Managers' intuitive judgment is most accurate in situations and environments they are familiar with, as it is very context-specific (Chakravarti, Mitchell, & Staelin, 1981). When confronted with new and complex challenges, the use of intuitive judgment can lead to errors or biases. The novelty of big data and advanced analytics is therefore expected to pose additional risks for managers relying on their intuition. Especially due to the often abstract nature of data and its derived information and knowledge, managers develop a psychological distance from this knowledge, which influences their judgment (Bryant & Tversky, 1999). The result of this distance are generalizations in situations that would require case-by-case decisions (Bhidé, 2010).

In contrast to the complex cognitive processes employed in expert decision making, simple cognitive processes are referred to as heuristics (Dane & Pratt, 2007). Also known as rules of thumb, heuristics reduce the decision maker's processing effort and time as they eliminate pieces of effortful information and therefore reduce complexity (Bazerman & Moore, 2013; Betsch & Glöckner, 2010; Tversky & Kahneman, 1975). In the two-system view, as part of System 1, heuristics are considered essential to limiting the number of available alternatives for System 2 processes (Stanovich & West, 2000), helping "the actor quite well to maintain a relatively high level of accuracy in different choice and judgment tasks" (Betsch & Glöckner, 2010, p. 279).

The finance industry is an example of this, where heuristics are applied in the form of category systems which help with the evaluation and comparison of firms (Carruthers, 2010). However, when heuristics are applied inappropriately, they can lead to biases that are reflected in the manager's decision (Bazerman & Moore, 2013; Betsch & Glöckner, 2010). This inappropriate application can result from an unawareness of using a heuristic, a misinterpretation of the decision's context, or a lack of feedback from previous decisions signaling the bad quality of an applied heuristic in the past (Bazerman & Moore, 2013).

Different types of heuristics and biases can certainly be identified. However, their exact number and denomination can differ across publications. Three well-known heuristics are introduced by Bazerman and Moore (2013) as availability, representativeness, and confirmation heuristic. The availability heuristic is based on research by Kahneman and Tversky (1973, 1975), postulating that the ease of information accessibility determines the decision maker's assessment of an event's probability. While often a useful tool for decision makers, for example when assessing the frequency of an event, this heuristic is also fallible (Bazerman & Moore, 2013; Tversky & Kahneman, 1973): "An event that evokes emotions and is vivid, easily imagined, and specific will be more available than an event that is unemotional in nature, bland, difficult to imagine, or vague" (Bazerman & Moore, 2013, p. 7f.). Vividness of past experiences can promote their availability in the decision makers memory, even though they might not be the most relevant ones for that particular decision (Bazerman & Moore, 2013; Wray, 2017).

The representativeness heuristic is applied when the decision maker has to judge a person, event or process (Bazerman & Moore, 2013; Tversky & Kahneman, 1975). For this purpose, the decision maker compares the object in question by its traits or characteristics to established categories or stereotypes (Bazerman & Moore, 2013). This heuristic is also fallible, and if used unconsciously, can cause biases in the form of discrimination.

The confirmation heuristic is described as the selective use of data when decision makers test hypotheses, which leads to the neglect of other instances of information (Bazerman & Moore, 2013). This can lead to an anchoring bias, meaning an initial assessment of a situation or a starting point impacts all further judgment of the situation (Bazerman & Moore, 2013; Tversky & Kahneman, 1975). Kahneman (2003) directly depicts anchoring as the third heuristic instead of confirmation.

Regarding System 1, this thesis will explore what role expert decision making, heuristics and biases play in the management decision-making process, and whether/how big data and analytics might have additional effects.

2.2.1.2. System 2 – Deliberate Decision-Making Process

Intuitive judgments made by System 1 can lead to several biases when it comes to decision quality, as discussed in the previous section. One of System 2's central tasks is therefore the monitoring and periodic correction of System 1 judgments if an irrational response is detected (Wray, 2017). The systematic procedures of System 2 allow decision makers to consciously gather and evaluate information (Dane & Pratt, 2007), and "[permit] abstract reasoning and hypothetical thinking" (Gilhooly & Murphy, 2005, p. 282). This offers an advantage over System 1 in situations that cannot be mastered by relying on previous experience (Evans, 2003). System 2 processing is utilized by rational decision-making models, and consists of deliberate process steps and analysis (Dane & Pratt, 2007). It is consequently often referred to as the rational system. Its key characteristics are summarized in Table 4.

Table 4. *System 2 Characteristics*

Characteristic	Sources
Relatively slow	Bazerman & Moore, 2013; Evans, 2003; Gilhooly & Murphy, 2005; Kahneman, 2003; Stanovich & West, 2000
Encompasses the processes of analytic intelligence (logical, analytic)	Bazerman & Moore, 2013; Dane & Pratt, 2007; Evans, 2003; Stanovich & West, 2000
Rule-based	Dane & Pratt, 2007; Kahneman, 2003; Stanovich & West, 2000
Hypothetical thinking	Dane & Pratt, 2007; Evans, 2003; Gilhooly & Murphy, 2005
Conscious	Bazerman & Moore, 2013; Betsch & Glöckner, 2010; Kahneman, 2003
Sequential	Betsch & Glöckner, 2010; Evans, 2003; Gilhooly & Murphy, 2005
Controlled	Betsch & Glöckner, 2010; Kahneman, 2003; Stanovich & West, 2000
Deliberate	Dane & Pratt, 2007; Kahneman, 2003
Acquisition by cultural, and formal tuition	Dane & Pratt, 2007; Stanovich & West, 2000
Effortful	Bazerman & Moore, 2013; Kahneman, 2003

While System 2 can be a useful tool for decision makers, it also has its limitations, which can especially impair its key function of monitoring System 1. It is considered effortful, involving often complex analysis and resulting in a considerably slower processing speed than System 1's (Bazerman & Moore, 2013; Evans, 2003). System 2's operations are further hindered by time pressure and simultaneous performance of other tasks, as well as a range of other factors (Kahneman, 2003). Positive influences on System 2 processing capability are a high level of fluid intelligence and working memory capacity, as well as experience with statistical thinking (Evans, 2003; Gilhooly & Murphy, 2005; Kahneman, 2003). Especially statistical training can support decision makers' awareness and avoidance of biases resulting from availability and representativeness heuristics (Kahneman, 2003). The knowledge itself, however, is often insufficient, and cues or reminders of the decision makers' training are required to prevent decision makers from making biased judgments.

When System 2 processes work unencumbered, they consist of several analytical steps. These logical decision-making steps vary throughout different publications in name as well as in number and extent of included steps. This thesis relies on the theoretical input of seminal pieces of work, which are still referenced in current research on decision making. Taking into account the simplicity and unchanging nature of basic decision-making process steps, these seminal works were considered to provide a reputable and solid foundation for this research. In their review of strategic decision-making literature, Eisenhardt and Zbaracki (1992) outline a basic decision-making model, referred to as ‘the rational model of choice’ (p. 18). This model involves cognitive assumptions: decision makers are aware of the decision’s objectives from the outset and assess potential outcomes accordingly. Subsequently, information is accumulated, and alternatives are developed. The best suitable alternative is then selected. Eisenhardt and Zbaracki (1992) further note extensions. Four further publications that demonstrate such variations are discussed in the following text and highlighted in Table 5.

Table 5. *Decision-Making Processes*

Source	**Steps**							
Eisenhardt & Zbaracki, 1992	Objectives			Alternative Development	Selection of best alternative			
Simon, 1960	Intelligence			Design	Choice			
Harrison, 1995	Setting managerial objectives			Searching for alternatives	Comparing and evaluating alternatives	Act of choice	Imple-menting decision	Follow-up and control
Mintzberg, Raisinghani, & Theoret, 1976	Identification			Development	Selection			
Bazerman & Moore, 2013	Define problem	Identify criteria	Weight criteria	Generate alternatives	Rate each alternative on each criterion	Compute optimal decision		

This basic succession of steps suggested by Eisenhardt and Zbaracki (1992) is echoed by Herbert Simon's (1960) suggested three phases: "finding occasions for making a decision; finding possible courses of action; and choosing among courses of action" (Simon, 1960, p. 1). During the first step, *intelligence*, the decision maker determines what the problem is. This step consumes a considerable amount of the manager's time, as the environment must be surveyed for changes that warrant action. With the next step, *design*, the manager–individually or in collaboration with colleagues–develops and analyzes potential consequences of alternatives that match the decision's needs, which extends over an even longer period. The last step, *choice*, marks the manager's decision for the best alternative, which can be considered a quick action based on the preparation of the previous steps.

While these steps concur with Eisenhardt and Zbaracki (1992), a slight variation from their rational model of choice can be seen in Simon's (1957) concept of bounded rationality, which challenges their underlying rationality assumptions. Simon (1960) also acknowledged the complexity of decision making and suggested that each step is a separate, self-contained decision-making process that might require intelligence, design, and choice.

An extension of these basic steps to a more detailed decision-making process can be found with Harrison (1995), who suggests six components. The first and second component are *setting managerial objectives* and *searching for alternatives*, which match the phases outlined by Eisenhardt and Zbaracki (1992) as well as Simon (1960). The third and fourth component split up what is the last 'Choice' stage in the previous two models. Harrison (1995) separates c*omparing and evaluating alternatives* from *the act of choice*, considering the actual choice as a mere moment that follows the elaborate stage of alternative comparison. Furthermore, two components are added after the choice, namely *implementing the decision* and *follow-up and control* (Harrison, 1995). While these components are not included in any of the decision models introduced here, they can be found in other publications (Intezari, 2013). In the context of this thesis, these steps will not be taken into consideration, as the emphasis lies on the decision-making process itself, and not on medium- to long-term implementations and consequences.

An example of decision-making processes that "accepted the rational model, but rearranged the pieces to allow repetition and variety" (Eisenhardt & Zbaracki, 1992, p. 18), can be found in Mintzberg, Raisinghani, and Theoret (1976). This seminal piece of work in the field of unstructured strategic decisions offers a model that is comprised of 25 different decision-making processes identified during the study. This dynamic model consists of three central phases: identification, development, and selection. The process starts with the identification phase, in which an occasion for a decision is recognized, and decision makers familiarize themselves with the key factors involved, as well as their interrelations. During the second phase, potential solutions to the identified problem are developed. The decision maker searches for existing solutions, which might then be modified or supplemented with new custom-designed solutions.

In the selection phase, all possible solutions are evaluated, and the decision maker commits to an action. Three different modes can be identified in this stage: judgment, bargaining, and analysis. The judgment mode can be compared to previous descriptions of System 1's intuitive judgment, in which the decision maker reaches a choice without being aware of the process that led to it. Bargaining refers to a decision being made by several decision makers that merge their diverse individual judgments to form a consensus. Analysis refers to an evaluation of facts comparable to System 2 processes, which are then followed by either judgment or bargaining.

While selection is considered the last phase of the decision-making process, "selection is typically a multistage, iterative process, involving progressively deepening investigation of alternatives" (Mintzberg et al., 1976, p. 257). This exemplifies the dynamic nature that Eisenhardt and Zbaracki (1992) and Simon (1960) identify as a form of variation to the classic three-step rational model outlined in their publication. Even though the basic three phases found in Mintzberg et al. (1976) are essentially unaltered, the model incorporates the non-sequential nature of strategic decisions, i.e. "operating in an open system where it is subjected to interferences, feedback loops, dead ends, and other factors" (Mintzberg et al., 1976, p. 263). The phases of the model account for those circumstances and allow for a number of subsets that vary depending on the decision maker and the decision itself (Mintzberg et al., 1976; Nicolas, 2004). This enunciated understanding of strategic decision making nonetheless remains a relevant piece of work for recent literature (Bradbury, Gressel, & Forsyth, 2017).

Another form of variation from the rational three-step model as outlined by Eisenhardt and Zbaracki (1992) can be found in the underlying use of rationality assumptions: "The most recent incarnation transformed the rational vs. boundedly rational dichotomy into a continuum, probing whether and when decision making is rational" (Eisenhardt & Zbaracki, 1992, p. 18). Bazerman and Moore (2013), for example, outline a process of six logical steps that they advise following when the decision maker applies a rational process. However, referencing dual process theory, they also concede that decision makers do not follow this rational reasoning most of the time. They argue that the logical steps, which they refer to as a prototype for System 2 thinking, are impractical in a variety of situations and are reserved for the most important decisions. System 1 processes are considered sufficient for most other decisions, depending on time constraints and other external factors (Bazerman & Moore, 2013).

The specific steps suggested by Bazerman and Moore (2013), are more detailed and quantitative than the basic models suggested by Eisenhardt and Zbaracki (1992) and Simon (1960). This can be seen in the first three steps of the process, which are considered one phase by all previously introduced models (Bazerman & Moore, 2013). Separate steps are identified for the definition of the problem, the identification of relevant criteria, and the assignment of weights to these criteria, adding a more quantitative component. The fourth step, the generation of alternatives, concurs with all prior models. The last two steps, considered as selection by three of the previous models, once again demonstrate the quantitative character of this process, as each alternative is rated on each criterion and the optimal decision is eventually computed.

While the introduced models differ in certain aspects, three core phases emerge as a common denominator, representative of System 2 processes: firstly, the identification of a problem or decision occasion occurs. This is followed by the development of alternatives, eventually leading to the stage of their evaluation and choice of the best solution to the scenario. In addition to these commonalities, each model provides interesting facets through their variations for the exploration of management decision making in the age of big data.

Both System 1 and System 2 have benefits and limitations, as well as the potential for collaboration. Which processes are most suitable for the decision maker is expected to depend to some extent on the nature and context of their decision. It is therefore paramount to understand the different types of decisions that managers are facing, which is discussed in the following section.

2.2.2. Decision Types

Managers face a variety of decisions, which can be divided into types based on their characteristics, such as their impact, complexity, or the manager's familiarity with the decision (Harrison, 1995). The differentiation of these decision types is important, as it informs the manager's approach to decision making and determines how much time and resources should be allocated to it. Strategic decisions, for example, make up a small percentage of the overall number of decisions a manager encounters. However, this decision type requires more time and resources than other decisions because of its significant long-term outcomes and often high levels of complexity (Harrison, 1995; Intezari & Gressel, 2017).

On the other hand, a routine operational decision would be more immediate and require less resources, as the decision maker is often familiar with the decision, which is fairly structured and rather inconsequential (Ackoff, 1990; Harrison, 1995; Intezari & Gressel, 2017). Decision types therefore influence the decision-making process' length, thoroughness and number of involved steps.

Extant literature offers different classification frameworks of decisions. Harrison (1995) collates several of these diverse classifications in his review and identifies two basic decision categories as their common denominator: the first category, routine decisions, is characterized as recurring, predictable, with clear cause and effect relationships. The appropriate decision-making approach is described as "relying upon rules and principles; habitual reactions" (Harrison, 1995, p. 21). Another viable approach is applying computational techniques, since the decision criteria are known variables in this category. The second category, nonroutine decisions, is described as nonrecurring, unique and complex. These decisions require intuition, judgment, and creativity; heuristics are also often applied.

A widely accepted classification that is part of Harrison's (1995) review is Simon's (1960) distinction between nonprogrammed and programmed decisions, which concurs with the identified two (non-)routine categories. Both schemes of decision categories suggest that routine/programmed decisions are approached through System 2 processes, which can be improved through training programs and–on an organizational level–through superior and standardized operating procedures (Simon, 1960). Nonroutine/nonprogrammed decisions, however, are approached through System 1 processes:

> When we ask how executives in organizations make nonprogrammed decisions, we are generally told that they "exercise judgment," and that this judgment depends, in some undefined way, upon experience, insight, and intuition […] we may be told that creativity was required. (Simon, 1960, p. 11)

Simon (1960) continues to suggest that this approach can also be improved to some extent by training managers in 'orderly thinking.' Decision types therefore not only influence the time and resources spent on decision making, but they also determine whether managers rely on System 1 or 2 processes, and how managers can be trained adequately to improve their decision-making skills.

While these basic decision types provide certain insights, their simplicity limits the extent of the implications that can be extrapolated for the decision maker. Furthermore, the distinction between programmed and nonprogrammed decisions cannot be seen as a binary differentiation, but more as a continuum (Harrison, 1995; Simon, 1960). That is, decisions cannot be clearly sorted into categories, but merely placed along a continuum ranging from programmed to nonprogrammed. More nuanced decision types can be found in frameworks provided by Ackoff (1990) as well as Snowden and Boone (2007), which are discussed below.

These frameworks offer a clearer distinction and variety and are therefore used as a lens in the exploration of management decision making in this study. Ackoff's (1990) framework is utilized to capture the dimension of longevity and impact, whereas Snowden and Boone's (2007) Cynefin framework is applied to express the dimension of decision context, capturing its complexity and circumstances. Both frameworks' decision types are summarized in Table 6.

Table 6. *Decision Types*

Decision Type	Description	Source
Operational	Mostly routine, well-defined decisions regarding immediate future	Ackoff, 1990; Mintzberg et al., 1976
Tactical	Medium-term decisions regarding the organization’s efficiency	Ackoff, 1990
Strategic	Important, high-level, long-term decisions that influence the organization's goals and objectives	Ackoff, 1990; Drucker, 2006; Eisenhardt & Zbaracki, 1992; Mintzberg et al., 1976
Simple	Decisions or problems are assessed, categorized and responded to with established practices.	Dykstra & Orr, 2016; Snowden & Boone, 2007
Complicated	Several potential solutions for a decision require thorough analysis and expertise.	Snowden & Boone, 2007
Complex	Unpredictable decisions that rely on probing and experiments	Snowden & Boone, 2007; Wray, 2017
Chaotic	Decisions defined by turbulence and without underlying cause-and-effect relationships	Dykstra & Orr, 2016; Snowden & Boone, 2007
Disorder	No other decision type or context is predominant.	Snowden & Boone, 2007

The differentiation among decisions according to longevity and impact as seen in Ackoff’s (1990) framework is commonly used in an academic and business context. The three decision types are namely operational, tactical, and strategic (Ackoff, 1990). Operational decisions are mostly short-term, and their primary objective is the company’s survival. They are considered routine, have clearer descriptions, and can be approached through quantitative analysis (Mintzberg et al., 1976). Tactical decisions are medium-term, typically do not exceed the fiscal year, and their primary concern is efficiency (Ackoff, 1990).

Lastly, “[s]trategic decisions are concerned with a period long enough to cover development of new products (as distinct from modifying old ones), development of new sources of product, or entry into a new business. The focus of strategic decisions is growth" (Ackoff, 1990, p. 523). Strategic decisions are characterized as important and significant, resulting in an increased allocation of resources (Drucker, 2006; Harrison, 1995; Mintzberg et al., 1976). These complex and infrequent decisions are made on a high level, conceptually and hierarchically (Drucker, 2006; Eisenhardt & Zbaracki, 1992).

Initially developed by David Snowden, the Cynefin framework presents an alternative or complement to Ackoff's (1990) by focusing on another dimension of decisions: their context (Snowden, 2000). The Cynefin framework posits that decision makers must identify the specific context of the decision at hand and adjust their approach accordingly (Snowden & Boone, 2007). Five different decision types, or contexts, are differentiated, according to the decision's inherent cause-and-effect relationship: simple, complicated, complex, chaotic, and disorder. Simple and complicated contexts are characterized by a clear cause-and-effect relationship, whereas in complex and chaotic contexts, this relationship is not instantly apparent. Disorder only finds application if none of the other four contexts is clearly predominant. The decision can then be separated into smaller parts and separately be classified as one of the four other contexts.

Simple contexts, also referred to as obvious, are often decisions with well-structured processes, which mostly result in self-evident solutions that are understood by all affected parties (Dykstra & Orr, 2016; Snowden & Boone, 2007). A categorization of the identified problem or decision suffices to find the correct response (Snowden & Boone, 2007). Complicated contexts differ from simple ones in having several potential solutions and requiring more expertise. This context requires an analysis of the available options rather than a mere categorization. Decisions in complex contexts are considered as unpredictable, because they are shaped by constant change inherent to the exploration of new terrains, such as mergers and acquisitions (Moore, 2017; Snowden & Boone, 2007). Only isolated parts of the situation are understood by the decision maker, and complete understanding of the context is often only achieved in hindsight (Snowden & Boone, 2007; Wray, 2017).

Complexity is furthermore seen as an important indicator for the ensuing decision-making process (Eisenhardt & Zbaracki, 1992). This context requires patience from managers, as they must rely on emerging patterns, probing, and experiments to reach a decision (Snowden & Boone, 2007). A chaotic context has constantly shifting cause-and-effect relationships and therefore displays no determinable patterns (Dykstra & Orr, 2016; Snowden & Boone, 2007). In this turbulence, the decision maker

> must first act to establish order, then sense where stability is present and from where it is absent, and then respond by working to transform the situation from chaos to complexity, where the identification of emerging patterns can both help prevent future crises and discern new opportunities. (Snowden & Boone, 2007, p. 6)

The Cynefin framework has previously been employed in information systems studies to delve deeper into decision circumstances and to make sense of changes in IS (e.g. Dykstra & Orr, 2016; Hasan & Kazlauskas, 2009; Moore, 2017). Moore (2017), for example, established a link between the Cynefin framework and the decision types outlined in Ackoff (1999). In her study on the visualization of information as decision-making support, strategic executive decisions are attributed to the complex context

(Moore, 2017). Another study by Dykstra and Orr (2016) applied the Cynefin framework to the area of cybersecurity, underlining the importance of understanding and adapting to the decision context to ensure prudent decision making. They posit that the Cynefin framework can reduce the risk inherent to cybersecurity by providing the defenders with a tool that allows them to quickly assess the situation and adjust their actions and decision making accordingly (Dykstra & Orr, 2016).

Both, Ackoff's (1990) decision types and Snowden and Boone's (2007) decision contexts are expected to have a significant effect on managerial decision making. The frameworks are therefore employed in this study to explore managers' choices to incorporate big data and analytics in their decision-making process. The decision types are expected to influence managers' use of System 1 and System 2 processes, as well as their balance of data and human judgment. The following sections will discuss an excerpt of the extant literature on the potential of using data, analytics, and human judgment in decision making.

2.2.3. The Role of Data and Analytics in Decision Making

Due to its progressively open and integrated nature, the business world is becoming more complex and challenging to managers, increasing their dependence on reliable and accurate information (Delen & Demirkan, 2013). In order to legitimize their decisions, managers have increasingly relied on analytics or technical reports (Bhidé, 2010; Nicolas, 2004; S. Shah et al., 2012). Big data enriches this area of traditional analytics and reporting, creating diverse and far-reaching opportunities for the application of analytics and providing a broader pool of accessible data. The following section discusses how extant literature sees the role of data and information systems in management decision making. Understanding the status quo builds a basis for exploring the effects of advanced analytics techniques and big data on the decision-making process.

While advanced analytics and big data currently pose challenges for organizations, traditional analytics capabilities and IS tools supporting decision making have been utilized for decades. Decision support systems (DSS) and knowledge management systems (KMS) have notably provided managers with valuable insights and played a prominent role facilitating decision making. DSS are designed to follow System 2 processes and assist the decision maker by introducing an optimized structure, particularly into unstructured and semi-structured decision types (Courtney, 2001). As big data’s novelty often contributes to the decision’s complexity, managers employing big data are expected to significantly benefit from DSS capabilities when making prudent decisions. While providing technological support and structure, DSS leave room for managerial judgment and act in a supporting role (Bohanec, 2009).

A KMS can be another important tool for the exploitation of big data, as it assists in the acquisition, creation and storage of knowledge. It enables users to access existing knowledge on an organizational level through a structured, large-scale and comprehensive knowledge base (Alavi & Leidner, 2001; Bhatt, 2001; Matthews, 1997; Swan & Newell, 2000). This allows employees to deduce the same conclusions from stored data or information (Tuomi, 1999).

Intezari and Gressel (2017) propose updated criteria for advanced KM systems to meet managers’ needs for a more agile and dynamic system in the age of big data. Especially when dealing with unstructured data, the systems must be social in order to facilitate group decision making, include the collaboration of IT and business, and offer a detailed evaluation of information. Advanced KMS are furthermore characterized as cross-lingual and integrative. As a result, knowledge seekers can gain insights from aggregated, formerly scattered data and knowledge, and assess its fit based on the knowledge sharer's expertise and background. Furthermore, an integration of freely attainable social media data with KM can enable a contextual comparison with competitors (He, Wang, & Akula, 2017). Organizations can gain additional customer insights, and previously limited access to competitors' data may now lead to a competitive advantage.

The general influence of DSS, KMS, and other information systems is addressed in Huber's (1990) theory of the effects of advanced information technologies on organizational design, intelligence, and decision making. Huber (1990) proposes that using communication and decision support technologies leads to several significant changes, such as fewer time-consuming meetings and an increased variety of people acting as information sources for decision making. At the same time, the number of employees involved in the decision-making process is expected to decrease, as these technologies can function as a source of expertise and therefore substitute for the respective expert. Overall, the use of these systems is proposed to have a positive effect on the identification of opportunities and problems, and to facilitate less time-consuming and higher quality decisions.

While Huber's theory was published in 1990, the pursuit of more accurate and timely decision making has remained the same. Today, advanced analytics and big data are applied to increase efficiency and gain a competitive advantage (LaValle et al., 2011). Big data has become a useful source of information for organizations in areas such as customer satisfaction and journeys, supply chain risk, competitive intelligence, pricing, and discovery and experimentation (Davenport, 2014b). The results of a survey of almost 3,000 executives, managers, and analysts show that about half of the top performing organizations employ analytics to gain insights into day-to-day operations as well as for guidance regarding future strategies (LaValle et al., 2011). Only about a quarter of the lower performers followed suit. The study also shows that using analytics is preferred over relying on intuition by both top and lower performers in the areas of financial management, operations and production, strategy and business development, and sales and marketing. Lower performers still preferred to rely on their intuition in areas such as customer service, product and research development, general and risk management.

Empirical work by Brynjolfsson, Hitt and Kim (2011) further supports the positive effects of data use on organizational performance. Their findings suggest that data-driven decision making increases a company's productivity by 5-6%, and furthermore affects asset utilization, return on equity and market value (Brynjolfsson, Hitt, & Kim, 2011). This sentiment is echoed by another empirical study, which finds that business analytics has a positive direct effect on information processing capability, as well as a positive indirect effect through the mediating facilitation of a data-driven environment (Cao, Duan, & Li, 2015). Information processing capability in turn is found to positively affect data-driven decision making, overall improving decision-making effectiveness.

The realization of such productivity and effectiveness gains posits a successful conversion of raw data into insights. These insights are gained when information is extracted from big data using fundamental principles of data science (Provost & Fawcett, 2013). This extraction, which is related to data mining, processes raw data into meaningful information and knowledge. When analytics is used as the basis for decision making, the quality of data is of utmost importance for creating valuable insights (Kaisler et al., 2013): “Big data basically focuses on quality data storage rather than having very large irrelevant data so that better results and conclusions can be drawn” (Katal et al., 2013, p. 407). Only with rigorous data selection can descriptive, predictive and prescriptive analytics offer valuable opportunities to the decision maker (Waller & Fawcett, 2013).

The quality of the data sources and their fit with the organization do not only impact the quality of the results or insights, but also the decision process itself (Bumblauskas et al., 2017). When the decision maker is overwhelmed by too much data or lacks trust in it, this can result in a paralysis by analysis, and therefore a prolonged decision-making process. Analysis paralysis is an often occurring problem, as “individuals tend to want too much rather than too little information and may take too long to arrive at decisions” (Harrison, 1995, p. 12). Decision makers must always weigh the necessity of gathering additional information against the cost and time its acquisition requires to reach close ‘proximity to optimum amount of information’ (p.350). Furthermore, the decision maker has to understand the meaning and collection context of the data used in the decision-making process (Janssen, van der Voort, & Wahyudi, 2017). A lack thereof can negatively impact the decision quality.

While managers may struggle with their cognitive limitations when confronted with the complexity and volume of big data, information technology has limitations of its own that can affect the usefulness of data for decision making. Managers’ views on the effectiveness of converting data into knowledge, for example, are twofold. Whereas some attribute a great role to IT, others are of the opinion that knowledge is embedded in the human mind (Bhatt, 2001). This echoes the prevailing sentiment of two opposing sides in decision making: the possibilities of analytics and the necessity of human judgment. Bhatt (2001) concludes that IT is capable of organizing data in order to receive information, but “IT is a poor substitute for converting information into knowledge” (Bhatt, 2001, p. 68). This conversion of information into knowledge is attributed to human factors and interpretation. Even judgment-based models or expert systems implemented to substitute for human judgment require antecedent design, which relies on qualified input such as specified information and judgmental estimates in order to enable a parameterization (Chakravarti et al., 1981). Without this initial human input of expertise, models cannot be effectively designed to optimize decision making.

The role of data, analytics and IS in decision making is significant and expected to increase in the age of big data. Bhidé (2010) depicts the rising importance of analytics as a clearly diminishing force on judgment: “The information technology revolution has shifted the balance between judgment and rules, giving a strong economic and psychological boost to judgment-free decision making” (Bhidé, 2010, p. 49). However, the rise of data-driven decision making does not necessarily entail the absence of human judgment. Data-driven decisions can accommodate big data and analytics as well as the decision maker’s intuition–all depending on the decision maker’s preferences and abilities (Provost & Fawcett, 2013).

As a result, managers are expected to benefit from a basic understanding of data and analytics, whilst still using their own judgment and expertise. These human factors can even be considered assets in the decision-making process:

> There remain many patterns that humans can easily detect but computer algorithms have a hard time finding in spite of the

> tremendous advances made in computational analysis. Ideally, analytics for Big Data will not be all computational–rather it will be designed explicitly to have a human in the loop. (Lodha et al., 2014, p. 3288)

In an editorial by Pauleen (2017) interviewing David Snowden, Snowden concurs with this view, pointing out the limitations of algorithms and highlighting the value of human reasoning.

The value of a balanced decision-making approach is evident in the example of the financial crisis of 2008. Its root cause was generalized agency models based on historical data applied to calculate the default rate of subprime mortgages (Carruthers, 2010). However, the utilized data was not fit for this purpose, and therefore not a dependable input for investment decisions, leading to severe misjudgment. The failure to incorporate this data into a wider context, and the resulting lack of accounting for socio-economic, political and cultural dynamics, was a contributing factor to this crisis (Pauleen, Rooney, & Intezari, 2017). The overpowering reliance and dependence on abstract analysis in this case overshadowed the need for human judgment: "the very possibility of fallibility seemed to be discounted because of the way the entire rating process was enshrouded with images of "rocket science" and quantitatively rigorous analytical methods" (Carruthers, 2010, p. 166). Due to the clear risks of a one-sided decision-making approach, the role of human judgment and relevant factors are further discussed in the following section.

2.2.4. The Role of Human Judgment in Decision Making

Human judgment in this thesis is used as an umbrella term for human factors that influence decision makers, such as their intuition, experience, and wisdom. Although managers often rely on those factors in their decision making, they can rarely express which of their skills or abilities they apply, but rather state that they "exercise judgment" (Simon, 1960, p. 11). As different factors are expected to also play a significant, if different, role in data-driven decision making, they will be further discussed in the following section.

Judgment itself is understood as combining “facts, past experiences, and imagination, different individuals faced with the same situation would respond differently” (Bhidé, 2010, p. 47). While human judgment constitutes System 1 thinking, the more structured and analytical System 2 processes also benefit highly from it. When looking at the three basic steps of the decision-making process, human judgment can be an incremental part in all of them. During the identification step, human judgment is essential for contextualizing available data and information and forming an understanding of the interacting decision variables (Nicolas, 2004).

Depending on the decision type and context, human judgment and analytics can be equally important for the step of developing and creating alternatives. Heuristics are particularly useful in this phase, as managers struggle with cognitive limitations when evaluating all available options (Kahneman, 2003), a phenomenon known as the concept of bounded rationality (Simon, 1957). The step of selection, while justified and supported by data, is highly affected by human judgment, specifically by emotion and intuition (Nicolas, 2004). As Simon (1960) states, managers often simply exercise judgment for this step. Human judgment can also be an asset for the analytics part of the decision-making process, the decision to acquire data, in what amount, from which sources, for which use, leads back to an initial managerial decision (Larreche &

Moinpour, 1983). Judgment, therefore, cannot be seen as a factor of declining importance in the age of big data, but rather as an expanding and evolving one.

The quality of judgment benefits from knowledge and experience. Senior managers with a higher knowledge level, therefore, tend to exceed novices (Dijkstra et al., 2013; Dreyfus & Dreyfus, 1980). In a series of experiments on the role of expertise in judgments, Dijkstra et al. (2013) demonstrate that experience is positively correlated with accurate judgment, i.e., experts in fact make more accurate judgments than novices. While an intuitive judgment might seem like acting on a hunch, the expert in fact relies on a vast 'repertoire of experienced situations' (Dreyfus & Dreyfus, 1980).

The involvement of conscious deliberation in expert decision making is often masked by automated processes that in fact simply enable the expert to reach a decision in fewer steps: "The expert appears to take giant intuitive steps in reasoning, as compared with the tiny steps of the novice" (Simon, 1987, p. 61). As Dreyfus and Dreyfus (1980) outline in their five-stage model, the novice is required to rationally analyze a problem, whereas the experienced manager can rely on their expertise and base the decision on their intuition. Expertise, therefore, enables intuitive judgments.

Bonabeau (2003) defines intuition as "the brain's process of interpreting and reaching conclusions about phenomena without resorting to conscious thought. […] this process draws on the mind's vast storehouse of memories" (p.118). Intuition is furthermore characterized as an emotional, unconscious process, which involves rapidly formed holistic associations and experiences (Dane & Pratt, 2007; Khatri & Ng, 2000). A study on intuition and decision making by Bradbury, Gressel, and Forsyth (2017) uses this characterization to explore national sports coaches' views on the use of intuition in their decision making. Their findings suggest that coaches who understand their intuition to be a clinical, experience-driven judgment are more confident in their use of it than coaches who see intuition as an emotional metaphysical 'gut feeling'. Coaches who were comfortable relying on their experience and prior knowledge saw intuition as a valuable tool, particularly in the context of their complex and rather unstructured decisions.

The Unconscious Thought Theory (UTT) developed by Dijksterhuis and Nordgren (2006) underlines this sentiment. Built on the insights of their previous experiments, UTT distinguishes between conscious thought (CT) and unconscious thought (UT) in decision making. The theory posits that while simple decisions should be approached with conscious thought, complex decisions benefit from unconscious thought. As can be seen in Figure 3, the decision quality is not affected by the complexity of the decision when relying on UT, whereas the quality of CT decision making declines with increasing decision complexity. Accordingly, intuition is expected to be more relevant in strategic decisions, as they often lack structure, are complex, and cannot be programmed (Mintzberg et al., 1976).

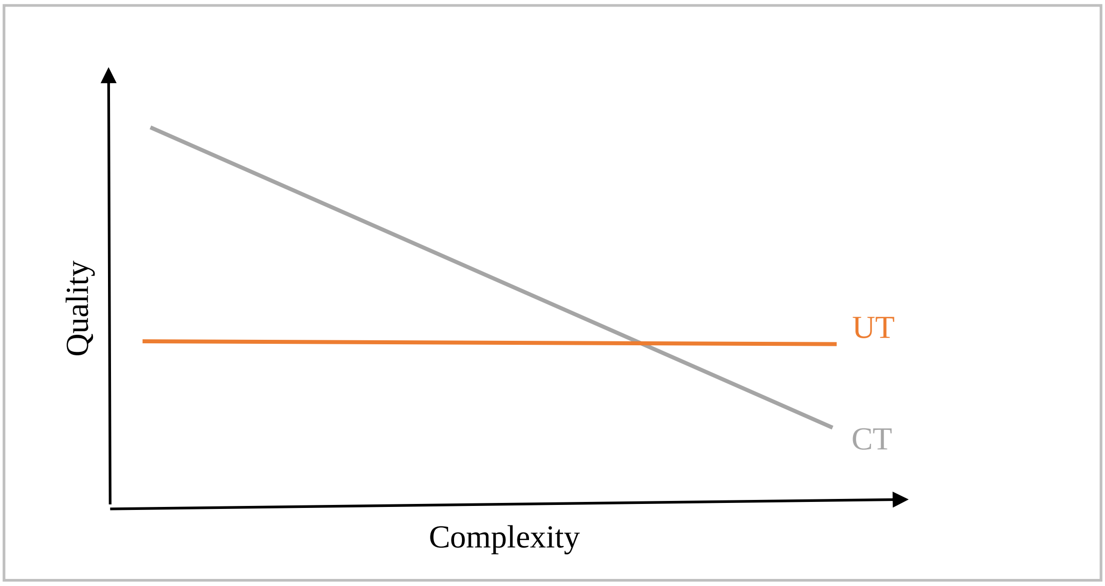

Figure 3. *Unconscious Thought Theory (Dijksterhuis & Nordgren, 2006)*

The use of biases and heuristics is also considered useful and often even necessary for complex decisions, in spite of their drawbacks (Busenitz & Barney, 1997; Tversky & Kahneman, 1973). Empirical work by Busenitz and Barney (1997) shows that entrepreneurs–in contrast to senior managers–rely on biases and heuristics to a vast extent, which leads the entrepreneurs to

> speculate that without the use of biases and heuristics, many entrepreneurial decisions would never be made. With entrepreneurial ventures in particular, the window of opportunity would often be gone by the time all the necessary information became available for more rational decision-making. (p.10)

It is therefore expected that particularly time-critical and complex strategic decisions will rely on unconscious thought, and more specifically on biases and heuristics.

However, opposing views can also be found in the literature. Some research strongly advises depending on analysis in decision types without available examples, since intuition on its own is not a dependable tool in complex and unfamiliar areas (Bonabeau, 2003; Chakravarti et al., 1981; Larreche & Moinpour, 1983; S. Shah et al., 2012). Necessary requirements for these cases are identified as the right selection of technological tools, managers' insight, experience and appropriate analytical skills (Bonabeau, 2003; Provost & Fawcett, 2013). Relying solely on intuition can lead to a decision that does not account for the problem's complexity, but rather simplifies it to match pre-existing patterns, impairing accurate judgments. This is supported by a study on decision making focused on experienced intelligence agents (Reyna, Chick, Corbin, & Hsia, 2014). The agents showed a clear bias towards choices that were put in a more positive light through the technique of framing. Their previous experience was concluded to be an influence on their intuition, and ultimately the reason for this bias and the negative influence on their decision making. Experts are particularly prone to this entrained thinking, which might lead them to dismiss novel ideas and fail to notice changes in a formerly familiar context (Snowden & Boone, 2007). Expert decision makers therefore need to challenge preexisting frames and consider new or deviating data (G. Klein, Phillips, Rall, & Peluso, 2007).

These limitations of experience and knowledge can be mitigated by the concept of wisdom. Wisdom, as an extension of knowledge, can contribute to big data decision making by applying better judgment and adding prudency, as well as moral and epistemic values, to the decision-making process (Intezari & Pauleen, 2013). A wise response is considered an 'embodied individual/organizational practice' (p.397), incorporating values essential to prudent decision making. Wisdom is furthermore connected to the concepts of intuition and judgment (Rooney et al., 2013; Sternberg, 2003). Rooney at al. (2012) state that being intuitive is characteristic for wise people, and in Sternberg's (2003) review of research on intelligence and wisdom, judgment is listed as an important component of wisdom.

Managers are ideally characterized by their openness to other people's opinions, ability to embrace new experiences, and open-mindedness toward new ideas (Rooney et al., 2013; Yaniv & Choshen-Hillel, 2012). Research shows that managers benefit most from the wisdom of others if they hold off on forming their own opinion until after they have considered the judgment of others (Budescu, Rantilla, Yu, & Karelitz, 2003; Yaniv & Choshen-Hillel, 2012). An unbiased mindset supports an intuitive identification of a central tendency in those opinions and outperforms judgment that is biased by the personal opinion of the decision maker (Yaniv & Choshen-Hillel, 2012).

Wisdom could therefore be a useful tool for experts for avoiding pre-existing frames and biases. As a result, Küpers and Pauleen (2015) suggest that a theoretical understanding of the concept of wisdom is insufficient, and advocate for embodied learning through habitualization in management education.

Wisdom is further expected to enrich managers' decision making that is informed by often abstract knowledge from big data sources. A main concern that arises when examining the central role of abstract knowledge in managerial decision making is that its "generalizing (even universalizing) nature is problematic when it becomes reified and becomes psychologically distant from a concrete, situated reality, and this is a challenge for ethics" (Rooney et al., 2013, p. 449). Especially in the finance industry, reification is a common mechanism, by which people "release debts from relationships, disembed them, and give them 'thing-like' qualities" (Carruthers, 2010, p. 161). Managers can apply wisdom to enrich this abstract knowledge with meaning and perspective. Only then will abstract knowledge lead to more prudent and sustainable decisions, which can result in a strategic advantage (Rooney et al., 2013).

In this section on management decision making, the benefits and drawbacks of data-driven as well as human judgment-driven decisions were introduced. While some of the extant literature seems to favor one or the other, the general consensus agrees on a balanced decision-making approach. For this research, managers are expected to benefit from both human judgment and data analytics:

> It is doubtful that we will find two types of managers (at least, of good managers), one of whom relies almost exclusively on intuition, the other on analytic techniques. More likely, we will find a continuum of decision-making styles involving an intimate

> combination of the two kinds of skill. We will likely also find that the nature of the problem to be solved will be a principal determinant of the mix. (Simon, 1987, p. 61)

No matter how experienced the manager, or the quality of their instincts, in order to realize the benefits of big data and advanced analytics, organizations need to provide their decision makers with a supportive environment and access to reliable data and analytics. These prerequisites for management decision making with analytics pose challenges to organizations, which will be discussed in the next section.

2.3. Organizational Prerequisites for the Use of Advanced Analytics and Big Data

The previous sections have outlined various big data opportunities and its potential to improve managerial decision making. To take advantage of these opportunities, organizations must establish an environment that is conducive to the use of advanced analytics. The implementation of big data technologies affects several, and sometimes all, business areas within an organization, and therefore requires thorough preparation. Organizations need to overcome various challenges, including the acquisition of data, lobbying for leadership support, building an integrated infrastructure, and finding the right opportunities. These challenges must be overcome on an organizational level to facilitate a supportive environment for decision making on an individual level.

The organization's preparedness for big data is therefore expected to have a significant influence in this study. The following section compiles several challenges outlined in the extant literature that organizations need to overcome in order to provide their employees with the foundation for data-driven decision making. Management challenges refer to business issues, personal decision-making style, and managerial problems that must be addressed. Technological challenges consist of problems around the IS infrastructure and the analysis of big data.

2.3.1. Management Challenges

Managers need to respond to the changes and challenges brought on by the age of big data in order to be and stay competitive with analytics in this new period (Davenport, 2013). As has been observed in previous evolutionary steps of data management, organizations will need to adapt their processes, develop new tools, and handle information overload accordingly (Bumblauskas et al., 2017; Petter et al., 2012). To ensure prudent use of big data, managers must also be aware of previous misuse of data and an overweening dependency on analytics, as the example of the financial crisis in 2008 demonstrates so well (Carruthers, 2010; Pauleen et al., 2017; S. Shah et al., 2012). Such lessons from the past, as well as from current big data use cases, enable the identification of three key challenges that are relevant for successfully and prudently managing big data: identifying appropriate opportunities, new ways of deciding and managing, as well as managing talent. Table 7 presents a summary of these challenges, which are discussed below in more detail. Each challenge requires thorough consideration and response to ensure the successful employment of big data.

Table 7. *Management Challenges*

Challenge	Requirements for Success	Sources
Identifying appropriate opportunities	• Clearly defined business requirements • Large-scale opportunities • Involvement of top management and best talent	H.-M. Chen et al., 2017; LaValle et al., 2011; McAfee et al., 2012; Shmueli & Koppius, 2011; Watson & Marjanovic, 2013; Watson, 2016; Wirth & Wirth, 2017
New ways of deciding and managing	• Receptiveness for data-driven decisions and experimentation • Shift in the role of business analysts and domain experts • Adapted governance	Davenport, 2013; Janssen et al., 2017; McAfee et al., 2012; Phillips-Wren et al., 2015; Watson & Marjanovic, 2013; Watson, 2016
Managing talent	• Skills gap analysis • Data scientists • Shortage of talent	Alharthi et al., 2017; H.-M. Chen et al., 2017; Davenport, 2013; Janssen et al., 2017; McAfee et al., 2012; Phillips-Wren et al., 2015; Watson & Marjanovic, 2013; Wirth & Wirth, 2017

The first challenge, and therefore the starting point of an organization's big data journey, is *identifying appropriate opportunities*, beginning with a clear definition of the business requirements (Watson & Marjanovic, 2013). Detailed business requirements ensure an alignment of big data and analytics with the goals and strategy of the organization (Shmueli & Koppius, 2011; Watson & Marjanovic, 2013). Wirth and Wirth (2017) emphasize the importance of defining use cases and addressing critical questions before diving into big data initiatives: "What are the crucial decisions that we take on a regular basis? Which decisions or business processes should be more data-driven and objective? What are our most important pain points? Where would we benefit most from data-driven solutions?" (p.33).

The challenge of answering these questions and identifying the right opportunities results from uncertainty and a lack of relevant experience when managers are confronted with new and advanced technology (Chakravarti et al., 1981; Huber, 1990). Most executives have an elementary understanding of big data and its occasional successful use in other companies, but are unsure of how to utilize it in their specific organizational environment (Watson & Marjanovic, 2013). To find appropriate opportunities and set detailed requirements for their organizations, managers therefore require a wide skill set that incorporates technological understanding, project management experience, creativity, innovativeness and calculated risk taking (LaValle et al., 2011; McAfee & Brynjolfsson, 2012; Watson & Marjanovic, 2013). The definition of use cases and business requirements informs the appropriate choice of technology and analytics tools (Wirth & Wirth, 2017). The technology and tools should therefore be the consequence of thorough planning, and not the starting point of big data initiatives.

In terms of project scale, a survey of 3,000 executives, managers, and analysts by LaValle et al. (2011) suggests seizing large-scale opportunities instead of small-scale big data projects, which paradoxically bare lower risk and have a higher potential of serving as a successful example. The lower risk can be explained by the involvement of top management and best talent in large-scale projects, lowering the risk of failure. While top management support has been a constant in prior eras of system implementation literature, it plays a particularly crucial role for the employment of big data (H.-M. Chen et al., 2017; Watson, 2016). This eventuates from the ownership of big data projects, which is more successfully driven by use cases and business requirements than by IT (Wirth & Wirth, 2017). Early success with big data projects demonstrates their value and subsequently encourages a more data-driven mindset throughout the organization, leading to its cultural transformation (LaValle et al., 2011; Watson, 2016).

Employees have to embrace this cultural change induced by big data use (Watson, 2016), which according to Davenport (2013), involves *new ways of deciding and managing.* Traditional decision-making styles, like the use of intuition or judgment, are substituted or at least complemented by data-driven experimentation (Davenport, 2013; S. Shah et al., 2012). Large-scale decisions about pricing or production cycles, for instance, are made after appropriate small-scale experimentation informed by big data outcomes. Trust in data, the prerequisite of (big) data-driven decision making, can only be built when previously intuition- or judgment-driven decisions are reduced in favor of a greater reliance on data (McAfee & Brynjolfsson, 2012). The establishment of such a cultural foundation is therefore crucial for the successful launch of analytics projects (H. Chen et al., 2012; Davenport, 2006; Nicolas, 2004).

To facilitate this required change in corporate culture, the roles of business analysts and domain experts must evolve. Business analysts and BI experts need to "know not only how to turn raw data and information (through analytics) into meaningful and actionable knowledge for an organization, but also how to properly interact with and communicate this knowledge to the business and domain experts of the organization" (H. Chen et al., 2012, p. 1183). The role of domain experts, then, shifts from being the provider of solutions and answers, to asking the right questions (McAfee & Brynjolfsson, 2012). This shift supports the overall aim of adapting the organization's decision-making structure to enable cross-functional collaboration, and places the decision-making rights with positions that have the relevant information (McAfee & Brynjolfsson, 2012; Ross et al., 2013). The collaboration among analysts, BI experts and decision makers is considered “a key condition to overcome fragmentation and create a BD [big data] chain”, eventually positively affecting the decision-making quality (Janssen et al., 2017, p. 5).

This new dynamic between IT and business highlights the importance of defining roles and responsibilities, as well as establishing effective data governance (Wirth & Wirth, 2017). While technical aspects should be attributed to IT personnel, the overall governance should be managed on the business side. IT is therefore responsible for the set-up of the infrastructure, while business oversees aspects such as data access, acquisition, storage and documentation (Phillips-Wren et al., 2015; Wirth & Wirth, 2017). An effective governance structure stretches from prioritizing big data initiatives from different business units, to assessing their strategic fit, to providing training to decision makers (Phillips-Wren et al., 2015). Governance processes should also incorporate legal compliance to effectively avoid security breaches and privacy concerns. Furthermore, mechanisms for the selection and processing of the most suitable data sources as well as knowledge sharing of the insights gained should be in place (Janssen et al., 2017; Phillips-Wren et al., 2015).

The last management challenge that organizations face is concerned with the lack of specialized human resources. The use of big data and analytics prompts an increased attention to *talent management*, i.e. acquiring, securing, and training employees in order to develop the necessary skills for exploiting big data initiatives (Bumblauskas et al., 2017; McAfee & Brynjolfsson, 2012; S. Shah et al., 2012; Watson, 2016). In early stages, a skills gap analysis serves as the most effective tool for assessing which big data and analytics skills are lacking in the organization (Watson & Marjanovic, 2013). Then, appropriate and tailored measures such as new hires, consulting services or training efforts can elevate the skill level. Otherwise, insufficient skills and knowledge around big data can negatively affect decision-making quality, especially if the decision maker has limited understanding of the data's meaning or context of collection (Janssen et al., 2017).

> Turning data into meaningful insights requires scientific rigor, solid knowledge of statistics, and expertise in the respective empirical methodology. Volume and quantity of data are often misjudged as the main prerequisite of a successful analysis but this misunderstanding can lead to weak or even wrong results. (Wirth & Wirth, 2017, p. 36)

Sufficient skills are therefore required to understand the limitations of the data, as it might be flawed, the context of its collection too specific or the dataset not suitable for the use case (Wirth & Wirth, 2017).

McAfee et al. (2012) especially emphasize the role of data scientists, who serve as an intermediary between business requirements and technological capabilities and represent a crucial part for the success of big data use. A background in statistics, computer science, and mathematics, combined with an understanding for business, enables them to communicate insights to both IT and business leaders (Phillips-Wren et al., 2015). Their role therefore exceeds the traditional responsibilities of business analysts as they "work on new product offerings and help shape the business" (Davenport, 2013, p. 67). Their focus is on the analysis and development of descriptive and predictive models (Phillips-Wren et al., 2015), while data engineers provide more technical support during this process, such as ensuring the availability of required tools (Wirth & Wirth, 2017). Data scientists, however valuable for the organization, are still a rather scarce and costly resource that must also be considered in the preparation of big data projects (H.-M. Chen et al., 2017).

Specialists for big data (and analytics in general) are a sought-after commodity, crucial for big data success, which poses a major challenge for organizations (Alharthi et al., 2017; Janssen et al., 2017): “According to the U.S. Department of Labor, the shortage of people with big data skills in the U.S. alone [was] predicted to be between 120,000 and 190,000 by 2018” (Alharthi et al., 2017, p. 288). This shortage is consequential for organizations, as a lack of analytics skills can result in data entry errors, leading to loss of information and the value of the insights gained being compromised (Alharthi et al., 2017). One of the ways this skills shortage is addressed on a bigger scale is via collaborations between industry and educational institutions, which provide early-on training and building up a more adaptable workforce.

2.3.2. Technological Challenges

After the first of the management challenges is addressed and careful consideration of the organization’s business requirements leads to the right big data opportunity, this choice will inform its technological requirements. This results in the organization encountering technological challenges, given that big data’s requirements exceed current data management and analytics capabilities (Alharthi et al., 2017; Jagadish et al., 2014; Watson & Marjanovic, 2013). The main challenges, as summarized in Table 8, are the selection of comprehensive technology, the collection and preparation of the data, as well as processing and interpreting big data. These challenges follow a sequential order, with each challenge relying on the successful completion of the previous step.

The first technological challenge organizations need to overcome is *selecting comprehensive technology*, which builds the foundation for successful long-term big data initiatives. LaValle et al. (2011) emphasize the need for an integrated and consistent information foundation that can be extended with further applications. Additional programs and tools can be added for specific analyses, with the foundation ensuring the compliance with the big data strategy (LaValle et al., 2011; McAfee & Brynjolfsson, 2012; Watson & Marjanovic, 2013).

Table 8. *Technological Challenges*

Challenge	Requirements for Success	Source
Selecting comprehensive technology	• Integrated and consistent foundation • Appropriate tools and framework • Keep existing capabilities	Alharthi et al., 2017; H. Chen et al., 2012; Davenport, 2013; LaValle et al., 2011; McAfee et al., 2012; Watson & Marjanovic, 2013, Wirth & Wirth, 2017
Collection and preparation of data	• Acquisition of data • Effective filtering of data • Addition of supportive metadata • ETL and data cleansing	Davenport et al., 2013; Jagadish, 2014; Janssen et al., 2016; Miller & Mork, 2013; Phillips-Wren et al., 2015; Shah et al., 2012; Wirth & Wirth, 2017
Processing and interpreting big data	• New methods for data querying and mining • Visualization tools • Analytical understanding in management • Embedded analytics	Davenport, 2013; Jagadish, 2014; LaValle et al., 2011; Miller & Mork, 2013; Moore, 2017; Phillips-Wren et al., 2015; Shah et al., 2012;

The variety dimension of big data in particular can render the organizations' existing legacy systems insufficient. The data's heterogeneity exacerbates its processing, specifically the integration of new unstructured data sources with structured data (H. Chen et al., 2012; O'Leary, 2013). However, a variety of new tools and applications facilitate the transformation of unstructured inputs, e.g. from social media, into structured data. Organizations can benefit from processes such as MapReduce, which are superior to parallel DBMS in terms of analytics as well as ETL (extract, transform, load) of semi-structured data (H. Chen et al., 2012). Developing an infrastructure that supports big data and advanced analytics is connected to substantial costs (Alharthi et al., 2017).

Legacy systems, such as Decision Support Systems (DSS), data warehouses and NoSQL databases, should be kept and added to instead of eliminated to keep existing capabilities (Alharthi et al., 2017; H. Chen et al., 2012; Davenport, 2013; LaValle et al., 2011). All legacy systems can be of use for big data analytics. However, management is confronted with the challenge of creating an appropriate architecture (Davenport, 2013). If in place, a Knowledge Management System (KMS) can, for example, be an important prerequisite for the exploitation of big data, enabling the organization-wide sharing of insights (Intezari & Gressel, 2017; Pauleen, 2017). These systems enable users to acquire, create and store knowledge by offering a structured, large-scale and comprehensive knowledge base (Alavi & Leidner, 2001; Bhatt, 2001; Matthews, 1997; Swan & Newell, 2000).

After selecting the right technology and establishing a solid foundation, the *collection and preparation of data* represents the next challenge for organizations. Various types of data have to be discovered, stored, and integrated (Alharthi et al., 2017; Davenport, 2013; S. Shah et al., 2012). This challenge begins with the acquisition of data, referring to the collection of traditional data in form of structured customer and transaction datasets, but also of new and unstructured sensor, web, or simulation data (Jagadish et al., 2014). Not all of these big data sources prove relevant or valuable to organizations, and therefore require that the data be filtered and evaluated to determine which of it will be stored (Davenport et al., 2013; Jagadish et al., 2014; S. Shah et al., 2012). The underlying interests of an organization, as well as its use cases, inform this decision (Jagadish et al., 2014; Wirth & Wirth, 2017).

Following the extraction of data, it is paramount to document the quality of the data source. Miller and Mork (2013) remark on the necessity of adding supportive metadata to grant decision makers in later stages of the data analysis the possibility to trace the original sources and their quality. Given that the quality of big data sources varies significantly, organizations should aim to acquire accurate, timely, complete, consistent, and relevant data in order to prevent unwise and costly decisions based on unreliable data (Janssen et al., 2017).While not all data sources will be of high quality, the metadata enables organizations to use a variety of different quality sources for their use cases by providing them with confidence of knowing the data's reliability and origin (Wirth & Wirth, 2017).

The subsequent preparation of data is the first step for "bring[ing] disparate data together in an organized fashion and create[ing] valuable information that can inform decision making at the enterprise level" (Miller & Mork, 2013, p. 58). The specific steps of preparing big data differ in detail and name across the literature, as Janssen et al. (2016) remark. However, the main steps include data cleaning and the ETL process, which refers to the extraction, transformation, and loading of the data into the target system (García, Ramírez-Gallego, Luengo, Benítez, & Herrera, 2016; Jagadish et al., 2014; Phillips-Wren et al., 2015). The data cleaning eliminates inaccurate or incomplete data after the extraction from its sources. Then, the data is transformed into an analyzable format, which presents an increasing challenge, due to big data's velocity complicating the integration of heterogeneous data (Davenport et al., 2013; Jagadish et al., 2014). These ETL processes are therefore reliant on expertise and build the foundation for later analysis (Phillips-Wren et al., 2015).

After the data is prepared and loaded onto the target system, the *processing and interpreting of big data* confronts management with technological challenges because of its variety, velocity and volume: “Many of these processes have been standard in data analysis for a long time. What is different in the case of big data is the larger amount and variety of data under consideration and, possibly, the real-time nature of data acquisition and analysis” (Phillips-Wren et al., 2015, p. 456). Therefore, the right infrastructure and tools must be selected, in order for management to gain access to valuable insights at a more rapid pace. To accomplish this, the organization’s technology must be capable of processing an immense volume of data in real-time or near real-time (Davenport, 2013).

Because “Big Data is often noisy, dynamic, heterogeneous, inter-related, and untrustworthy,” new methods have to be established for big data to be queried and mined successfully (Jagadish et al., 2014, p. 90). Due to its volume and the spreading of NoSQL databases, traditional SQL queries can no longer be considered efficient, posing a challenge to organizations (Moniruzzaman & Hossain, 2013). An example of a software framework that can provide organizations with these capabilities is Hadoop, which is able to store and process data, identify patterns and create flexible predictive models (Phillips-Wren et al., 2015). The developed models can also be used for further analysis in the data warehouse, offering more in-depth insights.

After the processing of the data, the manager is presented with analysis results, which must then be interpreted. The analysis and results therefore have to be presented clearly and be logically retraceable, so the decision maker can verify them and make a prudent decision (Jagadish et al., 2014). Metadata about the data sources used in the analysis, as well as about potential integrations of those sources, can support the decision maker in tracing the steps of the analysis and assessing the credibility of the sources (Miller & Mork, 2013). Data visualization tools can also assist in this aspect, facilitating the interpretation of big data for managers (LaValle et al., 2011; Miller & Mork, 2013; Moore, 2017). Another factor influencing the successful gathering of insights is the decision maker's analytical understanding, which is required for the interpretation of big data outputs and their implications, as well as for transforming the data into decision- and policy-making (Janssen et al., 2017; S. Shah et al., 2012). The manager's experience with data-driven decision making was found to have a positive effect on the quality and speed of decision making (Janssen et al., 2017)

Even faster decision making can be achieved by embedded analytics, which relieves management from the obligation of selected day-to-day decisions (Davenport, 2013). Embedded analytics, however, and ultimately prescriptive analytics, require that high-quality management secure and supervise the planning and execution of these influential tools. This supervision is required for further investigating the outcomes of big data analytics, like in the case of correlations, which not necessarily equal causation (Provost & Fawcett, 2013). Analytics outcomes therefore benefit from expert judgment and human input.

2.4. Summary

The literature review introduced the topics of big data and analytics, outlined the need for further exploration of their use in the managerial decision-making process, and compiled organizational prerequisites that are expected to support managers in this venture.

While data has been used for decision making since the 1950s, traditional datasets have evolved–in terms of variety, volume, and velocity–into big data. For big data to be valuable to organizations, it must be transformed into information, and eventually knowledge. Therefore, analytics tools and techniques have also evolved–into advanced analytics, catering to the needs of big data. Big data and advanced analytics have the potential to improve decision making and various business processes, leading to overall performance gains. The variety and transparency of datasets provide organizations and researchers with numerous opportunities, but also challenges, as the use of big data technologies is associated with technological and organizational changes as well as privacy concerns.

Despite its challenges, big data's potential results in ongoing interest from academia and practitioners. Especially due to its improved insights, the evolution of data and analytics is expected to significantly affect decision making. This effect is explored by following one of the dual process theory variations: the two-system view of decision making. This theory posits that there are two distinct cognitive processes that can lead to a decision, namely System 1 and System 2. System 1 is understood as rapid, automatic, unconscious, and is based on the decision makers' experience and knowledge. As this system contextualizes encountered problems and often simplifies them, it is prone to biases.

System 2 has the potential to overwrite System 1, and is generally characterized as more rule-based, regulated, and slow. As it facilitates hypothetical thinking, and is rather structured, this system is applied for the most important decisions. System 2 is also often connected to rational decision making, and a structured decision-making process.

This process consists of three basic steps, namely identification, development and evaluation of alternatives, and selection.

Different decision types and contexts are expected to determine which system will be applied by the decision maker, and which specific process steps will be followed. Furthermore, data analytics and human judgment significantly influence management decision making. While managers rely on their intuition, experience, and wisdom, the use of data and analytics is still considered limited. Data quality, analysis paralysis and missing trust in data are potential reasons for this lack of use. Managers display a certain degree of insecurity around the topic of data analytics, according to research that can provide valuable insights. The extant literature on the integration of big data insights into the actual decision-making process falls short. This thesis aims to address this shortcoming by examining managers' past decisions captured in the form of critical incidents, as well as their general perceptions of data-driven decision making.

For managers to make informed decisions based on big data, organizations need to provide them with a supportive foundation. Organizations are often at a loss for a starting point with their data initiatives and encounter various unexpected difficulties that might be the result of unpreparedness, misguided reasons for implementation, or unrealistic expectations. The first step should therefore be the clear definition of business requirements and use cases to identify appropriate big data opportunities. For big data initiatives to take hold in the organization, the establishment of a data-driven cultural foundation is a critical prerequisite. Trust in data must be built as a complement to intuition and experience in decision making. In addition, the analytics and big data skills of the organization must be addressed with a sophisticated HR strategy entailing training for current employees, temporary employment of consultancy services, and new hires of scarce data specialists.

Furthermore, organizations need to overcome a range of technological challenges, beginning with the setup of a consistent infrastructure foundation that aligns with their big data strategy and is informed by business requirements and use cases. The integration of legacy systems into this infrastructure should be considered, as well as its extension by tools and applications for analysis. This foundation must be suited to accomplish the preparation and processing of the acquired data sets, which are exacerbated by big data's three defining dimensions. In order to monitor the varying quality of big data sources, metadata should be applied. This practice supports management in retracing the analysis steps when interpreting big data outcomes and incorporating them into their decision making. While these management and technological challenges are well covered in the literature as obstacles in the big data journey, research on their actual effects on the decision-making process falls short.

As this literature review highlights, the explanation of the effects of (big) data and analytics on individual managerial decision making in general fall short. To address these gaps the following two research questions were formed:

1) How do managers perceive the role of advanced analytics and big data in the decision-making process?
2) How do managers perceive the alignment of advanced analytics and big data with more traditional decision-making approaches such as human judgment?

CHAPTER 3: METHODOLOGY

This chapter describes the rationale behind the research methodology of this study, outlines its research design, and discusses the use of research methods and data collection, as well as coding and analysis techniques. The chapter begins with the rationale for employing qualitative research methods, abductive reasoning, and the researcher's epistemological stance. Next, the research design is explained, elaborating on a combination of multiple case study research and Critical Incident Technique (CIT). Third, the data collection section discusses the purposive selection of cases and the design of the semi-structured interviews, as well as the conducted pilot study and the resulting changes to the interview questions. Lastly, the multi-level approach to data analysis is explained, addressing the relationship between method, units of analysis, and the report of the findings. The two different analysis techniques, content analysis and thematic analysis, as well as their relation to the research methodologies, are then further discussed.

3.1. Research Rationale

Big data and advanced analytics' potential and opportunities are manifold. The extant literature provides an overview of diverse use cases, promises improved decision making through better insights, and cautions about various technological and organizational challenges. However, the literature has so far not provided sufficient insights into exactly how big data and analytics are incorporated into the decision-making process. The subsequent research aims to provide an in-depth understanding of this topic and focuses on exploring the balance decision makers must find between relying on analytical inputs and their own human judgment. The managers' perceptions and understandings of advanced analytics, big data, and organizational challenges further enrich these insights and form the context of this research project.

Exploring management decision making in this rather new age of big data and capturing subjective views to gain in-depth and context-specific insights calls for interpretive exploratory research using qualitative methodology:

> Qualitative research is suitable where the research emphasis is on in-depth understanding of how, why and in what context certain phenomena occur; and what impacts upon or influences such phenomena. It is most appropriate where the explanation and understanding of behavior or activities matter more than specific measurements. (Carson et al., 2001, p. 66)

I applied a qualitative methodology to capture and analyze these underlying reasons and circumstances of managerial decision making, relying on the participants' perceptions and interpretations of their actions. The nomination of the interpretive paradigm at this point of my study does not simply fulfill the purpose of establishing a great fit between the topic of this research and the chosen approach, but signals the influences this interpretive approach has on "the way knowledge is studied and interpreted. It is the choice of paradigm that sets down the intent, motivation and expectations for the research" (Mackenzie & Knipe, 2006, p. 194).

Since advanced analytics is a rather new phenomenon and the context of decision making will be of a rather complex and dynamic nature, this study endorses an interpretivist approach, based on the understanding and interpretation of managers and decision makers (Carson et al., 2001; Leitch, Hill, & Harrison, 2009). The choice of a qualitative, exploratory approach reflects my interpretivist research paradigm, which aims to explore real-life events as they are experienced by managers in their organizations (Carson et al., 2001).

The research questions have been crafted to provide me with deeper insight into management decision making and the influence of data analytics in contrast to human judgment. The interpretive framework in this qualitative study consequently employs research procedures that “are sensitive to participants and context” (Creswell, 2012, p. 32). The findings of this research are grounded in the self-examination of managers and their decision making, which also corresponds to my interpretivist epistemological stance (Leitch et al., 2009). Leading back to the corresponding constructivist ontological consideration of the nature of reality, the subjects of this study are assumed to be influenced by their previous experience, social setting and organizational context (Intezari, 2013; Mackenzie & Knipe, 2006). Therefore, the aim of this study is not to capture facts of an objective reality, but to explore and interpret the managers’ perceptions within the given context of this research (Leitch et al., 2009; Mackenzie & Knipe, 2006).

This wealth of information was collected and analyzed using case study methodology and the Critical Incidents Technique (CIT). Case study research was chosen as the primary methodology to capture a holistic picture of managerial decision making that exceeds the mere decision-making process and incorporates potentially influential and contextual aspects, such as personal characteristics and organizational factors. Case studies can be seen as a useful approach to gather “well-grounded, rich descriptions and explanations of developments that are relatively weakly understood” (Popovič et al., 2018, p. 3). CIT was selected as a secondary research method for gaining an in-depth view on the decision as an embedded unit of analysis, not only to focus on general answers from the manager and their context, but also to hone in on specific characteristics and circumstances of actual decisions. While CIT is mostly used as a stand-alone technique, it also finds application in 'cross-case comparison studies' (Gogan, McLaughlin, & Thomas, 2014, p. 2).

Other research methodologies had been considered but were dismissed due to their subpar fit. For example, extant empirical decision-making literature, particularly sources placing emphasis on the use of human judgment and/or analytics, relies on a variety of research methods. Quantitative data in the studies mentioned in this literature was mostly collected in the form of surveys (Brynjolfsson et al., 2011; Cao et al., 2015; LaValle et al., 2011; Müller & Jensen, 2017; S. Shah et al., 2012). While these quantitative studies provided thought-provoking impulses, their positivist underpinning often restricted insights to rather broad and generic statements, leading to a lack of depth in terms of relevant context and detail. Furthermore, subjective survey data, such as the data collected in LaValle et al. (2011), which relied on self-reported performance and analytics maturity levels, gives rise to validity concerns (Bertrand & Mullainathan, 2001). Quantitative methods were dismissed for these reasons.

Qualitative studies in the field of decision making with the focus on human judgment and/or analytics employed a variety of research methods that better suited the overall aim of this study as well as the interpretivist stance: case study research (Cavaye, 1996; Popovič et al., 2018; Walsham, 1995), CIT (Coetzer et al., 2012; Trönnberg & Hemlin, 2014), experiments (Dijksterhuis & Nordgren, 2006; Dijkstra et al., 2013; Elgendy & Elragal, 2016; Reyna et al., 2014), or other qualitative approaches (Dean & Sharfman, 1996; Dreyfus & Dreyfus, 1980; Hensman & Sadler-Smith, 2011; McAfee & Brynjolfsson, 2012).

However, experiments as a data collection method for this thesis were dismissed, as "experimental results produced by restricting experiments to precisely controlled but highly artificial situations" (p.2) have been criticized regarding their significance (Dreyfus & Dreyfus, 1980). Since the use of big data and analytics is considered a rather complex subject involving several varying contextual and situational factors, an experiment did not appear to be a satisfactory method for answering the research questions. Particularly given the exploratory nature of this study and the range of unknown factors, surveys or experiments would have led to subpar results and superficial or fragmented insights. Other options, such focus groups or the Delphi method, were also dismissed. These methods were not considered efficient in obtaining insights into real-life individual decision making. The aim of this research was to understand individuals, their past decisions, influences that they experienced, and their own subjective accounts and views of these decisions. Interpretive case study methodology and CIT were a better fit for this research, as the participants' views were not affected by other participants' experiences or opinions during data collection.

The field of information systems (IS) particularly values interpretive research: "[i]nterpretive research can help IS researchers to understand human thought and action in social and organizational contexts; it has the potential to produce deep insights into information systems phenomena including the management of information systems and information systems development" (H. K. Klein & Myers, 1999, p. 67). However, in contrast to quantitative research, the quality of qualitative research cannot be evaluated with control variables and validity tests. Klein and Myers (1999) therefore have developed a number of principles for interpretive field research that, if followed, facilitate a more robust research design and a more consistent practice of data collection and analysis. I used these principles as guidelines throughout this study, beginning with the contextualization of my research by outlining the history of data analytics.

In addition to these interpretive principles, guidelines for qualitative research can also be found in the literature (Patton, 1999). These guidelines are similarly aimed at improving the quality of research. Patton (1999) advocates integrity in the analysis process by including alternative explanations for analysis findings. This extends to the inclusion of negative cases, i.e. cases that do not fit the identified patterns. I applied these techniques during my analysis, not only to follow the guidelines, but also as an integral part of the abductive approach I followed, which will be explained in the next paragraph.

Patton (1999) furthermore introduces various forms of triangulation, which enable the researcher to view different aspects of the research topic. Triangulation is a prominent subject in case study methodology, and will therefore be specifically discussed in part 3.2.1., alongside further guidelines that specifically address case study research (Benbasat, Goldstein, & Mead, 1987; Yin, 2014).

Given the novelty of the research topic, the exploratory nature of this study, and a range of only partially applicable theories, the analysis process and resulting findings are based on an abductive approach to theory building. Abduction enables researchers "to break out of the limitations of deduction and induction, which both are delimited to establish relations between already known constructs" (Kovács & Spens, 2005, p. 136). Its objective is the exploration of the collected data, the identification of themes and patterns, and lastly the application of some level of guessing and intuition as to their significance and meaning, eventually resulting in logical propositions (Lipscomb, 2012; Shannak & Aldhmour, 2009). The applied intuition is triggered by unexpected findings that existing theories are unable to explain, which initiates the abductive reasoning process of systematic analysis (Kovács & Spens, 2005; Shannak & Aldhmour, 2009; Timmermans & Tavory, 2012).

Abductive reasoning follows a spiral process instead of linear logic, using theoretical lenses for data interpretation (Blaikie, 2007). An exemplary depiction of this spiral process can be seen in Figure 4 below. The process begins at the point of a surprising observation that does not align with the study's established theoretical foundation, leading to additional questions and a search for fitting frameworks in an iterative process step that is referred to as 'theory matching' (Shannak & Aldhmour, 2009).

These iterations are aimed at finding a suitable theoretical framework as an explanation for the empirical observation, or for extending the initial theory. Abduction can also result in the proposition of general rules (Kovács & Spens, 2005). In this capacity, the primary objective of abductive reasoning is not generalization, but a focus on context and specific circumstances, highlighting the distinction between generalizable and context-specific results. The attention to environmental influences and context-specific observations was mirrored in my choice of case study methodology and embedded CIT.

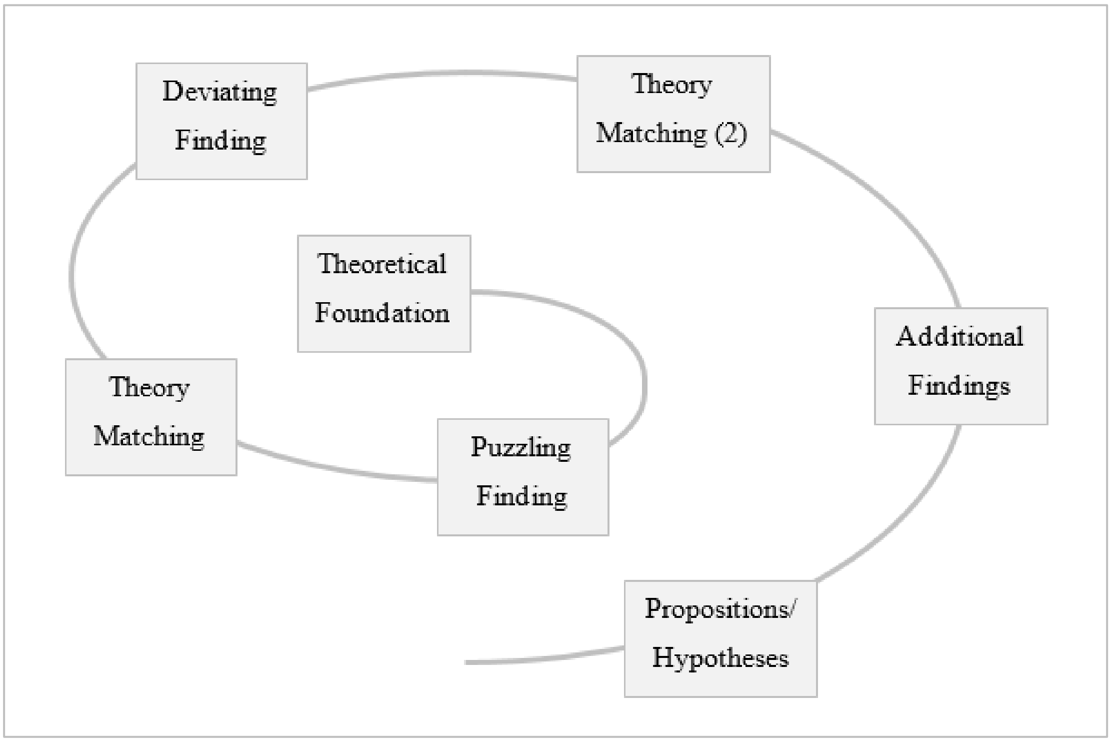

Figure 4. *Abductive Reasoning*

I made surprising observations at several points during my research journey, beginning with the recruitment of participants and my initial impressions during the early stages of data collection. These surprises led me to delve deeper into the collected data, addressing questions such as ‘Why is big data/analytics not being used?’, ‘Which individual/decisional/organizational factors influence whether or not big data is being used?’, and so forth. The spiral process of matching findings to theories that had been identified during the literature review, exploring new theories, and exploring propositions put forward in recent publications, led to a thorough and holistic multi-level picture of managerial decision making.

3.2. Research Design

The research design of this study reflects its exploratory nature, as well as its holistic approach to delving deeper into the managerial decision-making process from an individual, as well as from a decision-specific and organizational point of view. This is accomplished by employing case study methodology with the individual managers (M) as the unit of analysis, with several managers having the same organizational context. The managers were interviewed about their general perceptions on the research topic and were additionally asked to provide a number of critical incidents (CI), i.e. recalling critical data-driven decisions that these managers had made in the past. These incidents served as an embedded unit of analysis, which will be discussed in more detail in section 3.4.1.

The various critical incidents were each analyzed in the context of their case (the manager), but also cross-analyzed with all other incidents in form of a content analysis that informed the first findings chapter on decision-making processes (Chapter 4). The cases were individually and cross-analyzed, informing all three findings chapters, but particularly the second one, which specifically addresses the varied types of managerial decision makers. The organizational context facilitated the development of a management decision-making environment that captures influences on the managers and their decision making, which forms the third findings chapter. The research design is outlined in Figure 5, and the individual research methods will be explained in detail in the following sections.

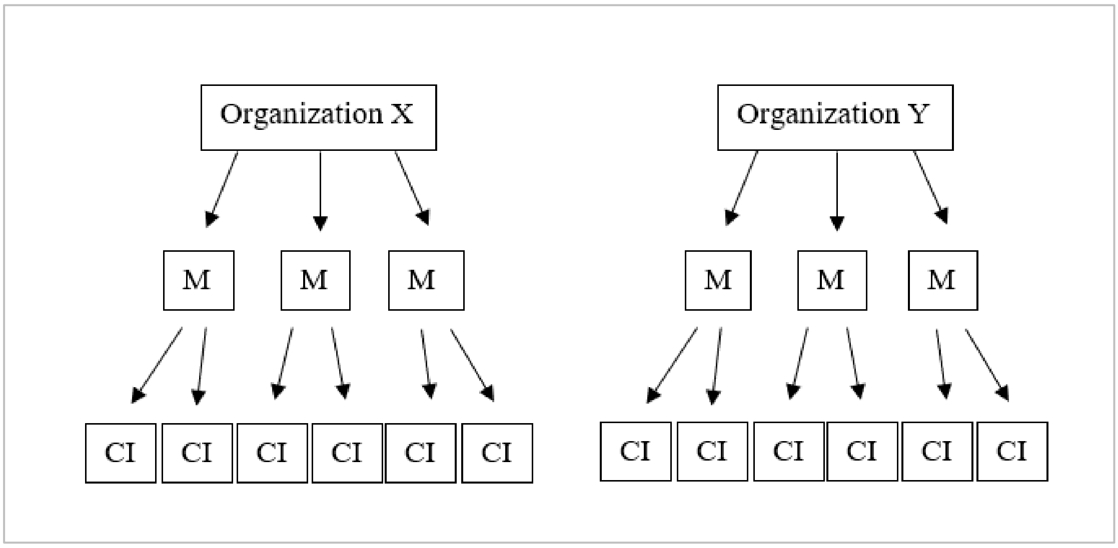

Figure 5. *Research Design*

3.2.1. Case Study Research

I chose case study research as the main methodology for this study for addressing the exploratory research questions. It is commonly used in this capacity and is understood as a well-founded approach for furthering knowledge and discovery in the discipline of information systems (Benbasat et al., 1987; Cavaye, 1996). In their review of case study research in the IS field, Benbasat et al. (1987) conclude that "case study strategy is well suited to capturing the knowledge of practitioners and developing theories from it" (p.370). In contrast to surveys and experiments, case studies provide "a broader view on a problem" than surveys or experiments (Blumberg, Cooper, & Schindler, 2011, p. 256), and are more suitable for researchers who have less a priori understanding of which variables will be significant during the study (Benbasat et al., 1987).

This broader view lends itself to theory building, enabling me to explore explanations and connections that I had not considered from the outset (Blumberg et al., 2011), but emerged through pattern recognition during the analysis (Patton, 1999). Big data and analytics research is still considered to be in the early stages, and therefore benefits greatly from a broad view and insights from diverse cases (Popovič et al., 2018).

Case study methodology is commonly chosen to explore phenomena in their natural setting and real-life context (Benbasat et al., 1987; Blumberg et al., 2011; Darke, Shanks, & Broadbent, 1998; Yin, 2014). This study uses multi-case research, which provides the additional benefit of expanding the exploration of the phenomenon to more than one context (Blumberg et al., 2011; Stake, 2006). These contexts were expected to influence the cases, i.e. managers, and their decision making. Therefore, the phenomenon of managerial decision making with big data and advanced analytics was explored in its real-life setting, considering the managers, their various decisions, and their organizational and industrial environments.

The context was thus not stripped from the results to achieve generalization, but rather examined to identify key aspects that influence managerial decision making. This allowed me to "shed light on a phenomenon from multiple perspectives defined by its context" (Blumberg et al., 2011, p. 256). For this aspect, multi-case studies are considered more appealing and also more robust than single case studies (Blumberg et al., 2011). Particularly for postgraduate research, the use of several case studies is recommended, as they enable cross-case analysis, allowing for 'richer theory building' (Perry, 1998, p. 792).

This research relied on the decision maker as the unit of analysis when qualitatively exploring the role of intuition in decision making, similar to a study on intuitive decision making in the banking sector by Hensman and Sadler-Smith (2011). An embedded unit was the decision. Selecting these units of analysis enabled me to explore how the decision types, managerial characteristics, and organizational context affect the managerial decision-making process. Therefore, the case fulfills Creswell's (2013) requirement to have natural boundaries and supports the study's aim of developing an in-depth analysis. Each case captured the manager's perceptions of advanced analytics' role in decision making, and also provided insights into his/her organizational background, taking the manager's specific context into account while also providing a holistic view of the research problem (Carson et al., 2001; Leitch et al., 2009).

This holistic approach, and how it applies to the research questions, is depicted in Figure 6. The central part of this figure is adapted from Miles et al. (2014), who use the heart as the focus and therefore the unit of the analysis. The circle around it outlines the boundaries of the case, with the inside representing the case context. I added the center of the heart to display the embedded unit of analysis.

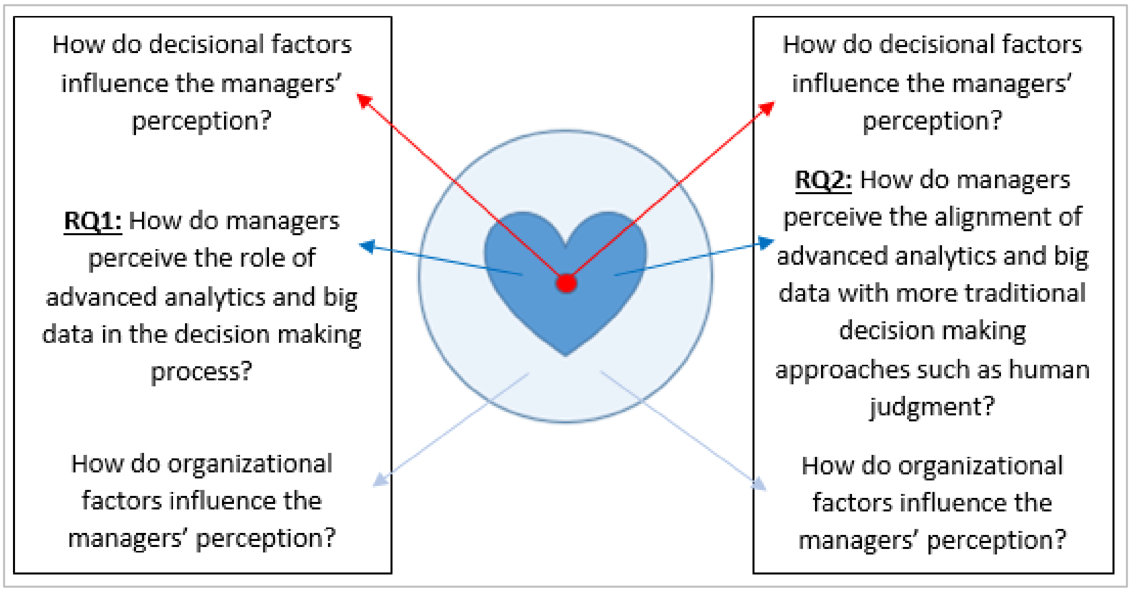

Figure 6. *Holistic Case Study Approach (adapted from Miles et al. (2014))*

The primary data collection method for this holistic research approach was semi-structured interviews with decision makers. Case study research often relies on several data collection methods (Blumberg et al., 2011; Stake, 1995; Yin, 2014), which in this study was mainly achieved by applying a second research methodology, i.e. CIT. Data for CIT was also collected through interviews; however, these were of a more structured nature addressing real-life events. The specific interview setup, preparation, and questions will be discussed in the next section. Additionally, secondary data was used to a limited extent when available, in the form of supportive news articles, articles/memos authored by the managers, or information gained from the companies' websites. As significant and often key strategic decisions are the subject of this research, supporting documentation was not accessible. Observations or shadowing of managers was additionally deemed impractical, considering the length and complexity of the decision process.

The focus was therefore on data collection through interviews, which "are the most widely used source for collecting information for evidence" (Blumberg et al., 2011, p. 258), and are considered "one of the most important sources of case study evidence" (Yin, 2014, p. 110). The semi-structured interviews, as demonstrated by the questions presented in 3.3.2., were rather structured to ensure consistency and completeness throughout all participants. Another positive argument for using semi-structured interviews was to capture the managers' views on previous participants' perceptions. After the managers voiced their own views on certain questions, selected parts of the other participants' opinions were shared with the interviewees and they were asked to evaluate them. These reflections from other participants were simply used to "confirm insights and information the researcher already holds" (Blumberg et al., 2011, p. 258).

An important aspect of case study methodology is the concept of triangulation, which aims at strengthening the cases put forth, as well as increasing the depth of the research's presented information and transferability. Triangulation generally refers to the convergence of several data sources to strengthen the findings and their validity (Yin, 2014). In essence, it is “mostly a process of repetitious data gathering and critical review of what is being said […] to assure that the right information and interpretations have been obtained” (Stake, 2006, p. 34f.). There are four common types of triangulation, namely data triangulation, methodological triangulation, theory triangulation, and investigator triangulation (Denzin, 1989; Patton, 1999; Stake, 1995, 2006; Yin, 2014), which will be discussed in more detail below.

Data source triangulation is primarily used to assess whether the studied phenomenon changes across different spaces, times or with the people involved (Stake, 1995). Theoretical sampling can be considered a form of data source triangulation, as the selection of systematically divergent settings help the researcher to identify commonalities across these settings (Denzin, 1989). Applying theoretical sampling in this particular study, for example, enabled me to discover patterns that were unaffected by variables such as industry or character traits, but also patterns that were unique to certain groupings of people or decisions. In that sense, data source triangulation was a useful tool for me “to see if what we are observing and reporting carries the same meaning when found under different circumstances” (Stake, 1995, p. 113). To explore the managers’ perceptions on their decision making in different circumstances, they were asked about different decision types and situations. CIT was an especially useful technique in this regard, as it exposed real-life decisions under various circumstances, including potential shortcomings.

This form of triangulation was particularly relevant during the cross-case analysis, as several different data sources (i.e. the interviews conducted with the 25 participants) could be evaluated for their perspectives and meanings. In two different instances, two participants each reported about the same decision during the CIT part of the interview, providing different perspectives. Data triangulation within the case was used to a minimal extent, as most of the data was generated during one interview. Only in very few cases could documentation and online sources be used to gain further insights. Generally, while data triangulation can be considered crucial for the exploration of certain phenomena, managers' perspectives on their decision making are more personal and individual. This limits the use of different data sources, as the only valid and meaningful data source in this case are the managers themselves.

However, triangulation is still important for the accurate representation of the manager's meaning and perspective. Therefore, I provided the managers with several opportunities during the interviews to express their opinions and perceptions. At critical points during the interview, I also inquired as to whether my interpretations of their answers were correct, as "triangulation has been generally considered a process of using multiple perceptions to clarify meaning, but it is also interpreted as verifying the repeatability of an observation or interpretation" (Stake, 2006, p. 37). Stake (1995, 2006) furthermore suggests the technique of member checking, which refers to the practice of providing participants with a summary or report and giving them the opportunity for feedback. Accordingly, preliminary reports with initial findings were sent out to the participants with the opportunity for comment. While interest in these preliminary reports was shown, no changes were suggested.

A second form of triangulation, methods triangulation, was applied using a technique identified by Patton (1999) and Denzin (2009). This allowed me to gain deeper insights by relying on more than one data collection method, i.e. adding CIT to the case study methodology. The critical incidents provided the participants with the opportunity to describe their perspectives on the use of data during decision making through actual examples. This gave me the opportunity to explore beyond the managers’ general and hypothetical opinions, which added more facets to each case. The result was a more detailed and practical view of real-life decisions that managers had faced, and it often revealed a contrast between the theoretical and practical decision making of the managers.

As a third form, theory or perspective triangulation, i.e. the use of multiple theoretical perspectives to examine and interpret the data, was employed (Jick, 1979; Patton, 1999). This resulted naturally from the use of an abductive approach, which, as explained above, uses a spiral process to match and test diverse theories to the collected data. Several theories were therefore used as lenses or as potential explanations during the data analysis, which is further discussed in the respective findings chapters. The fourth and last form, triangulation of different evaluators, was not employed. A doctoral thesis is considered a single-author piece of work, and it was therefore not considered appropriate to involve several interviewers or researchers for the analysis. Supervisors were, however, presented with exemplary evidence from the cases and the interpretation of the results. These interpretations were not objected.

Often considered a limitation of interpretive case studies is their generalizability, which limits this methodology to the explanation of past data that can only be regarded as tendencies in the prediction of future events because of their setting in a specific context (Walsham, 1995). Nevertheless, the contribution of rich insights from multiple cases can benefit organizations and provide them valuable guidelines. They can also be considered impulses for further quantitative research and theory testing. Case studies therefore, while not necessarily suitable for the purpose of generalization, are a good approach for developing theory and very appropriate for "How?" and "Why?" questions (Blumberg et al., 2011; Yin, 2014).

Thus, case studies facilitate an understanding of real-world problems, as their findings are used to develop foundational theoretical explanations (Blumberg et al., 2011). This constitutes a good fit for the abductive approach of this study, which is also primarily concerned with offering such a potential form of explication instead of pursuing generalization. The analysis of case study data, which will be further discussed in section 3.4., equally matches the spiral processes of this abductive study: "With a case study, theories are developed and tested in a sequential, step-by-step, manner. Starting with a previously developed theory the researcher compares the results of the case study with the theory" (Blumberg et al., 2011, p.256).

3.2.2. Critical Incident Technique

An embedded unit of analysis (Carson et al., 2001; Eisenhardt, 1989) in this exploratory multi-case study are managerial decisions that were collected using the Critical Incident Technique (CIT) (Butterfield, Borgen, Amundson, & Maglio, 2005; Flanagan, 1954). The critical incidents were embedded in the main unit of analysis, i.e. the manager. Each manager's decisions therefore had to be analyzed and compared with one another before all managers could be cross-analyzed (Carson et al., 2001). Whereas the case study part of the interviews served to capture the managers' perceptions of their general decision making, the CIT part was used to gain an in-depth view of the actual practice, success, and requirements of decision making with advanced analytics. The sharing of these real-life events provided a different perspective from the managers' general answers (Coetzer et al., 2012), and generated rich descriptions of the managers' personal experience (Leitch et al., 2009; Serenko & Turel, 2010). Another strength of the technique is the reduction of the researcher's bias, as the participants are required to select themselves which incidents were most critical (Serenko & Turel, 2010).

CIT has mostly been employed in the area of psychology (Butterfield et al., 2005) and medicine (Bradley, 1992b); within the field of business studies, the technique has been used primarily for marketing, organizational learning, and performance appraisal (Butterfield et al., 2005). In the field of information systems, CIT has been used sparingly (Guimarães, Arce, & Mattos, 2013; Islam, 2014; Thomas & Bostrom, 2010), and is still considered an underutilized method (Gogan et al., 2014; Islam, 2014). It is, however, recognized as an effective exploratory tool in studies on decision making (Bradley, 1992b; Coetzer et al., 2012; Kaufmann et al., 2017; Powell & Greenhaus, 2006; Trönnberg & Hemlin, 2014). Coetzer et al. (2012) suggest that the "close correspondence between the broad elements of a decision-making situation and the elements of a typical critical incident is suggestive that the CIT is ideally suited to the study of managerial decision making situations" (p.174). This research therefore contributes to its expansion in the field of IS and the topic of decision making.

CIT is considered a rather flexible technique that can be modified and adapted according to the study's requirements (Butterfield et al., 2005; Coetzer et al., 2012; Flanagan, 1954). It provides a repertoire of procedures for collecting data on significant incidents that meet the researcher's predefined criteria (Flanagan, 1954). A critical incident is in this context defined as:

> any observable human activity that is sufficiently complete in itself to permit inferences and predictions to be made about the person performing the act. To be critical, an incident must occur in a situation where the purpose or intent of the act seems fairly clear to the observer and where its consequences are

> sufficiently definite to leave little doubt concerning its effects. (Flanagan, 1954, p. 1)

While originally focusing on direct observations, almost the entirety of CIT studies has been based on retrospective self-reports in recent years (Butterfield et al., 2005; Coetzer et al., 2012; Islam, 2014). A drawback of this retrospective retelling of an event is its potential risk of incurring biases (Gogan et al., 2014). Therefore, only critical incidents are considered in CIT studies, since “validation studies have confirmed that while it is difficult for respondents to confidently report on outcomes from typical behavior, recall is more accurate when they are asked to report on critical behaviors” (Gogan et al., 2014, p. 3). Kraajienbrink (2012) echoes this sentiment and considers these reports as accurate for processes. In this study, I asked participants to share decisions with me that had either significantly positive or negative outcomes, to ensure that the decisions were memorable to them.

CIT is primarily a content analysis method used for the classification of occurrences, events or activities (Islam, 2014), to further explore their requirements (Flanagan, 1954). The method ideally follows five steps as advocated by Flanagan (1954). The first step is the determination of the activity’s general aim (Urquhart, Lehmann, & Myers, 2010), which serves to establish the objectives of the researched activity, and therefore the criteria for assessing whether or not the activity is successful (Flanagan, 1954). The second step is data collection planning, during which the researcher specifies which incidents are relevant (Flanagan, 1954; Urquhart et al., 2010). According to Flanagan (1954), the incident must make “a "significant" contribution, either positively or negatively, to the general aim of the activity” (p.12) to be classified as critical. The third step is the actual data collection, either through (group) interviews, questionnaires, or record forms (Butterfield et al., 2005; Flanagan, 1954).

The fourth step is the analysis of the data, in which categories are formed in order to increase the data's usefulness (Coetzer et al., 2012; Flanagan, 1954). These categories facilitate easier reporting of the incidents, and enable the researcher to compare them and gain insights (Flanagan, 1954). The categories are created in a way that represents a useful summary of the data, but at the same time preserves as much of the incidents' context and comprehensiveness as possible (Butterfield et al., 2005; Coetzer et al., 2012; Flanagan, 1954). As a last step, the requirements of the activity that were identified during the data analysis require interpretation and reporting (Flanagan, 1954; Urquhart et al., 2010).

For this study, the general aim was explored with high-level employees and contact persons from the participating organizations, as well as the interviewees directly. I defined the critical incidents as decisions with significantly negative or positive outcomes, concentrating on exploring the roles of data and human judgment, as well as the requirements for successful decisions. The data was then collected in the form of retrospective self-reports through semi-structured interviews. During the analysis, three categories were identified according to the managers' use of data and human judgment in their decisions. These categories were further subdivided according to various factors, as can be seen in findings chapter 4. More information about the interviews is provided in section 3.3.2.; the coding and analysis is further explained in section 3.4., as well as in Chapter 4.

I considered CIT to be a suitable method for this study, particularly because it is described as "easy to use, and effective and robust. Its use allowed the identification of some trends […] it presents […] a methodology to aid scholars and practitioners to study managers in their information seeking and use behavior" (Guimarães et al., 2013, p. 781). The technique allowed me to generalize the incidents to an adequate extent while still preserving their context (Thomas & Bostrom, 2010). CIT, therefore, fulfilled its purpose of exploring the embedded unit of analysis, i.e. the decision, and of providing valuable insights into the main unit, the manager. It furthermore facilitated a holistic view on managerial decision making, the big picture results this study aimed for:

> CIT generates data which gives the researcher a holistic view of decision making situations. This includes data about factors leading up to the decision making situation, data about the actual decision that was made, and data about outcomes of the decision. (Coetzer et al., 2012, p. 174)

CIT was also compatible with the interpretive case study methodology. Next to the shift from direct observation to retrospective self-report, CIT has furthermore evolved over the years with regard to its underlying paradigm. Initially positioned in positivism (Flanagan, 1954), the technique has also become a valuable research tool for the interpretive research paradigm (Butterfield et al., 2005; Coetzer et al., 2012; Leitch et al., 2009; Thomas & Bostrom, 2010).

3.3. Data Collection

Both methodologies of this study utilized semi-structured interviews as their main data sources. The following elaborates on the planning and process of this data collection. First, the research context of New Zealand is specified. Second, the selection of cases for the case study methodology is discussed, expanding on selection criteria, replication logic, and demographics of the participating managers, i.e. the cases. Third, the interview questions for both the case study research and CIT are introduced, and their formulation is outlined. Last, the piloting of the interview questions and resulting changes to the questions are explained.

3.3.1. New Zealand Context

This study was limited to the context of New Zealand, as all participating companies and managers were based in New Zealand. Although some of these organizations were subsidiaries of international companies and several of the participants had international backgrounds, the decisions and environments explored in this study were set in New Zealand.

As big data is a worldwide phenomenon and its effects are also seen in New Zealand, the results and insights of this study are not just relevant to a New Zealand audience, but have international significance. Already in 2014, The New Zealand Data Future Forum was held to discuss the state of big data, its potential, risks, and opportunities, concluding that although not yet fully utilized, big data would have a transformative effect on New Zealand (Kirk, 2014). By 2016, an estimated spending of $4.5 billion in big data and sophisticated analytics across New Zealand businesses was reported (Ryan, 2016).

New Zealand also fares well in a study focusing on the leaders of the data economy. By determining a new GDP–abbreviated from 'gross data product'–30 countries were ranked taking into account four criteria: the absolute amount of broadband consumed, number of users active on the internet, institutional openness to data flow, and volume of broadband consumption per capita (Chakravorti, Bhalla, & Chaturvedi, 2019, p. 3). Achieving place 12 of 30 in this ranking, New Zealand can be considered a serious contestant among the international leaders of the data economy. Its position in the upper half of the ranking makes it a good research context as a representative setting for an international audience of this thesis.

3.3.2. Case Selection

The planning of the data collection for case study research begins with the identification of the research subject. After identifying the phenomenon to be explored, the cases can be considered as opportunities to study this phenomenon (Stake, 2006). Accordingly, the cases selected for this study had to be relevant to big data and analytics-driven management decision making, provide diversity, and facilitate insights into different contexts with varying complexity (Stake, 2006). This sentiment is echoed by Miles, Huberman, and Saldana (2014), who emphasize the importance of including a comprehensive sample that offers users a variety of cases with which they can identify.

The diversity of contexts is evident in, for example, the different degrees of data use in decision making, resulting in an inclusion of managers (cases) in organizations (contexts) that have always relied on data-driven decision making, have recently bought into it, or are still in the planning stage. Several more components were considered as distinguishing features that contribute to the cases' diversity, such as participants' positions, experience, or industry. The diversity this range provided for my study is considered a strength of multi-case studies, as it enables the researcher "to examine how the program or phenomenon performs in different environments" (Stake, 2006, p.23).

To facilitate this diverse exploration, typical as well as atypical settings must be selected (Stake, 2006) in a way that makes this selection purposive and not random (Miles et al., 2014; Stake, 2006). Therefore, I based my case selection on literal and theoretical 'replication logic': "The main idea behind replication logic is that according to a theory, one would expect that the same phenomenon occurs under the same or similar conditions or that the phenomenon differs if the circumstances change" (Blumberg et al., 2011, p. 257). Literal replication refers to the selection of very similar cases, which are expected to deliver similar outcomes and processes (Benbasat et al., 1987; Blumberg et al., 2011). On the other hand, theoretical replication assumes that selecting dissimilar cases will lead to contradictory results (Benbasat et al., 1987). Theoretical dimensions should inform the selection of these differing cases (Blumberg et al., 2011).

Case selection therefore requires careful consideration, and should not simply be opportunistic (Benbasat et al., 1987). I chose purposive case selection based on replication logic in an effort to select cases that are of theoretical value, i.e. confirming or opposing the theory in development (Eisenhardt, 1989; Perry, 1998; Stake, 2006). The main criterion for selecting companies was therefore their "information richness", which determined the overall number of cases (Perry, 1998, p. 793). The sampling was directed at diversity in various conceptual categories (Eisenhardt, 1989), such as the use of advanced analytics by the organization, the manager's department, position, experience, industry, and organizational size and culture.

An example of an often-suspected theoretical difference is corporate culture (Blumberg et al., 2011), which is described as an important aspect in the use of advanced analytics and big data, with large, data-driven and competitive corporations being mentioned as especially able to benefit from the increase in analytical competencies (Davenport, 2006; Huber, 1990; McAfee & Brynjolfsson, 2012). The industry background and its history of reliance on analytics was therefore expected to have an influence on the successful use of advanced analytics, leading to the inclusion of managers from diverse industries. The finance and banking industry, for example, is known for its reliance and use of analytics. Decision making in this sector is often highly dependent on the support of ‘hard data’, which leads to a constraint on intuitive decisions (Hensman & Sadler-Smith, 2011). Managers rely more on deliberative decision making than on intuition, and show a high reliance on hard information, such as financial information and economic circumstances in lending decisions (Trönnberg & Hemlin, 2014).

Anticipating a significant effect of organizational culture and setting on managerial decision making, I made efforts to recruit several individuals per identified organization. Managers within the same organization were considered to have a similar context (literal replication). Managers from a differing organization to those mentioned above, particularly in another industry, were expected to have a different context (theoretical replication). While several managers per organization were initially envisioned to draw conclusions about the organizational context’s effects on individual decision making, this was not always feasible in practice. As Perry (1998) points out, particularly small businesses can be a challenge in terms of participation numbers due to a limited participant pool, and I was often limited to one or two participants per company. However, similarities in terms of context were also found inter-organizationally.

The recruitment for data collection began through personal networking, which granted access to the first two organizations, resulting in the pilot case and several additional cases. Employment of a snowballing tactic led to further referrals (Noy, 2008); participants had been asked to inform potential contacts in other suitable organizations about the research project. This eventually led to the participation of Organization 4. Another recruitment effort was the publication of a press release about the research project in a New Zealand Sunday newspaper and corresponding website (Atherton, 2015). The participation of two additional organizations resulted from this exposure, Organizations 3 and 5. The snowballing tactic was also applied with these companies, not resulting directly in the addition of further participants but leading to the opportunity of presenting at the New Zealand Analytics Forum. This exposure led to connections with Organizations 8 and 9 that contributed several participants. A final effort for recruitment of more diverse New Zealand businesses was supported by an academic advisor from Massey University. Organizations 6 and 7 were ultimately identified through this approach.

After initial contact with the organizations, I provided the main contact person with an information sheet containing an outline of the research project which can be seen in Appendix A. If the organization showed interest, the information sheet was forwarded internally. After clarification of all questions and a discussion about participant characteristics, the most apt and interested managers were identified by the respective liaison of the organization as participants for the study. Prospective participants as well as their organizations were evaluated according to certain criteria in order to be considered a good fit for the study. Particularly in the later stages of data collection, the following points were considered when assessing each case's fit with the replication logic:

Key Criteria for Participation:

- Analytics Maturity: organizations had to use data analytics for their decision making or show an interest in employing data in the near future.
- Positions: participants were required to have managerial positions, or more technical roles, such as Business/Data Analyst.

Literal and Theoretical Replication Criteria:

- Industry
- (Non-) Profit sector
- Organizational size
- Experience with analytics and decision making
- Department
- Decision types
- Gender

Suitable participants were then sent the information sheet (see Appendix A) and consent form, as well as a preparation document for the CIT part before the interview. This preparation document can be found in Appendix C and will be further discussed in the next section.

The result of these recruiting and replication efforts was a diverse sample of 25 participants, who provided a variety of opportunities for an in-depth exploration of decision making with big data and advanced analytics. A complete table of demographics can be found in Appendix B, while Table 9 and 10 summarize some of the key demographics. Table 9 outlines the number of participants per department, industry, and organizational size. Managers from nine New Zealand organizations participated in the study, granting insights from the industries of financial services, computer and software, transportation, as well as agencies and non-profits. The participants' departments/functions were categorized as operations, finance, marketing, analytics and the position of CEO. Organizational size was categorized as small (<10 employees), medium (10-99), or large (>99) (Lawrence, Collins, Pavlovich, & Arunachalam, 2006).

Table 9. *Participants by Industry, Organizational Size, and Department*

Industry			Department/Function					Total
			Marketing	Finance	Operations	Analytics	CEO	
Financial Services	Org. Size	<10	0	0	0	0	0	0
		10-99	0	0	0	0	0	0
		>99	**1**	**1**	**5**	**3**	**1**	**11**
	Total		**1**	**1**	**5**	**3**	**1**	**11**
Transport	Org. Size	<10	0	0	0	0	0	0
		10-99	0	0	0	0	0	0
		>99	0	0	**5**	**1**	0	**6**
	Total		0	0	**5**	**1**	0	**6**
Non-Profit	Org. Size	<10	0	0	0	0	**1**	**1**
		10-99	0	0	**1**	0	**1**	**2**
		>99	0	**2**	0	0	0	**2**
	Total		0	**2**	**1**	0	**2**	**5**
Agency	Org. Size	<10	0	0	0	0	**1**	**1**
		10-99	0	0	0	0	0	0
		>99	0	0	0	0	0	0
	Total		0	0	0	0	**1**	**1**
Computer/ Software	Org. Size	<10	0	0	0	0	0	0
		10-99	0	0	0	**1**	**1**	**2**
		>99	0	0	0	0	0	0
	Total		0	0	0	**1**	**1**	**2**
Total	Org. Size	<10	0	0	0	0	**2**	**2**
		10-99	0	0	**1**	**1**	**2**	**4**
		>99	**1**	**3**	**10**	**4**	**1**	**19**
	Total		**1**	**3**	**11**	**5**	**5**	**25**

Table 10 provides an overview of the participants' average years of experience with analytics, big data, general decision making, and in their role–sorted by position. Participants interviewed were categorized as managers, heads of departments, general managers, C-level executives, and analysts (which includes business analysts and data scientists). Expectedly, across all positions the participants had fewer average years of experience with big data than with analytics. However, the already low number of average years was skewed, as most participants had under one year or no experience with big data at all. Only six participants had more than a year of experience with big data, nevertheless raising the average significantly. While the on average 44.7 year-old participants had vast experience with decision making (18.5 years), their experience with analytics was more limited (10.1 years). This serves as the first indicator of analytics being a more recent addition to the management decision-making process.

Table 10. *Participants' Experience by Position*

Experience with	Position					Combined Average
	Analyst	Manager	Head of Department	General Manager	C-Level	
	n=4	n=5	n=6	n=4	n=6	
Analytics	3.3	7.8	9.9	14.4	14	10.1
Big Data	1.3	0.9	4.1	8.6	3	3.5
Role	2.1	2.4	2.8	5	7.1	4.0
Decision Making	6.1	15.6	24.4	23.5	20	18.5

The sample consisted of 23 males and 2 females. The low number of female participants can be explained by a comparatively low number of female managers and executives in the participating companies. The organizations were asked to nominate individuals for this research, which in turn were almost exclusively male. When possible, I made an effort to recruit female employees in accordance with purposive sampling to add ‘diversity of context’ (Stake, 2006, p. 23). The absence of more female participants was, however, not considered to be a major limitation, as the two female participants’ answers did not significantly vary from their male counterparts’; a focus on gender was also outside of this study’s scope. Furthermore, as Harrison (1995) states: “There is little hard evidence to support a contention of significant differences in the behavior of males and females enacting managerial roles in formal organizations” (p.271). Another IS study by Thomas and Bostrom (2010) interviewing IS Project Virtual Team Leaders has a similarly low number of female participants: 2 out of 13.

During the planning phase of data collection, a sample size of 12 to 15 cases was initially set, which is a common sample size for multi-case studies to provide literal and theoretical replication (Benbasat et al., 1987). The number of cases was then increased to incorporate more diverse perspectives, and to allow for the collection of additional critical incidents. Eventually, theoretical saturation was reached after 18 interviews, at which point "incremental learning is minimal because the researchers are observing phenomena seen before" (Eisenhardt, 1989, p. 545). While all case studies have unique settings and therefore unique qualities, the experiences that were gathered after the 18th interview did not lead to the creation of new themes and offered only marginal additional insights. The additional seven interviews did, however, enable me to ensure that saturation had been reached (Kraaijenbrink, 2012), and enriched the dataset by reinforcing the themes, providing a deeper understanding of some facets, and delivering more critical incidents (decisions).

For the CIT part of the interview, the participants were asked to recollect three to five critical incidents (decisions) which were memorable to them and resulted in a significant outcome, both positive and negative. Most interviewees shared between one and three incidents, which led to a total number of 43 usable incidents. A similar sample size of 12 to 15 interviewees with four to five incidents has been used in studies by Ellinger, Watkins and Bostrom (1999), Coetzer, Redmond and Sharafizad (2012), as well as Thomas and Bostrom (2010). In their review of CIT studies, Gogan et al. (2014) state that several studies reached theoretical saturation at around 40-50 incidents.

3.3.3. Interviews

The primary data collection method for both the case study methodology and CIT were semi-structured interviews, since this method provides the best access to interpretations of actions and past events (Walsham, 1995). The interviews were therefore well suited to exploring the participants' perceptions on critical incidents of management decision making with analytics and big data. To sufficiently answer both research questions, I designed the interview in a way that provided a fundamental structure covering all relevant factors expected to affect data-driven decision making, which had been identified during the literature review. At the same time, the semi-structured nature of the interviews allowed for a more natural conversation with the participants, during which new factors and aspects could emerge (Blumberg et al., 2011).

Blumberg et al. (2011) notes that the interviews conducted with key informants, such as, for example, the business analysts in this study, are often of a more informal nature. These participants had a deeper understanding and multi-faceted views, which I found to vastly enrich my insights into the topic and assisted in highlighting central factors and aspects. Interviews with managers from Pacifica organizations were similarly conducted less in a formal way, as this was suggested by the Pacifica advisor to create a better climate for the interview.

All interviews were recorded and transcribed verbatim, so as to preserve accurate wording and decrease the variation of interpretation (Flanagan, 1954). Twenty-four interviews were conducted, predominantly in person; one was conducted over the phone due to logistical reasons. On average, the interviews lasted about 46 minutes, with a minimum of 22 minutes, and a maximum of 75 minutes. About one hour is the expected duration for short case study interviews, as they tend to focus on following the case study questions. This results both from a comparably large number of cases, and from the research objective being the participants' perceptions, which requires more focus on the developed questions (Yin, 2014). In terms of the CIT portion of these interviews, participants shared on average 1.7 incidents, with a maximum of four incidents, and four participants were without incidents. In total, 43 usable incidents were collected, which is considered a sufficient sample for CIT studies (Coetzer et al., 2012; Ellinger et al., 1999; Gogan et al., 2014; Thomas & Bostrom, 2010).

3.3.3.1. Interview Structure

I began every interview with a brief introduction to the study and its aims, explained the participants' rights and obtained their written consent (Yin, 2014). The interview questions, which will be discussed below, consisted of three parts, beginning with a demographics section that incorporated a clarification of the terms analytics and big data. This was followed by a section capturing the participants' past decisions, which was designed according to the Critical Incident Technique (Flanagan, 1954). Lastly, questions which are referred to as case study questions were posed addressing general managerial decision making. While the CIT questions addressed real-life examples, the case study questions aimed to gather the participants' general impressions and perceptions.

Conducting the CIT part of the interview ahead of the case study questions was an intentional choice to reduce bias in the recollection of the incidents–i.e. before the interviewee could be influenced by certain terminology or factors covered in the case study questions. The incidents could then be revisited (if appropriate) during the case study question portion to gather more details about the participants' understanding of their use of human judgment and analytics during the respective decision. This offered participants a chance to reflect on these decisions, and subsequently their general decision-making process. This reflection also lent additional depth to the collected data.

Demographic information was collected first via a set of traditional questions requesting the participants' age, education, experience, and department. I also inquired about the participants' understanding of big data and analytics. This provided insights into their a priori knowledge of the topic. Common definitions were shared with the participants afterwards to ensure a mutual understanding of the following questions.

Furthermore, participants were not only asked about their position, but specifically how their role related to data/analytics. This was used to gain an understanding of the participants' exposure to analytics before the interview, as well as of their role–enabling me to ask more specific and targeted follow-up questions. It also presented a convenient way of easing the participants into talking about the often difficult and not well understood area of analytics. It furthermore served as a confirmation or specification of the general aim of decision making with analytics, which was an important prerequisite for the following CIT portion of the interview.

3.3.3.2. CIT Questions

During the second part of the interview, participants were asked to share critical incidents, for which the majority had prepared in advance. For this part, information-rich data collection depended on the participants sharing specific details about their decision-making process in real-life situations. The key objective was to determine if the applied process had been efficient and effective, i.e. led to a positive decision outcome. It was thus important to identify which steps were perceived as factors contributing to a successful decision, as well as which factors posed obstacles and hindered the decision-making process. Gathering this information required participants to lead me through the process by outlining their experience as a sequence of steps or events that occurred, beginning with the leadup to the decision, and ending with lessons they learned.

The Critical Incident Technique provided a supportive structure for gathering this information in a consistent manner that facilitated the comparison of incidents during data analysis. This part of the interview began by asking the participants to recall significant decisions they had made in the past relying at least partially on data/analytics, and which had a significant negative or positive outcome. This encouraged the participants “to do most of the talking, [so] the interviewer can usually get unbiased incidents” (Flanagan, 1954, p. 16), a crucial element of the technique. If participants left out critical parts during their narrative, the main CIT questions, as well as probing questions, were asked, as seen in Table 11. These questions were adapted from Flanagan’s (1954) seminal piece of work as well as CIT studies by Thomas and Bostrom (2010), Hensman and Sadler-Smith (2011), and Bradley (1992). They are further discussed below. Another way of clarifying details and encouraging participants to continue their narrative was to summarize and restate what they had said (Flanagan, 1954).

Depicted in the first column of Table 11 are the three phases of a critical incident. These phases or elements represent a typical critical incident. They were informed by Coetzer et al.’s (2012) findings report, and Butterfield et al.’s (2005) CIT review. In this research, the first phase addressed the circumstances leading up to the decision. This prompted the collection of information about the decision type and its time frame, as well as about the decision’s initiative and the involvement of other parties.

Phase 2 focused on the details of the decision-making experience and factors that had a significant effect on it. I then gathered information about the specific steps that were taken during the decision-making process, which sources were used, and which role data and human judgment played in it. Additionally, I enquired about the influence of the decision type in question, and about potential organizational factors. In phase 3, participants shared the outcome of the decision with me; specifically, whether they perceived the outcome as positive or negative, and whether they learned any lessons from it, which they could apply to their decision-making process in the future.

Table 11. *Interview Part 2 (CIT)*

CIT Phase	CIT Question	Probing Questions
Phase 1: What led up to the incident?	What were the circumstances leading up to this decision?	• Was this a one-off decision, or is it an iterative one? • What were the general circumstances leading up to this incident? • Who initiated this project/decision? • Who was involved in making this decision or contributing to it? Individual or group decision? • When did this incident happen?
Part 2: The experience itself – key factors influencing decisions	Did you follow a certain process when making the decision?	• Did you follow specific steps? Or guidelines? • Which sources did you consider when making the decision? • Did you have any doubts based on your intuition or experience? • Did you follow up on these doubts? • Tell me exactly what you did that was so helpful (or had a negative impact) at that time. • Why do you think this was helpful (or had a negative impact)?
	Was the process related to a specific type of decision?	
	Was the process affected by specific big data characteristics/ problems with analytics?	• Were there any problems or concerns with the data sources or systems?
	Were there any personal/organizational factors that influenced this process?	• Were there any organizational influences on this decision?
Part 3: Outcomes of the incident	What was the outcome of this incident?	• What was the specific outcome? • Did you learn any lessons from this? • Would you have changed any of the actions you took in retrospect?

While the first column indicates which data had to be collected in each phase of the incident, the second column shows the main questions that were asked during the interview. These questions were also provided to the managers before the interview–as part of their preparation document, which can be found in Appendix C. I encouraged participants to use the preparation document, as it assists with the recollection of events and ensures the completeness of the retrospective narrative (Coetzer, 2012). The document could be taken into the interview to serve as a memory-aid (Bradley, 1992b; Coetzer et al., 2012). The questions in the last column served as probing questions to follow up on some aspects or left-out details of the participant's recollection of the incident.

3.3.3.3. Case Study Questions

The final part of the interview consisted of several general case study questions, which particularly served to benefit the exploratory nature of this study. Potentially influencing factors of the research topic were addressed in this portion, which allowed participants to voice their general perceptions and helped determine the importance of those factors. Through this exploration, my understanding of the key factors of this study evolved, in turn leading to an evolution of the questions. Table 12 shows the initial interview questions and which factors they addressed. The next section discusses the minor alterations to them following the pilot study.

Table 12. *Interview Part 3 (Case Study Questions)*

Interview Section	Interview Question	Explored Factors
Decision Making: System 1/2	Is there a typical process you go through when making strategic (tactical/operational) decisions? If yes, please name some integral steps that you would take when making a strategic decision and order them sequentially.	• Decision Type • DM Process • Analytics Role • Human Judgment Role
	When making decisions, what percentage is based on your own experience/gut feeling, and what percentage is based on a more rational, sequential process?	• DM Process • Analytics Role • Human Judgment Role
	What effect does (big) data analytics have on your decision making? In what ways has (big) data analytics enriched or maybe even hindered your decision-making process?	• DM Process • Analytics Role
	Which data sources do you rely on for your decision making? Which datasets do you query?	• Analytics Role • Organizational Prerequisites
Data/ Analytics	How comfortable are you with using information systems and analytics in your day to day tasks?	• Analytics Understanding • Analytics Role
	Is the use of information systems, especially analytics, wide-spread and promoted within your company/ industry?	• Analytics Role • Organizational Prerequisites • Industry
	Would you say that big data has an important role in your position?	• Analytics Role
Human Judgment	How would you define wisdom?	• Wisdom
	How would you define a wise decision?	• Wisdom
	Which role does wisdom play in your decision making?	• Wisdom • Human Judgment Role
	How would you define intuition?	• Intuition
	Which role does intuition play in your decision making?	• Intuition • Human Judgment Role
	How would you define judgment?	• Human Judgment Role
	Do you still trust your own judgment when confronted with results from big data analytics?	• Human Judgment Role • Analytics Role

		• Experience
	Would you say that the use of big data analytics provides you with better insights?	• Human Judgment Role • Analytics Role
Balance of Human Judgment and Analytics	When making a decision, what percentage is based on human factors, such as your own intuition, experience, and colleagues' opinions, what percentage is based mainly on the results from big data analytics?	• Human Judgment Role • Analytics Role • Intuition • Experience • Wisdom
	How do you proceed when you encounter ambiguous information from big data analytics while making a decision?	• DM Process • Analytics Role • Human Judgment Role • Organizational Prerequisites
	How do you react to finding outlying data, e.g. spikes in sales?	• DM Process • Analytics Role • Human Judgment Role • Data Quality • Organizational Prerequisites
Industrial/ Organizational Factors	Is your decision-making style influenced by organizational guidelines or the organizational culture?	• DM Process • Organizational Prerequisites
	Would you say the industry you are working in influences your decision-making style?	• DM Process • Industry
	Is there a difference between your personal decision-making style and the decision-making style that is predominant in your organization or industry?	• DM Process • Organizational Prerequisites • Industry

The questions in this part were developed through referring to case study literature, as well as by thematically drawing on extant literature in the areas of decision making, human judgment and analytics. Following case study research guidelines (Yin, 2014), the case questions were designed to facilitate an unbiased and 'nonthreatening' (p.110) interview climate. As an example, 'How?' questions were preferred to 'Why?'

questions, to prevent defensive participant reactions. Thematically, the case study questions were influenced by the studies of Shah et al. (2012), Kathri and Ng (2000), and Intezari (2013). Additional questions were added to cover all elements of the research questions.

As demonstrated in the first column of Table 12, this resulted in the creation of five thematic sections, namely decision making, data/analytics, human judgment, the balance of human judgment and analytics, and industrial and organizational factors. Several questions per section gave me sufficient opportunity to gather information about all relevant factors, as are indicated in the last column of the table. Due to the semi-structured nature of the interview, I did not have to ask all questions explicitly. Often, participants readily volunteered the required information in previous parts of the interview.

3.3.3.4. Pilot and Alterations of Questions

As recommended by case study literature, the designed interview questions were piloted (Stake, 1995; Yin, 2014). Piloting can assist with refining the data collection content and procedures (Yin, 2014). After an initial review from academic peers, the questions were therefore used in a pilot case with a participant from the first organization. This organization was very accessible, which made the piloting possible. Next to the accessibility criterion, Yin (2014) also suggests not to select a typical, but instead a comparably complicated case, in which potentially arising issues might be encountered.

After careful selection, my pilot case was therefore an analyst with rather limited decision-making experience employed in an organization that exhibited a high level of analytics maturity. While I considered analysts to be a rich and valuable source of information for this study, they would not make up the majority of my sample, and the questions had been designed with seasoned managers in mind. During the piloting, the questions proved to be flexible enough to accommodate a wide range of participants, including the pilot case.

As the questions had been thoroughly designed before the piloting, and all essential information was successfully collected from the participant, the pilot test could also be considered a pretest (Blumberg et al., 2011; Yin, 2014). I only made minor alterations in phrasing–the initial plan for data collection was not changed. Since these changes after the pilot were minimal, the pilot was included in the sample for data analysis. Four more cases were studied at the same company, with three senior managers and the CEO. An initial thematic analysis of these first five cases revealed that all main concepts identified in the literature were addressed by the participants' answers, and additional themes could already be identified just from the participation of a single organization.

However, this initial analysis also highlighted that a few aspects about the questions could be improved, which led to a small number of added and removed questions. These alterations can be seen in Table 13. The added questions were included to emphasize important aspects that had not seemed important to highlight during the development of the questions. They also addressed links between different concepts, that emerged in the thematic analysis. Some of the added questions simply provided an additional opportunity for participants to expand on key aspects of the research, which provided more depth.

The removed questions were eliminated because they were either answered previously in other parts of the interview or resulted in the same answers as previous questions. To ensure consistency and for the purpose of reaching saturation, I made sure not to remove relevant questions. Demographic and CIT questions remained unchanged, as they both serve a rather positivist approach that includes analysis methods such as counting.

Table 13. *Alterations of Interview Questions*

Interview Section	Questions Added/~~Removed~~ after Pilot Case	Explored Variables
Decision Making: System 1/2	Would you say that the influence and reliance on analytics has increased over the last few years? Were there any major changes in the data sources you had access to, for example, or in the ways of analyzing them?	• DM Process • Analytics Understanding • Analytics Role • Human Judgment Role
	Do you analyze data yourself, or is there an analytics department that manages your data needs, and sends out reports, for example? Do you have access to all the data you require to make an informed decision?	• DM Process • Analytics Role • Organizational Prerequisites
	How would you rate the overall data quality?	• Analytics Understanding • Organizational Prerequisites
Analytics	~~Would you say that big data has an important role in your position?~~	• Analytics Role
Human Judgment	Would you say the role of judgment, your intuition, and your own experience has decreased since the use of analytics in decision making? For which parts of your decision-making process?	• DM Process • Human Judgment Role • Intuition • Experience
	In your opinion, do data analytics contribute to good judgment and making wise decisions? Or do you think analytics and data should be relied on with caution?	• Human Judgment Role • Analytics Role • Wisdom
	~~How would you define intuition?~~	• Intuition
	~~How would you define judgment?~~	• Human Judgment Role
Balance of Human Judgment and Analytics	~~When making a decision, what percentage is based on human factors, such as your own intuition, experience, and colleagues' opinions, what percentage is based mainly on the results from big data analytics?~~	• Human Judgment Role • Analytics Role • Intuition • Experience • Wisdom

Industrial/ Organizational Factors	Are decisions based on data analytics encouraged? Are decisions based purely on intuition valued by the organization?	• DM Process • Organizational Prerequisites • Analytics Role • Human Judgment Role • Intuition
	~~Is there a difference between your personal decision-making style and the decision making style that is predominant in your organization or industry?~~	• DM Process • Organizational Prerequisites • Industry

3.4. Data Coding and Analysis

This section serves as an introduction to the employed coding and analysis techniques. As is further explained below, due to this study's multi-level analysis, each findings chapter draws on different parts of the dataset and applies different analysis techniques. Therefore, each findings chapter has a separate analysis section, which elaborates on the specific data sources and analysis techniques used for the respective chapter.

The section begins with an outline of the multi-level analysis that ties the research design to the analysis and the resulting findings and discussion chapters. This is followed by a justification for the use of content analysis for the CIT part of this study, as well as an overview of the coding and categories employed. Last is a section on thematic analysis that outlines the coding and analysis process for the case study research.

3.4.1. Multi-level Analysis

This study employs multi-level analysis to provide an in-depth and holistic view of the managerial decision-making process with advanced analytics and big data. The choice of case study research as the study's methodology was the first step to facilitate this multiple level approach: "Case studies can employ an embedded design, that is multiple levels of analysis within a single study" (Eisenhardt, 1989, p.534). In this study, these multiple levels of analysis refer to three levels in the organizational environment that affected management decision making. These levels are the organization, the individual, and the decision. The research design, which was presented in Figure 5 and Figure 6 above, was the next step in enabling this multi-level approach. By introducing an embedded unit of analysis, the level of 'decision' was added to the main level of 'manager' as the unit of analysis, and the case's context, the 'organizational factors'.

Various quantitative studies have employed this form of multi-level analysis (Andersson et al., 2001; Kidwell et al., 1997; Simard & Marchand, 1995). Exploring a similar set of levels, a conceptual study by Staw, Sandelands, and Dutton (1981) researched threat rigidity effects on three levels within an organizational system, namely the individual, group, and organizational level. A further exploratory study by Andersson, Forsgren, and Holm (2001) focused on business embeddedness at three different levels, namely the relationship, subsidiary and corporate level. Their study concludes that an understanding of the relationship level is essential to understanding processes at the other two levels.

Expecting similar dependencies between the three levels of decision making, the three findings chapters of this research report on decisional factors and processes, types of managers and their characteristics, and the manager's environment or context, respectively. This can be seen in Figure 7, which outlines the connection between research design and data analysis approach. The underlying assumption of this approach was that managerial decision-making processes are firstly influenced by the type of decision, and therefore its context and impact. Secondly, it was expected that managerial characteristics, such as their openness to data-driven approaches and domain experience, influence their decision making. Lastly, the ecological systems framework forming the manager's environment was suggested to impact managerial decision making.

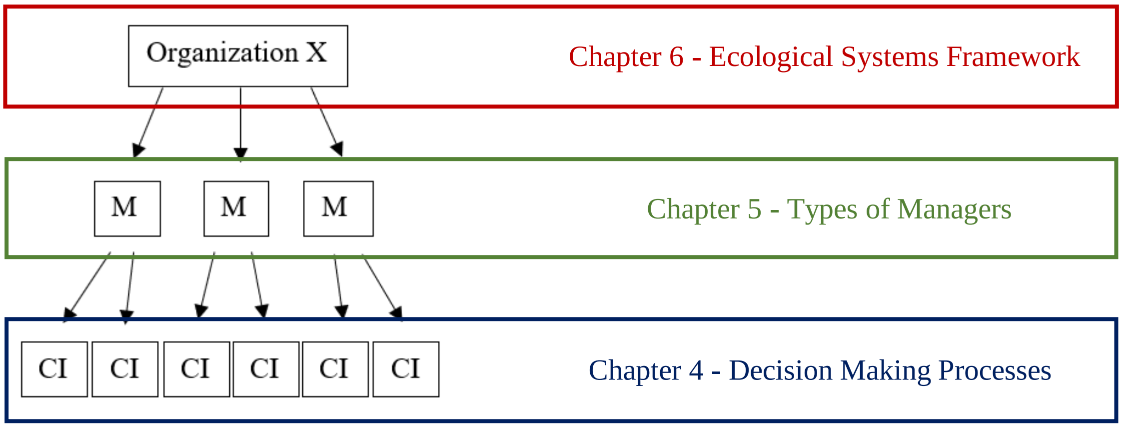

Figure 7. *Multi-Level Analysis*

Chapter 4 focuses on the embedded unit of analysis. Findings in relation to the decision-making process are reported and discussed. During the data analysis, each decision was summarized as an incident. A content analysis of all incidents was then conducted–a common CIT analysis technique (Coetzer et al., 2012) that will be discussed in more detail in the following sections. This led to the identification of several distinct decision-making processes, characterized by impact and longevity of the decisions, as well as the different roles of analytics and human judgment. Additional insights and reflections from the case study questions were incorporated.

Chapter 5 centers around the main unit of analysis, i.e. the manager. Each interview, including the critical incidents, was thematically analyzed as a case with regards to the managers' characteristics, such as their position, perceptions, experience, and preferences. This led to a classification of different manager types. These types were then connected to the distinct decision-making processes identified in Chapter 4, to assess how managers' characteristics impact their decision-making processes.

Chapter 6 focuses on findings regarding the context of the cases, i.e. organizational factors. Similar to Chapter 5, each manager's perception of their organizational environment was thematically analyzed, taking into consideration the organization's culture, industry, maturity of analytics capabilities, and the manager's department. A priori and emerging themes led to the design of an ecological systems framework specifically for managerial decision making with advanced analytics and big data. This framework was then connected to the types of managers and decision-making processes also identified in Chapter 5 in order to discuss the effects of the organizational context on the managers.

By focusing on these three levels, the findings chapters are able to examine different aspects of the cross-case analysis, avoiding the having to present each individual case separately or in isolation. This is an acknowledged form of reporting results for case study research:

> There may be *no* separate chapters or sections devoted to the individual cases. Rather, [the] entire report may consist of the cross-case analysis, whether purely descriptive or also covering explanatory topics. In such a report, each chapter or section would be devoted to a separate cross-case issue, and the information from the individual cases would be dispersed throughout each chapter or section. (Yin, 2014, p.186)

This focus on cross-case analysis was already embedded in the research design, represented by the high number of cases. The objective was to exceed the limitations of a merely descriptive narrative of a small number of cases. Instead, cross-case analysis of differences and similarities allowed me to form a more in-depth understanding and to develop ‘more sophisticated descriptions and more powerful explanations’ for my findings (Miles et al., 2014, p. 101).

3.4.2. Content Analysis

After the data was collected, a content analysis of the critical incidents was conducted. This analysis primarily informed findings Chapter 4 by developing decision-making processes from the CIT data gathered based on the various decisions participants had shared. As the coding unit was the decision, all critical incidents were extracted into separate files and assigned numbers that indicated the participants who shared the incident. The incidents were then analyzed across the different cases, focusing solely on the embedded unit of the research design, which represents the first level of this multi-level analysis. The cross-incidents analysis enabled an examination of a direct relationship between the decision making and its success or failure (Kraaijenbrink, 2012), outside of the organizational and individual context. After the content analysis, the incidents were also thematically analyzed as part of the main unit of analysis, i.e. the respective managers, to gain a deeper understanding of the decision makers and their context.

CIT data analysis consists of four key steps: the determination of the frame of reference, coding, the formulation of categories, and a determination of the level of specificity (Butterfield et al., 2005; Flanagan, 1954; Kraaijenbrink, 2012; Thomas & Bostrom, 2010). Originally described as a rather subjective process by Flanagan (1954), the data analysis begins with sorting a small number of incidents into groups which reflect the frame of reference (Butterfield et al., 2005). The frame of reference is generally chosen by considering the use of the determined classifications (Flanagan, 1954). In the context of this study, classifications are therefore related to decisions and decision making.

After initial categories are created, the rest of the incidents are classified according to these categories (Butterfield et al., 2005), which can be altered and expanded until all incidents are classified.

I followed this traditional form of analysis as a first step during the familiarization with the CIT data, which allowed a broad categorization of the incidents. However, to delve deeper into those categories and explore further details for the development of the decision-making processes, I chose a more structured approach as the next step–a content analysis. This was done to address a limitation of the CIT analysis, i.e. that the

> categories may or may not capture the context of the situation and are reductionist by definition. This is not necessarily consistent with the goals or aims of the grounded theory, content analysis, or descriptive phenomenological psychological approaches to analyzing data. (Butterfield et al., 2005, p. 481)

In answer to this limitation, CIT analysis has evolved over the years (Butterfield et al., 2005), and can now be better described as an 'interpretive content analysis' (Thomas & Bostrom, 2010, p. 121). Given that the two main qualities of content analysis are 'objectivity and being systematic' (Bryman & Bell, 2015, p. 289), this form of analysis further balances out the limiting effects of the rather subjective CIT analysis process.

Relying on both the subjective traditional CIT analysis and the more objective content analysis benefited my overall analysis process. During the more traditional form of CIT analysis, I had created a set of categories based on a first impression of similarities among the critical incidents, centered around the extent and role of data/human judgment use during decision making. The categories emerging from the more detailed content analysis, which was based on an a priori coding scheme, however, did not line up with these initial categories, and also failed to group similar incidents.

To address this when confronted with the ill-fitting coding scheme, which consisted of factors that might have an influence on the decision-making process, as identified by the extant literature, I applied abductive reasoning. Key elements of the initial coding scheme, such as the decision types, as well as decision triggers and outcomes, proved insufficient for grouping truly similar incidents together, and did not match my initial categories. They furthermore seemed insufficient to address a key segment of the research questions: how managers balanced data and human judgment in decision making.

Therefore, I added further elements to the coding scheme, namely the 'role of data' and the 'role of human judgment' in the decision-making process, as well as a measure for the extent of 'use of data' and 'use of human judgment'. Use of human judgment and data were measured using a 7-point Likert scale. A similar approach had previously been used in a quantitative study on the dual process theory (Kaufmann et al., 2017).

As this value was assigned by me during the analysis and not by the participants themselves, it can be considered consistent across participants. These additions enabled a classification of the incidents into low/high data- and low/high human judgment-driven decisions. These were ultimately the categories that most accurately grouped similar incidents together. Table 14 displays the coding manual, which entails the final set of codes used for the content analysis (Bryman & Bell, 2015). During the actual analysis, these codes were converted into a coding schedule in Excel, which can be found in Appendix D.

Table 14. *Coding Manual*

Code	Sub Code
Decision Context	Simple, Complicated, Complex, Chaotic, Disorder
Decision Impact and Longevity	Operational, Tactical, Strategic
Decision Mode	Individual, Group
Use of Data	1-7
Use of Judgment	1-7
General Aim	Consumer Behavior, Risk Management, Planning and Efficiency
Role of Data	Open (thematic)
Role of Human Judgment	Open (thematic)
Behavioral Bias	Open (thematic)
Type of Data Used	Internal (several), External (several)
Process: Identification	Open (thematic)
Process: Alternative Development	Open (thematic)
Process: Selection	Open (thematic)
Outcome	Positive, Negative, N/A
Lessons Learned	Open (thematic)

After coding all 43 incidents according to the above manual, I placed the incidents on a graph with the two axes displaying the 'use of data' and 'use of human judgment' measures, which will be presented in Chapter 4. The incidents were then clustered into four categories, namely high-data decisions, high-judgment decisions, low-data/low-judgment decisions, and high-data/high-judgment decisions. Common themes and patterns were identified within these categories, such as, for example, decision types.

This process enabled a first overview of the incidents provided by the managers and identified several subcategories and key factors that influenced the use of data and judgment in these decisions. The presence of identified themes and categories was counted by incident to establish the importance and frequency of their occurrence (Thomas & Bostrom, 2010). The code counts and exemplary incident summaries were then included in the findings to increase the transparency of the analysis procedure (Gogan et al., 2014).

The overall aim of the CIT part of this study, and therefore this content analysis, was to determine the most successful processes for certain decision types, and to furthermore explore a balance of data use and human judgment. The content analysis was a suitable tool for answering questions of a more quantitative nature (Bryman & Bell, 2015), such as 'For which decision types was the use of data most useful?' and 'Which decision-making processes most likely led to a positive outcome?'. Chapter 4 consequently relies to a large extent on the categorization and clustering of these incidents, as well as process coding (Miles et al., 2014).

While content analyses often rely on quantitative measures for data analysis, Bryman and Bell (2015) state that text can also be coded in terms of themes or subjects in order to categorize the phenomenon of interest, which was applied for this study. Meaning was extracted from the data through noting patterns and themes as well as clustering and counting (Coetzer et al., 2012). The categories and themes identified in this content analysis were subsequently used as a priori codes in the following thematic analysis.

3.4.3. Thematic Analysis

Following the content analysis of the embedded unit, a multi-level thematic analysis was conducted across all three levels in order to extract more detailed insights into management decision making with analytics. While the content analysis focused on actual decisions and identified key factors that influenced managerial decision-making processes, the thematic analysis was used to delve deeper into those initial insights. The participants' reflections on their decisions, as well as their general perceptions of the topic, provided a more holistic perspective encompassing the effects of individual characteristics and organizational components on decisions. The thematic analysis therefore informed all three findings chapters.

Thematic analysis is considered a rather flexible approach to qualitative data analysis which, as broadly outlined by Braun and Clarke (2006), consists of six general steps. The first step is a familiarization with the data through transcription and repeated reading. This is followed by the creation of an initial set of codes, which eventually leads to the development of potential themes. These themes are reviewed for compliance with all coded passages, and after continuous refinement, are given clear definitions and names. The last step is described as the reporting of the analysis results. These general steps can also be found in Miles, Huberman, and Saldana's work (2014) on qualitative data analysis methods, which additionally offers a more detailed manual of various techniques for data coding, analysis, display and reporting.

I followed Braun and Clarke's (2006) steps during the data analysis and utilized several coding techniques, as outlined by Miles, Huberman, and Saldana (2014). The systematic process relied on iterative comparison of the data with emerging themes and extant literature (Eisenhardt, 1989; Miles et al., 2014; Popovič et al., 2018). This comparison served the purpose of finding the best suited explanation for the findings (Popovič et al., 2018; Yin, 2014) and supported the abductive approach to theory building.

The coding process began with an initial set of a priori codes, that were informed by theory, literature, the research questions and the results of the prior content analysis (Miles et al., 2014; Yin, 2014). These codes were set up as nodes in the software NVivo. While a priori constructs and theoretical propositions can provide theoretical grounding (Eisenhardt, 1989; Yin, 2014), the use of theories and hypotheses must always initially be considered as tentative in order to ensure theoretical flexibility, as the actual collected data may change the applicability of theories and even research questions (Eisenhardt, 1989). As codes and themes therefore often emerge from analysis (Eisenhardt 1989), other coding techniques are added to a priori coding. During first cycle coding, which refers to the initial assignment of codes to data chunks, I employed process coding, descriptive coding, in vivo coding, and evaluation coding (Miles et al., 2014).

Process coding was applied for the open coding section in the content analysis, as well as for the general case study questions referring to the decision-making process steps and factors that are directly connected to these steps, such as ‘data sources’. Descriptive coding was used for predefined themes that referred to the literature or the research problem and required further subthemes, such as ‘intuition’ or ‘organizational culture’. “In Vivo” coding was particularly used for emerging codes and themes, such as for the roles of human judgment and analytics, as well as for the definitions of big data and analytics. These are concepts that vary widely or are not mentioned in the literature. In vivo coding provided the best option to capture and preserve the participants’ understanding and their perceptions. Evaluation coding, as a supplement to descriptive and in vivo coding, was used to capture the managers' judgments and perceptions of analytics, as well as decision outcomes of critical incidents.

An extract of the resulting codes can be seen in Figure 8. 'Analytics' and 'Perception' are examples of a priori codes. 'Analytics' was identified as a key theme in the decision-making literature. Managers' 'perception' was part of the research questions and categorized as a subtheme. 'Positive' and 'Negative' are evaluation codes summarizing the managers' perception of analytics. Several in vivo sub codes are attributed to these perceptions, which express specific aspects of the managers' evaluation.

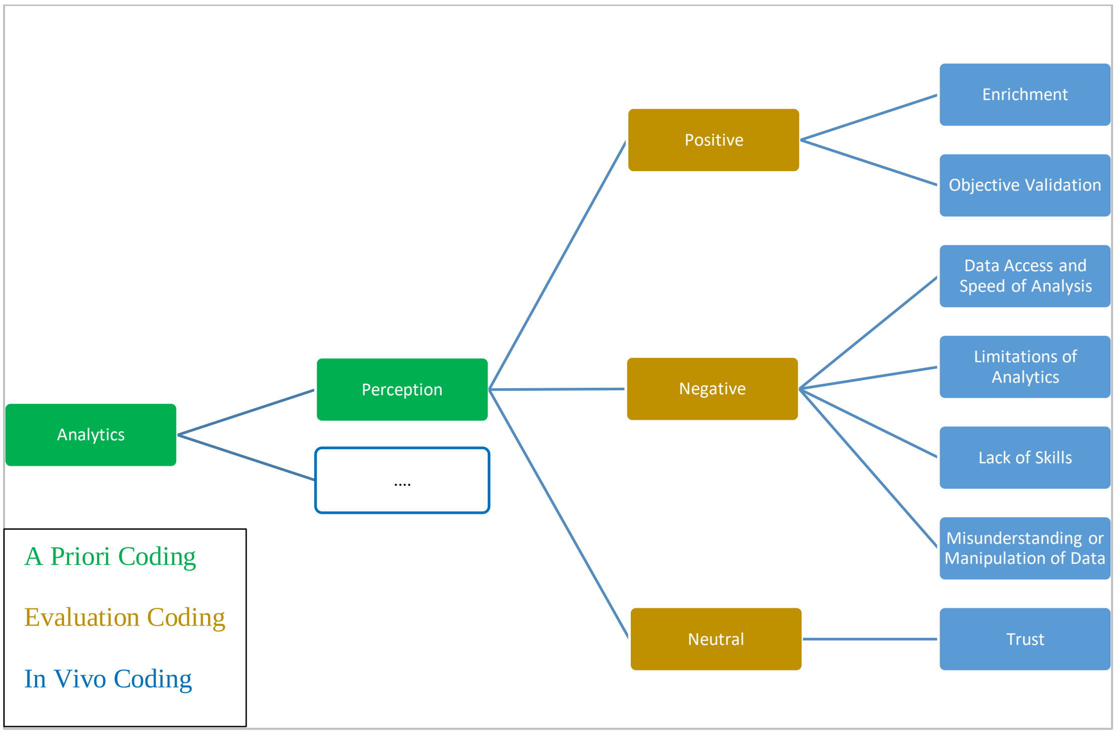

Figure 8. *Coding Extract*

After applying these coding techniques, first cycle coding was completed. Subsequently, second cycle coding works with the results from first cycle coding, "lay[ing] the groundwork for cross-case analysis by surfacing common themes and directional processes" (Miles et al., 2014, p. 86). During this cycle, clustering and chunking of the data led to categories of pattern codes. Manipulations of the data supported this process of pattern recognition, leading to the tentative creation of themes (Yin, 2014). The forms of manipulations I used for this thematic analysis were the creation of category matrices and flow charts, as well as sorting information into chronological order (Miles et al., 2014; Yin, 2014).

The codes and themes identified during the content and thematic analyses enabled a cross-case analysis on several levels. As is recommended for multiple-case analysis, my familiarization with the data began with a focus on within-case analysis: "The overall idea is to become intimately familiar with each case as a stand-alone entity. This process allows the unique patterns of each case to emerge before investigators push to generalize patterns across cases" (Eisenhardt, 1989, p. 540). The within-case insights I gained through this familiarization provided me with valuable first impressions about differences and similarities that seemed to affect the managers' decision making. The following cross-case analysis enabled me to consider the data through different lenses, and therefore to move beyond my first impressions (Eisenhardt, 1989).

Within- and cross-case analysis can lead to the identification of themes, concepts, and relationships between variables (Eisenhardt, 1989). Particularly during the cross-case analysis, the findings of each case are applied to themes that characterize and describe the research topic (Stake, 2006). This process helps to identify similarities between cases, leading to a grouping or type of case (Eisenhardt, 1989; Stake, 2006; Yin, 2014). This approach of cross-case analysis serves to aid the retention of key situational characteristics of the single cases, but simultaneously can be considered a move towards generalization (Stake, 2006). Findings are merged across cases; special findings that only occur in one case are also recorded if they are significant enough. These findings are then sorted into clusters and ranked in order of importance. Eventually, tentative assertions are generated from the most important or significant findings. These assertions can be based on one or several of the merged findings.

The cross-case analysis and the emerging profiling of the cases result in different types of decisions, as well as analytics and human judgment roles discussed in the first findings chapter. The second findings chapter demonstrates that types of managerial decision makers also could be distinguished. The third findings chapter centered around the profiling of the managers' decision-making environments.

CHAPTER 4: MANAGERIAL DECISION-MAKING PROCESSES

This is the first of three chapters outlining the main results of the data collection and analysis. Each chapter covers one level of the multi-level analysis and is divided into three sub-sections, beginning with the specific data analysis techniques applied for each level of analysis, followed by a section summarizing the key findings, and ending with a discussion of the findings in the context of current literature.

This particular chapter focuses on the embedded unit of analysis, and therefore the decision level of this multi-level analysis, primarily centering on data collected using the Critical Incident Technique, supported by data from the case study analysis. CIT was an especially useful technique for this level of analysis, as it provided rich insights into instances of actual managerial decision making, enabling a detailed analysis of the decision-making processes in diverse decision contexts and with different decision impacts.

The key contributions of this chapter are threefold:

- The extension of decision-making processes as captured in the extant literature, accounting for the managers' use of data analytics. This is supported by a comparison of the actual versus ideal managerial decision making.
- The categorization of decision processes based on the extent of the use of data analytics and human judgment.
- The identification of distinct data analytics and human judgment roles. These roles highlight the different facets of both analytics and human judgment, countering their often one-sided representation in extant literature.

The chapter is structured as follows: first, the specific analysis techniques are outlined in detail, describing the application of CIT data for the development of different decision-making processes. Next, the chapter breaks down the use of case study data to highlight the contrast between actual and ideal decision making, as well as its use for the identification of key decision-making influences. In the findings section, the decision-making process steps identified during the data analysis are explored first. This is followed by a differentiation of the roles of human judgment and analytics in managerial decision making. Subsequently, actual decision-making processes, as captured by CIT, are introduced, and placed in contrast to the managers' thoughts on ideal decision making.

The discussion section explores an extension of decision-making processes outlined in current literature by the findings of this thesis. The dual process theory is then applied to the findings, highlighting its relevance in this context for explaining the balance between human judgment and the use of analytics in managerial decision making.

4.1. Data Analysis

The data analysis for this chapter is centered on the Critical Incident Technique. As discussed in the methods section, each decision the managers shared during the semi-structured interviews was content-analyzed using a list of a priori codes that were informed by extant literature, as well as a posteriori codes. However, the findings were not only drawing on the content analysis, but also the thematic analysis, which was conducted afterwards and included the case study data.

Interview data is referenced according to its source, differentiating whether the reported data was part of an incident or part of the case interview with the manager. A total of 25 managers (M) shared 43 critical incidents (C). The participants are numbered according to their organization and their interview order at the organization; e.g. Manager M41 was the first manager interviewed at organization 4. Incidents are named accordingly, with the third digit indicating the order of reported incidents; e.g. C411 was the first incident reported by the first manager interviewed at organization 4. When reporting on findings from an incident, e.g. C411, the respective manager is still referred to as manager M41.

Managers are furthermore referred by their positions, as discussed in section 3.3.1. This means that participant M01, for example, is referred to as 'analyst M01'. The number zero indicates pilot studies, with M01 being the first pilot overall, and M10 being the first pilot in the first organization.

4.1.1. Content Analysis: CIT

The content analysis first focused on the determination of a general aim of management decision making with data analytics. The general aim is considered a prerequisite of using the Critical Incident Technique, as it establishes the task's objectives, and therefore the criteria of successful and unsuccessful incidents (Flanagan, 1954). Determining a general aim was critical to assessing if each decision outcome was to be considered positive or negative. As Flanagan (1954) points out: "…unfortunately, in most situations there is no one general aim which is the correct one. Similarly, there is rarely one person or group of persons who constitute an absolute, authoritative source on the general aim of the activity" (p.10).

The general aim of decision making with data analytics was therefore expected to vary, depending on the manager's role or department. Consequently, the aim was determined with every manager at the beginning of the interview with the question: "Please describe your position in more detail and what role data/analytics plays in it?" As managers often fulfill several roles, the general aim could also vary between the different decisions they shared.

Three groups of general aims emerged, namely improving understanding of 'consumer behavior' (n=12), 'planning and efficiency' (n=12), and 'risk management' (n=22). Identifying these general aims therefore showed that a successful decision outcome would result in better consumer understanding, efficiency gains, or the avoidance of risk. The general aim was, as expected, mostly related to the department of the manager who shared the decision. Marketing managers, for example, were therefore often aiming at understanding 'consumer behavior', whereas operations managers were mostly aiming at improved 'planning and efficiency', or 'risk management'.

While every incident was assigned a general aim, these aims were not always mutually exclusive (n=3). Incident C931, for example, a decision about the reorganization of a customer service team, could be considered to be related to consumer behavior, but also to efficiency and planning. In general, the three different aims could be grouped into one general aim: 'Making more effective and better decisions, leading to the best possible outcome', or simply 'better decisions'. This is in accordance with Flanagan (1954), who states that useful general aims are often simple phrases around "such words as 'appreciation', 'efficiency', 'development', 'production', and 'service'" (p.11).

Several participants had reflected on the general aim of their decision making, as it was critical to evaluating their performance as well. Head of department M21 captures this sentiment:

> 'Ok, what benefit are we actually chasing – is it hard dollars or is it about engagement and impact?' And no matter what benefit we're chasing, they must be measurable. So how do we measure things and

> how do we use that data then to inform us if that was a good investment and did it actually pay back? (M21)

This awareness and reflection speak of a level of maturity in terms of using data analytics on an individual and organizational level, as will be discussed in Chapters 5 and 6. Determining the general aim was therefore not only a required component for this CIT part, but also delivered valuable insights for further findings.

Further questions addressing CIT elements, such as the incident's circumstances, involvement, triggers, lessons learned, and outcomes functioned as an information source for the codes of the content analysis. The incident's circumstances provided information about the decision type, as it outlined the context and impact of the decision, as well as the resources that were available to the decision maker. The specific decision types that were differentiated are further discussed below. The CIT involvement provided information about the decision mode, i.e. whether the decision was an individual or group decision. Triggers were coded as the identification stage of the decision-making process and provided information about the origin of the decision, as well as its source.

Outcomes functioned as an indication of the decision process' success, and therefore supported the practice of identifying the positive and negative influences on decision making. Lessons learned were considered a review of the decision-making process, particularly informing the 'ideal decision making' section of this chapter. The outcomes of the recorded decisions were mostly positive (n=30), including only a small number of negative incidents (n=3). However, several of the positive incidents involved significant obstacles to be overcome, which also provided insights into negative aspects of the use of analytics for decision making. This balanced the lack of negative incidents to some extent.

If an outcome was neither positive nor negative (n=10), it was categorized as 'not applicable' ('n/a'). Decisions without a known outcome had initially been planned for dismissal from the study; however, their content was assessed as a useful source of information to the study. The (lack of) outcome alone was not seen as a sufficient reason to exclude those incidents from the sample.

The 'n/a' outcome was attributed to decisions that were only recently implemented and had not yet been evaluated in terms of their success. In addition, decisions that led to the rejection of opportunities were considered as 'n/a', as a hypothetical evaluation is not possible. Furthermore, decisions were considered 'n/a' if they were passed on to superiors, boards, or other departments, leading to an unknown outcome. Lastly, the 'n/a' categorization was applied for decisions that only allowed for negative outcomes, as exemplified by incident C843, which revolved around downsizing: "Like I say, there's no good outcome here; it's just which one is worse." (C843).

4.1.2. Content Analysis: Extant Literature and Emerging Findings

Complementary to the CIT elements discussed above, further codes were analyzed during the content analysis. These were either informed by extant literature or emerged during the analysis. They are discussed in the following section.

In an effort to capture the impact and context of the decisions, the coding scheme used the decision-making frameworks of Ackoff (1990), and Snowden and Boone (2007), as outlined in the literature review. Most decisions reported during the interviews were categorized as a combination of tactical/strategic and complicated/complex, as well as a high number of complex/tactical and complicated/strategic decisions. Only a few incidents were categorized as operational or simple decisions. Given the research emphasis on managerial decisions, this distribution was expected. Complex/operational or simple/strategic decisions were also not identified. Furthermore, none of the shared decisions was labeled ‘chaotic’ or as ‘disorder’. Below, Table 15 summarizes the different types of context and impact that were captured during the data collection.

Table 15. *CIT Decision Types*

Decision Context/Impact	Strategic	Tactical	Operational
Complex	10	7	0
Complicated	6	13	2
Simple	0	1	3
Chaotic	0	0	0
Disorder	0	0	0

As the decisions analyzed in this chapter are an embedded unit of analysis, and therefore part of the unit of analysis, namely the manager, the retelling of these decisions is limited to the manager’s perceptions. Each decision is recounted from the manager's point of view and limited to their involvement and contribution to it. This affected the determination of the decision-making mode as ‘group’ or ‘individual’; decisions were considered as individual (n=9) when the interviewed manager was the sole decision maker for the recorded incident. If the decision was used later on as a recommendation for superiors, making it a group decision, it was still not declared a group decision, as the manager was not involved in these further stages.

Decisions were only categorised as group decisions (n=34) when other parties were directly involved in the selection stage of the decision-making process. The influences of those involved parties on the decision-making process were solely captured from the manager's perspective. Other involved parties were usually not questioned for their perspective, except in the case of two incidents that were both coincidentally shared by two different managers.

Opportunities and problems were differentiated in the analysis of decision initiatives (Harrison, 1995). However, the influence of decision motives, referred to as opportunities and threats in Shepherd and Rudd (2014), are not seen as significant in the extant literature. Their impact was similarly insignificant for this study.

The extent of human judgment and data use in the decision-making process was captured through a 1-7 Likert scale measure, with 1 representing a low use of data/judgment and 7 representing a high use of data/judgment. This served as a simplified and consistent measure, which facilitated the comparison of all critical incidents based on their use of human judgment and analytics. As the balance of these factors is a key aspect of this research, the measure enabled a clustering of the decisions.

For this purpose, all incidents were organized in a diagram, which can be seen in Figure 9 below. Clusters were established by characterizing decisions as ‘low-data’ when their data use measure was equal to or below 4. Accordingly, decisions were also characterized as ‘low-judgment’ when their judgment use measure was equal to or below 4. The incidents were therefore divided into four clusters:

- low-data/low-judgment decisions (n=0). No incidents fell into this category of ‘uninformed decisions’, which effectively left the following three distinct clusters of decisions
- high-data/high-judgment decisions (n=18), which are referred to as ‘balanced decisions’

- low-data/high-judgment decisions (n=13), which are referred to as 'high-judgment decisions'
- low-judgment/high-data decisions (n=12), which are referred to as 'high-data decisions'

Data							
7			C011 Complicated, Tactical C133 Complex, Strategic	C141 Complex, Tactical	C143 Complex, Strategic C822 Complicated, Strategic C841 Complex, Strategic	C121 Complicated, Strategic	
6	C122 Complicated, Strategic C222 Complicated, Tactical	C911 Complicated, Operational	C111 Simple, Tactical C931 Complex, Strategic C142 Complicated, Tactical	C921 Complicated, Strategic C932 Complicated, Tactical C861 Complicated, Tactical	C132 Complicated, Tactical C223 Simple, Operational C411 Complex, Strategic C511 Complicated, Strategic C612 Complicated, Strategic C922 Complex, Tactical	C131 Complicated, Strategic C211 Complicated, Tactical C831 Complicated, Tactical C852 Complicated, Operational C912 Complex, Strategic	C123 Complex, Strategic
5							C221 Complex, Strategic C811 Complicated, Tactical
4						C311 Complicated, Tactical C843 Simple, Operational C851 Complicated, Tactical	C134 Complicated, Tactical
3					C113 Complex, Tactical, negative outcome	C112 Complex, Tactical C312 Complicated, Tactical	C711 Complex, Strategic C821 Complex, Tactical
2					C812 Complex, Tactical, negative outcome C842 Complex, Tactical, negative outcome		
1						C212 Complex, Strategic	C611 Complicated, Operational
	1	2	3	4	5	6	7
				Human Judgement			

Legend:

Numbering:
C001 - C932 indicate the seperate incidents that were shared by the managers. The first number refers to the organization, the second to the manager, and the last to the incident.

Decision Context:
Complex: Unpredictable decisions that rely on probing and experiments
Complicated: Several potential solutions to a decision require thorough analysis and expertise.
Simple: Decisions or problems are assessed, categorized and responded to with established practices.

Decision Types:
Strategic: Important, high-level, long-term decisions that influence the organization's goals and objectives
Tactical: Medium-term decisions regarding the organization's efficiency
Operational: Mostly routine, well defined decisions regarding immediate future

Outcomes:
Only negative outcomes were highlighted

Clusters:
Green: high-data decisions
Blue: balanced decisions
Orange: high-judgment decisions

Figure 9. *Clustering of Critical Incidents*

The extent of data/judgment use was, however, not enough to capture their role in the decision-making process. Therefore, the codes of ‘role of human judgment’ and ‘role of data’ were added to the coding scheme. These codes enabled a more qualitative assessment of the role of data/judgment, and eventually led to the establishment of seven distinct roles for data (analytics) use, as well as five distinct roles for the use of human judgment in the decision-making process. These distinct roles are further discussed in section 4.2.2.

The decision-making process steps were openly coded during the content analysis under 'identification', 'development of alternatives', and 'selection'. These steps match the decision-making process as identified by Simon (1960). These codes covered the managers' answers sufficiently, with no need for the addition of more codes relating to the steps. The detailed findings regarding these process steps are outlined in section 4.2.1.

4.1.3. Case Study Analysis

This chapter focuses on the critical incidents, but also incorporates insights from the thematic coding of the case study research. This data adds a hypothetical perspective of the managers’ ideal decision-making processes, providing an opportunity to highlight a contrast between their actual decision making and their ideal processes, which is captured in section 4.2.5. Several managers took this as an opportunity for reflection and identified key factors that hindered their ideal decision-making process.

In other cases, however, managers were not aware of a mismatch between their theoretical decision-making process and the critical incidents they had shared. Nevertheless, these managers still shared interesting insights into important factors that caused the deviation from their ideal decision-making process.

4.2. Findings

The findings section is organized into five parts. First, as a foundation to this decision-making study, the decision-making process steps identified during the CIT analysis are described and significant differentiators are added. Second, the key finding of diverse roles of human judgment in the decision-making process is outlined, and their categorization is explained. Thirdly, the roles for data analytics are discussed. Fourthly, the critical incidents are categorized according to their processes, or more specifically, their extent of human judgment and data use. This is followed by a comparison with the findings from the case study data, which provides a hypothetical view of decision making and a reflection on actual decision making.

4.2.1. Decision-Making Process Steps

The steps identified during the data analysis broadly matched the three basic steps from Simon (1960) previously discussed in the literature review: Identification, Development, and Selection. With a focus on the use of data and analytics in decision making, however, several further distinctions could be made within each step.

4.2.1.1. Identification

Beginning with the first step, Identification, four distinct categories of decision-making initiatives were found, further referred to as triggers, in the analysis of the critical incidents. These triggers are summarized in Table 16, and are identified as Evaluation, Routine Check, External Trigger, and Anecdotal. The differentiation of these triggers as the first decision-making step is important, as they influenced the managers' use and roles of data analytics and human judgment in their further decision making, which is discussed in more detail in section 4.2.4.

Table 16. *Decision Identification - Triggers*

Trigger	Description	n=
Evaluation	An internally triggered, intentional review of current practices, or an evaluation of future opportunities.	16
Routine Check	An ad hoc problem identified during a routine check or review.	12
External Trigger	An external impulse, i.e. opportunity or problem, prompting a decision.	9
Anecdotal	Concerns, often longstanding, based on employees' perceptions that require a decision.	6

An evaluation (n= 16) is initiated internally in an effort to review certain aspects of the status quo with the hope of improvement. It is not an ad hoc problem, but a deliberate effort, often led by new hires (C123, C111, C851). Incident C132 captured a typical example of this, as the newly hired general manager M13 evaluated a key problem of the department:

> So this is a driver about understanding my business better, I guess. So I came in here, and things have always been good at [the company], but I just couldn't get my head around how we seemed to lose so [much business] in a month. (C132)

Further examples of this category are the evaluation of an existing marketing strategy when a new marketing manager was hired (C111), a review of old decisions (C132), and the use of unique expertise to assess new opportunities (C143).

Routine checks (n= 12) are regular efforts carried out either by employees or automatically through a reporting system, which result in the identification of an acute ad hoc problem, often supported by some form of data. An example of this is incident C811, the trigger for which was the identification of changes during regular market observation: "So that was driven by watching the market for all the value of things […] And once you can spot there's a change, you can then try and capitalize on that" (C811). These decisions are characterized by the interviewees' use of words such as 'always', 'usually', or 'generally' in the description of the incident. Routine checks can also be embedded into automated work processes carried out through workload automation and job scheduling software. These processes automatically identify problems or errors, which then need to be addressed by employees (C911).

An external trigger (n= 9) is an impulse from outside the organization that unexpectedly presents an opportunity or problem that requires a decision. In contrast to a routine check, the external trigger is not actively sought out. External triggers can therefore be initiated by existing or potential business partners (C312), agencies (C113), or external circumstances (C922), for example. Externally triggered decisions often encounter the problem that internal data or reference points are not available; the decision is therefore based on missing, incomplete, or external information that might not fit the organization (C312, C711, C812, C842).

Several examples for external triggers in the incidents were identified, including an offered business partnership (C411) and an offer to a not-for-profit organization to apply for funding (C711). These offers led to decisions by the organizations that were based on incomplete and incompatible external data. When asked about what initiated a marketing decision with a negative outcome in incident C113, the manager responded that the decision was based on their partner agency's (external) data. The agency had provided M11 with case studies from other clients regarding the use of a certain marketing channel. However, these clients were targeting different customer segments, and this discrepancy led to an unsuccessful campaign for M11's company.

Anecdotal triggers (n= 6) refer to employees' perception of a problem or opportunity, which is solely based on intuition or coworkers' anecdotes, without the backing of data. These decisions often address long standing problems or complaints. Examples for this trigger are managers demanding more staff for their teams (C932), as well as suspicion and eventual detection of systematic fraud (C142). Anecdotal triggers usually require a high level of data use in the development step, as they are only informed by human judgment during the identification step. In order to assess the problem or opportunity holistically, data is consulted to enable a prudent decision. In incident C134, general manager M13 had gathered anecdotal evidence, but in order to move the decision forward, the CEO requested the input of data analytics:

> So we have been debating this for a long time […] but we don't seem to be able to get it across the line. And I said, well, in my view, I've validated it just through sitting with people and seeing what happens. And he goes: 'right let's get the data'. (C134)

Data analytics had a direct effect on the identification stage of the decision-making process by functioning as an additional source of problem and opportunity identification. The use of data analytics also enabled managers to improve the definition of requirements in this step by providing them with more detail early in the decision-making process. When analysts become involved and are consulted by the business units, they often encourage managers to deepen their understanding of the problem (M14, M93). This leads to an overall more prudent decision-making process.

Data analytics is therefore seen as a valuable tool in the identification step at the beginning of the decision-making process, as general manager M93 emphasized: "It's a spark, an idea, the thought that we develop, and that's what helps in distribution […] It's good to get those sparks when you start and when you develop something (M93)."

More on the managers' perceptions of analytics in decision making is discussed in section 5.2.1.

4.2.1.2. Development

In the collected incidents, the development stage was mostly comprised of a combination of varying degrees of human judgment and data analysis, depending on the decision trigger and the decision cluster, e.g. high-data, high-judgment, or balanced decisions, which are further discussed in section 4.2.4. Further influencing factors can be personal characteristics, which are discussed in Chapter 5, as well as environmental factors, which are covered in Chapter 6.

The availability of additional data sources and ubiquitous information can lead to an extended development step. This enables a more thorough development and evaluation of alternatives, as general manager M13 pointed out: "We're working with our internal analytics team now to develop reports which are much richer for our process, which enable us to make better decisions" (M13). However, this thorough approach can also lead to an increased duration of this step. Analysis paralysis can therefore become a more common problem due to the larger amount of available data. Manager M41 cautioned that data has to be gathered and analyzed in a timely manner, as the decision must at some point be made. Organizations often struggle with this, spending too much time on data analysis, as head of department M94 observed:

> And some organizations tend to get consumed by trying to understand why, but actually all they need to do is find out that people like you

> like to buy a certain type of product. It doesn't really matter at the end of the day, why. And that's an interesting distinction. So a lot of people spend a lot of effort trying to analyze, analyze, analyze, why, why, why – all you need to do is just to have the insight. (M94)

Delays due to data analytics could also be traced back to technical, procedural, and human resources problems, which are further discussed in Chapter 6. After these problems have been solved, analytics can be a valuable contribution to the development step. Analyst M86 particularly recognized the value of data for the evaluation of alternatives after overcoming initial problems with analytics:

> Even though it started with a hindrance, but once I streamlined the data, I got rid of the duplicated source of information–whose sources were outdated. So I realized data was actually quite powerful to make decisions, because then you're giving people a real-time scenario. (M86)

4.2.1.3. Selection

Like the development step, the selection of an alternative was found mostly to consist of a combined input of data analytics and human judgment, depending on various factors as mentioned above. Data analytics is particularly an enrichment for the selection step, as it allows management to justify their decision in a more objective manner than solely basing it on subjective human judgment. This objective justification is an important aspect for stakeholders and shareholders in the age of big data, and not only within data-driven organizations. Executive M51, for example, used data analysis to provide the general manager of the company with new and surprising insights regarding the profitability of key customers. Having data at hand as a form of objective evidence enabled M51 to significantly influence the selection step of this decision:

> I've done this profitability statement; I've shown that to the general manager and he said to me: 'How could that be so, they're our biggest customer?' – 'So here are the reasons…' So he turns to the CFO: 'Is this right, are these numbers right?', and the CFO said: 'Yes, that all reconciles back to our financial statement' – 'Wow, I had no idea'. (C511)

This signifies the power of analytics to sway unpopular or controversial decisions in a diplomatic way, and to ensure stakeholder buy-in. In a similar incident C932, general manager M93 was able to influence the selection stage of a decision about human resource allocation by confronting team leaders with key data on their employees' workload capacity:

> So it's really to make sure that we had the data to say "well actually, in your team […] you have got some capacity if we rework things like this." And everyone is sincere and agreed that's accurate and that's a fair reflection of what's going on in those businesses. (C932)

All of this being said, the most significant impact on the development and selection steps in the age of big data were the actual roles of data and human judgment in managerial decision making. These roles defined the decision-making steps, and are discussed in the next two sections, 4.2.2. and 4.2.3.

4.2.2. Roles of Human Judgment

Traditional decision making relies heavily on judgment, whereas data-driven decision making in recent years has put more emphasis on the role of data analysis. However, data is not necessarily seen as a substitute of judgment, but as a complement. During my exploration of the role of data analytics in the age of big data, managers acknowledged that while data enriches their decision making, it also has its limitations. When asked about the role of human judgement in the decision-making process, manager M41 replied that “it’s got to” be part of the process as well: “You’re not going to know everything, and your data is not going to show you everything. So you always got to have some reliance on your own judgment, and experiences and all that.”

While human judgment in decision making should not be replaced, managers still need to find a balance incorporating both their judgment and analytics, into their decisions. During the interviews, it became apparent that managers see both as important aspects of successful decision making, and that both have the potential to cancel out each other’s limitations. Both can also have very different influences on the decision-making process and additionally play a role in different parts of the process.

Human judgment, for example, was used in many instances (n=30) to form an initial assessment of a given situation or decision that was informed by the managers’ business understanding and experience. On the one hand, this initial assessment was seen as a good way to gain an initial impression of the problem and its scope. On the other hand, the use of intuition was also considered a cognitive bias in some instances, when not all variables of the decision were taken into consideration. Therefore, data and human judgment were categorized as fulfilling different roles, which were identified as themes during the analysis. These roles reflect data analytics' and human judgment's influence and their place in the decision-making process.

Five distinct roles of human judgment were identified in the decision-making process: human judgment was used as initial assessment of the problem, enrichment of analytics, sense-check and data challenging tool, identifier of need for analytics, and to outweigh analytics. A list of the identified roles can be found in Table 17, sorted according to their frequency in the critical incidents. The roles are further discussed below, relaying both the findings of the critical incidents as well as further insights from the case study questions.

Table 17. *Human Judgment Roles*

Human Judgement Role	Description	N=
Initial Assessment	Human judgment is used by managers to create an initial impression of the situation.	30
Enrichment of Analytics	Human judgment adds valuable insights and additional aspects to the data analytics results.	15
Sense-Check and Data Challenging	The analysis results are challenged and run through a sense-check.	8
Identifier of Need for Analytics	Decision makers recognize the need for additional, more sophisticated decision-making support.	5
Outweighing of Analytics	Factors such as relationships, intuition, and cultural aspects can outweigh fact-based analytics results.	4

4.2.2.1. Initial Assessment

In most cases (in 30 different incidents), managers used their human judgment to form an initial assessment of the decision they were facing. In these cases, managers relied on their previous experiences, intuition, and business understanding. These initial assessments in some cases assisted managers in determining a starting point in the decision-making process, as general manager M93 pointed out: “Given sort of my history and experience and some others’, that was a logical place to start, but we didn’t want to let that be the driving force” (C931).

However, as M93 cautioned, this initial assessment informed by previous experience should not be the only influence in the decision-making process. Initial assessments also introduce biases into decisions and can lead to assumptions early on. Negative outcome incident C122 was based on just such a biased and eventually erroneous initial assessment, which then had to be corrected through the use of additional data:

> In the […] example it was a negative impact, because that was based on an assumption that we shouldn’t lend to [customer segment]. But then when you get the data and you see the portfolio performance for that customer demographic, you can lend to [customer segment] all day long. (C122)

It is important to note that managers are often aware of these biases and recognize the limitations of their own initial assessments. Therefore, this practice is often used in combination with analytics in the roles of confirmation or challenger, which are further discussed in section 4.2.3. Head of department M85 elaborates on this relationship of human judgment in the form of intuition, and further information used to test it:

> So I think at the beginning I use my intuition to say ‘you know, it’s probably here, but I know enough to go and test it here and therefore the decision process will go this way’. And having got the extra information, then look at it again and go ‘Ok’. (M85)

When data is not available to challenge an initial assessment and balance out the limitations of human judgment, seemingly insignificant assumptions can ultimately diminish the overall decision outcome' effectiveness. Head of department M84 retells the negative outcome of incident C842, in which the lack of data led to a decision based purely on the managers' initial assessment:

> So we had to make a call on what we expected they would have. And unfortunately, they didn't meet our expectations […] It's a bad outcome for us, because it's used a heap of extra people and time that we hadn't allowed for in our labor forecast. (C842)

<u>4.2.2.2. Enrichment of Analytics</u>

In 15 incidents, human judgment functioned as an enrichment of data analytics. As analytics also has limitations, the managers' experience and business understanding could often add nuances and context that could not be captured purely from the data. As executive M10 described, managers are looking at "what comes back from a data perspective and then overlaying that with, I guess, intuitive knowledge or saying 'why would that be?'" (M10). The development of scorecards is one example, which heavily relies on data analytics, but also requires the input of human judgment. As analyst M14 pointed out, 'subjective business understanding' (C141) is applied to adjust scorecards in order to incorporate factors that the algorithm is not (capable of) tracking and incorporating.

Furthermore, the collection of data depends on human judgment calls on selecting relevant factors, determining scope and constructing initial theories. When asked how variables and parameters were selected for analysis, M14 referred to intuition in most cases. For incident C143, this intuition was further confirmed by the added insights from the company's CEO:

> In discussion with the CEO, getting the business understanding, he said: 'try this, try this, try this' and gave me lots of variables to try. And I would throw them in and try them, and use statistics to say how important each variable is. (C143)

A similar view was expressed by executive M22, who also relied on 'gut feel' (C223) to select data parameters and criteria.

Particularly decisions that involve a degree of creativity and include artistic elements incorporate a significant amount of human judgment. M84, for example, explained that they are not dealing with "just 1s and 0s", but that they require experience and intuition to make the best decisions. M22 expressed a similar thought when reporting on incident C221. This decision was the optimization of a production process that required the employees' input in order to determine key variables for a more data-based approach: "I talked to, we had a lot of production staff, to understand the different parts of the art, if you like" (C221).

While data and information can provide objective insights into a situation, human judgment enables managers to make more holistic assessments. Wisdom is especially highlighted for its ability to combine experiences from several sources in the case of head of departments M84 and M85. For incident C843, M84 had to gather insights from several employees to make a risk assessment decision based on some initial data:

> So that was a clear set of information that we knew, but experience being the guide on what was actually going to be wrong […] And it

> was the collective wisdom that was being used for that decision; and how bad [it] could be. (C843)

4.2.2.3. Sense-Check and Challenging

While data analytics is often seen as a more objective resource for decision making than human judgment, it also has limitations and should be questioned. The role of sense-check emerged as an in vivo code taken from one of the managers, when asked if the organization encouraged their employees to question data:

> So yes, we do a lot of that, and it's sort of encouraged just to get a sense-check on it. Especially if it's going external–just to say: 'does this actually make sense? Does that read properly', and all that sort of stuff. (M41)

This sense-check and data challenging role was employed relatively frequently (n=8), as blind trust in data is seen as one of the pitfalls of data-driven decision making. Executive M31 cautioned that when confronted with "something that doesn't make sense, don't act to move the data point, act to understand what/where the data points made a mistake". The manager furthermore added that organizations would be well advised to foster a culture of double-checking data instead of 'un-skeptically' relying on it (M31). Executive M10 confirmed this sentiment and recommended that data should be challenged by intuition:

> Data is great, but you have got to have a little bit of intuition behind the back of it and reconfirm and check the data's integrity, quality and the way it's been presented is impartial. (M10)

For managers to be able to challenge data and confidently use it in their decision making, they need to understand the data and trust it. This is further discussed in section 5.2.1., but its importance is evident in the role of sense-checking data analytics. As M41 remarked, understanding the data is crucial for managerial decision making, “because if you don’t understand the data yourself, you’re probably not going to question it.” Executive M22 and manager M83 furthermore add that familiarity with the data and recurring metrics enables managers to be more sensitized to spot errors and inconsistencies in the data: “You just look at something and then you almost like… smell it. You know there is something not right” (M83).

Challenging data was particularly recommended in cases with outlying and surprising data (M82, C851). This was advised by executive M71 as a lesson learned from “when you see a lunacy of making decisions just using analytical data and a single focus on the analytical data.”

The data challenging does not always have to result in the detection of incorrect data analytics results but can also point out human error in the interpretation of the data and its analysis (M91), or the omission of input data (C134). In order to sense-check the results, analyst M01 and executive M31 therefore follow similar processes, beginning with the challenging of calculations and the outlying data point. Next, a wider investigation is conducted to consider a broader range of factors that might have negatively affected the data analysis, such as the used data sources or the selected process/thinking.

Furthermore, the challenging of results is not one-sided. Data results should be challenged by human judgment, but human judgments should also be similarly challenged with data results, as M01 points out, and will be seen in 4.2.3.6.:

> And I think that goes both ways. I think if you intuitively, or based on your experience think: 'this would be a good outcome', but the analytics says: 'that's the good outcome', it's good to check both. So either your wisdom and experience could be wrong, but your data and analytics could also be wrong. So it's good to match up both, and really use both in any decision that you make. (M01)

Data challenging requires leadership support and needs to have its roots in the organizational culture (M41, M51), which will be further discussed in Chapter 6.

4.2.2.4. Identifier of Need for Analytics

Human judgment is seen as critical not only in challenging data, but also in recognizing the need for (more) data analytics (M84). Human judgment was used as an identifier of the need for analytics in five incidents – exclusively in combination with the role of initial assessment. This initial assessment of the situation is required before the manager can ask for supporting data or begin an analytics initiative. This also supports case study insights from business analysts stating that they are not pulling data or creating reports if they do not know the purpose of it (M94, M13). Managers are therefore forced to carefully assess the decision and determine its requirements beforehand.

Human judgment can therefore be used as part of the initial assessment role to identify further information needs, after initially building some context and summing up the situation (M85). Analyst M01 confirmed this notion, and described the process of the identification step of the decision-making process, using the roles of initial assessment and identifying analytics needs:

> So first of all, I start thinking about how would I tackle this problem or question. And then based on that I am thinking what kind of information would I need to tackle this problem? (M01)

Expanding upon that, general manager M13 provided a list of questions that are routinely answered during this stage: “What information do I need? And how can I get that? Who can I talk to? What can I get to make sure that I have an informed base from which to make a decision?” (M13). However, as M13 further pointed out, the role of identifier of need for analytics can also extend beyond the initial step of the decision-making process and recur at a later stage, when data results are not clear, or the results need to be challenged. Head of department M84 confirmed this sentiment. When managers are confronted with insufficient access to data, the decision can also come to a halt in this early stage of initial assessment, when the need for analytics is identified, but cannot be met.

Wisdom can be understood as an important part of this human judgment role, in that identifying the need for analytics can be considered wise in some cases. When asked if there was a connection between analytics and wisdom, executive M22 responded: “a wise choice may be to use analytics”.

4.2.2.5. Outweighing of Analytics

Human judgment was furthermore found to take on the role of outweighing analytics results. In four incidents, human judgment was used to factor different aspects into a decision that could not be captured by data. These factors were able to outweigh the data result, as executive M10 explained:

> Data might say one thing, but there might be other […] influences in there that are actually heavier weighted than that initiative you started to begin with. You might not see that in the data, so intuitively you have to weigh that up and say 'hang on, there's three other key influences here, that may also trigger this'. (M10)

The outweighing of analytics results occurs in the later stages of the development and selection steps of the decision-making process. In these stages, human judgment is often perceived as the final step prior to making the decision. Data analytics is a factor that plays into this decision but can be overwritten by intuition, as general manager M91 described:

> Occasionally on a business decision side, you sort of go: 'Is this the right thing to do intuitively in your gut?' You feel it is or it isn't and you make a call. And sometimes you just do that because there is no other way–you've got every bit of information you can possibly get to make the decision, and at the end of the day you just got to make the call–and that's intuition: is it the right call or not. (M91)

The role of outweighing or overriding analytics becomes critical when analytics cannot consider all relevant factors. Such factors are, for example, learning opportunities (C312) and the improvement of relationships (M11, M85) that could be an intangible outcome of decisions. To uphold business relationships with key suppliers, manager M11 voted to grant contracts to them, even if they were less cost-effective. Executive M31 elaborates on the value of gained experience, which could not be measured by analytics, when retelling incident C312:

> We have to layer in things that aren't in the data to make it make sense. I've got one client who is marginally unprofitable, we'd probably turn it over best, but I really like him and I'm learning by working with him, because he is at a different level in a different business. And so I can go 'Actually what the data says, we should move this on, because it's time we don't have, and where we not make any margin, but there are personal benefits and professional benefits and social benefits that mean that is ok.' (C312)

Relationships play a major role in the field of human resources and people management, as data analytics are limited in capturing relevant factors: "Intuition plays a big part when it comes to people, because that's the most difficult bit to get the analytics side on, and the hard data and so around" (M92). Recruiting decisions fall into this category, as the assessment of organizational fit was characterized as an 'intuitive feel' (M92). Considering fairness in a decision is at the manager's discretion and another example of a factor that cannot be portrayed by data (M72).

Altruistic motives can also be a reason to outweigh data analytics and were particularly identified in incidents in the not-for-profit sector. Executive M61 described situations in which he decided not to apply for funding because their projects would have consumed most funds of specific grants, leaving no funds for smaller and newer organizations that would also depend on that funding. Another not-for-profit decided to take on projects that were not particularly profitable but added value to the community: "And similarly we bid for very small bits of work recently, where we thought we could bring a cultural element to it" (M71).

4.2.2.6. Relation between Human Judgment Roles and Decision Triggers

Decision triggers have a significant effect on the decision-making process. As the development and selection step consists of an interaction between human judgment and analytics roles, this section looks at the relationship between these roles and decision triggers as identified in the critical incidents. A summary of these relationships can be found in Table 18 below.

Table 18. *Human Judgment Role in Identification Step*

Trigger	**Human Judgment Role**				
	Initial Assessment	Enrichment of Analytics	Sense Check and Challenging	Need for Analytics	Outweighing Analytics
	n=30	n=15	n=8	n=5	n=4
Anecdotal	5	0	1	**2**	0
External	6	1	1	1	**2**
Evaluation	**12**	**7**	2	1	1
Routine	7	**7**	**4**	1	1

Initial assessment saw the most significant prevalence of human judgment in the incidents (n= 30) and had the highest occurrence in evaluation-triggered decisions (n=12). This percentage can be explained by the fact that these evaluations often rely on the experience of specifically hired managers. Evaluations in the beginning stages of the decision-making process therefore require a rather high quotient of human judgment and collaboration to gather sufficient business understanding as well as diverse perspectives and experiences.

Enrichment of analytics is present at equal rates in evaluation- (n= 7) and routine- (n=7) triggered decisions. As discussed above, evaluations require a high level of experience, indicating the importance of this role. This role is essential in order for managers to enrich data analytics results with further layers and facets of their business experience. Routine-triggered decisions often result from outlying data or data anomalies; human judgment can therefore be a supportive tool for managers to assess the results and add their business understanding in the context of such decisions.

Sense-check and challenging is particularly important for routine-triggered decisions (n=4). When outlying data triggers a decision, this needs to be challenged by managers in order to establish credibility and accuracy. For anecdotal decisions (n= 2) on the other hand, the role of identifying the need for analytics is important. Anecdotal decisions are informed by human judgment and personal observations, resulting in the need for more objective data. Managers frequently identified the need for analytics in order to make more balanced and therefore more objective decisions.

Outweighing analytics was most often used in externally triggered decisions (n= 2). As these decisions are based on externally provided data, managers need to first assess the fit of this data to their organization. If the fit is deemed unsatisfactory, managers can outweigh these analytics results with their business understanding and experience.

4.2.3. Roles of Data Analytics

Seven distinct roles could be identified for the use of data analytics in the decision-making process: enabler of judgment, confirmation, identification, exploration, justification, challenger of judgment, and 'no brainer'. These roles are summarized in Table 19 and further discussed below.

Table 19. *Data Analytics Roles*

Data (Analytics) Role	Description	N=
Enabler of Judgment	Data is applied for choices that are too complex to determine without analytics.	23
Confirmation	Data is used to confirm initial assessments.	21
Identification	Analytics (e.g. reporting) identifies a problem or opportunity that requires a decision.	10
Exploration	Data sources are explored for trends or potential solutions to problems that were not considered previously.	10
Justification	During the selection stage, data analytics results are used as objective validation to justify decisions.	9
Challenger of Judgment	Initial assessments and cognitive biases are challenged with the assistance of data analytics.	9
No-Brainer	Data analytics results are black and white, and the decision is therefore solely based on them.	3

4.2.3.1. Enabler of Judgment

Decisions that incorporate several variables are often too complex for managers to judge confidently. Data was used in 23 incidents to help form a judgment based on insights from data analytics in these cases. This role provides managers with greater confidence in their decisions, as manager M11 highlighted when asked to which changes data analytics led: “Previously you were kind of flying a little bit blind, when you don’t know what sort of results you’re getting. So it is quite refreshing to understand that” (M11).

Data as an enabler of judgment can therefore assist managers in making decisions that their human judgment cannot evaluate completely. General manager M13 discussed an example of this regarding customer service staff assessments, which were significantly improved by introducing analytics metrics to monitor customer calls:

> And each of those calls is tracked through that database and we're working with our internal analytics team now to develop reports which are much richer for our process, which enable us to make better decisions about rostering effectiveness of staff and KPIs. (M13)

Data was furthermore used in this role to enable manager M11 to evaluate the performance of certain marketing materials, leading to the elimination of costly and ineffective materials (C111). Simpler forms of this practice were also regularly applied by executive M71 to assess the profitability of contracts using a cost center analysis.

One of the key benefits of this role, especially for early-career professionals, is that it also offers managers the opportunity to balance a lack of personal experience and business understanding. Analyst M14 highlighted this aspect of analytics' role when relating wisdom to data:

> As I said, wisdom is about experience, but it doesn't have to be your own. So you can learn from the experience of many others, if you use data. Definitely, and we do that systemically through a lot of our processes. (M14)

The potential and extent of this role depends on the available data and the analytics capabilities of the organization. If organizational prerequisites are met, the role of enabler of judgment can become quite extensive and prescriptive. Head of department M82 described a tool that assesses current workload and assigns priorities, therefore enabling them to plan more efficiently. In incident C121, the general manager and a supporting business analyst reviewed a balanced scorecard that informed their lending policy, and in turn, a large number of financial decisions.

4.2.3.2. Confirmation

While traditional decision making is based on making judgment calls informed by intuition and experience, managers tend to value the additional support of data to confirm their initial assessments. This is confirmed by the data: data analytics was used in 21 incidents as an assurance to increase managers' confidence in their own decisions. Overall, the role of confirmation was used for "really just trying to support our own thinking and to test our own views on things" (C912). Addressing the balance of human judgment and data analytics, manager M41 added that this role of data does not diminish the value of human judgment, but simply adds to it: "I think you probably use intuition just as much, but you've got the data now to better prove or disprove your intuition" (M41).

However, once managers are accustomed to relying on data to confirm their assessments, the unavailability of data in certain situations becomes particularly apparent. During these excepting circumstances, managers might not have the expected data at hand, leading to insecurity about their decisions, as head of department M21 pointed out when reporting on an incident during which data was not readily available:

> And I was nervous about that because I did not have the backing of the maths and the data and the information. I had some 'these things are telling me, this is what we should be doing', but I cannot justify that with data and maths. (C212)

The role of confirmation is particularly relevant in strategic and high-impact decisions to confirm initial assessments or theories. Executive M10 emphasized this relevance for strategic decisions, as they led to significant changes: "So you have a theory–check the data, does it tell you, like confirm or deny your theory? So I wouldn't just jump wholeheartedly into any changes in that regard" (M10). General manager M12 confirmed this sentiment by saying that creating a new strategy needs the additional confirmation from the data.

While managers agree on the significance for data confirmation in high-impact decisions, their role is less pronounced in operational decisions. In these day-to-day decisions, confirmation is still a valuable contributor, but the data analysis is less time-intensive. Analyst M14 highlighted that these decisions are mostly informed by personal experience and knowledge, but that data can still function as confirmation, albeit in a diminished capacity:

> If it was a day-to-day, I would probably be more likely to rely on what I already knew, hopefully supported by data that I already understand. But probably less analysis, maybe just more of a 'let's quickly check the report that we already have–and yes, it's still saying what it should say'. (M14)

The overall sentiment shared by the managers on the role of confirmation, was that the amount of data that should be collected depends on the manager, and how confident they feel about the decision at hand: "Get as much data as you can to ensure that you are satisfied that the decision you've got to make is the right one" (M91).

4.2.3.3. Identification

Data analytics was used in the role of identification in ten incidents. For this role, data analytics is used to identify problems or opportunities that require a decision. Data that fulfills this role is usually presented in the form of recurring reports. This was the case for incident C821, as the daily report data pointed out problems with operational procedures of the head of department's team that had to be considered carefully:

> And every day that I read those, it was almost like: it was discouraging. Everything we were doing had problems and wasn't done properly. So we used that as evidence that we needed to improve what we were doing as a planning team. (C821)

A similar scenario could be found in incident C931, when general manager M93 and his team observed negative customer satisfaction scores to determine potential solutions for improvement:

> When we look at data, things like customer satisfaction–points that customers score us–it was pretty clear that we were failing in that. So we needed to find a different model to sort of deal with all those customers. (C931)

Outlying data in reports or ad hoc analyses can also highlight errors or negative circumstances that require immediate attention. This identification often originates from the analytics or business intelligence department, for example in the form of unexpected "bubbles" that are detected in recurring reports (M12). These bubbles can be understood as sudden spikes or drops that need to be investigated further. When reports or ad hoc analyses reveal outlying data, this data is forwarded to the respective business unit for clarification: "Probably if the [analytics team] find[s] anything weird, they might promote that back up further. So they say 'here's some recommendations or decisions', and then the management team can act based on this" (M10).

There are also other sources of identification besides efforts driven by a designated analytics team. The identification can also come from the business unit through the course of their own research, market observations, or internal analytics efforts (M11). Furthermore, data can also be provided by external sources. As general manager M12 pointed out, their business units receive regular updates from external sources regarding how they compare to the competition: "We were having a look at market share data provided to us and showed that our market share was going backwards a little bit compared to other […] companies" (C121). This external market share data triggered internal strategic decision making.

Issues can also be identified during an analysis for a different purpose, and potentially highlight further tactical or even strategic issues (M41). The role of identification is in these cases very valuable, as it provides managers with insights and points out issues that they 'need to be aware of' (M93).

While the identification of problems is accomplished through the role of data analytics, human judgment is unarguably still required for further steps of the decision-making process. Conveying data results to other business units or top management is an example of this, as the uncovered insights might be sensitive or highlight shortcomings of other departments and current policies (C852). Human judgment is furthermore required in the role of sense-check and data challenging, as outlying data could also be the result of an analytics error (M82). More on the role of sense-check and data challenging can be found in chapter 4.2.2.3.

4.2.3.4. Exploration

Data served as an exploratory tool in ten incidents, providing managers with an opportunity to assess a wide range of complex factors and their potential influence on their decisions. Often, the number of variables involved in a decision became too large to assess their interaction and effects on the decision alternatives. In many cases, managers may also not know all contributing factors from the outset. As head of department M94 pointed out, these situations benefit from insights provided by data: "Analytics generally would be the use of statistical modelling or sophisticated tools to try to unearth patterns in the data that might not be evident to intuition" (M94).

In this role, data analytics can be used to explore correlations and dependencies in order to assess business performance and determine significant influences. As executive M10 highlighted, business analysts can use data to explore a wide range of relations to identify enablers, disruptors, risks and opportunities:

> Are there decision rules in there that are starting to be the performance enablers or performance disrupters in the business? So, 'I'm trying to understand this: can you [business analyst] please give me a summary of how that looks, what are the behaviors in that, are there any clusters or otherwise that we need to be aware of–that may be risks or opportunities?' (M10)

Particularly in the field of marketing, exploration can be a valuable role of data analytics to assess consumer behavior by evaluating, for example, marketing channels (M21, M22) or campaigns (M01), and by looking for trends (M61). These decisions will inform future investments and further marketing plans. As executive M61 emphasized, the role of exploration is of key importance to the marketing team, who regularly reports findings regarding the drivers of marketing success or failure:

> [The marketing team] does report to me, gives me a view, tells me when there's no movement. And then we try to work out what happened: either that we had no events on, or there wasn't anybody pumping things out. (M61)

Exploration was also essential in the field of operations to determine the cause of operational issues, as well as the future steps to address these issues (M10, M41, C911). Data analytics in this capacity contributed to the daily business and provided managers with an understanding of current events (M41). When probing deeper, data exploration enabled general manager M91 in incident C911 to assess the root cause of an operational problem and plan further steps to mitigate the situation:

> So as part of the root cause analysis, that's where we had to tap into the data to find out what was the cause … understanding that was a key component and where we went to from there. (C911)

4.2.3.5. Justification

Data analytics as justification was used in nine incidents and was considered critical to managers in data-driven organizations, as well as in companies that required a more formal decision process involving stakeholders or funders. Whereas decisions solely based on judgment might be accepted in more traditional organizations, a data-driven environment demands the support of these judgments with data and facts. Data allows for a more objective form of reasoning, and–since data analytics results and related efforts can be easily documented–functions as a basis for discussion and justification of a decision. In incident C931, described by general manager M93, data was not only used to identify a preferred option among several alternatives in the decision-making process, but was furthermore employed as a tool to justify the decision to executives:

> Obviously had to convince other people it's the right thing to do. And I think that's where the data helped with that–we had several options– to come up with a preferred option and then just talking the exec[utive] team through that. (C931)

Controversial decisions in particular benefit from the support of data analytics, as they enable decision makers to provide an objective form of justification that is not solely based on subjective judgments. When facing a critical decision about the allocation of new equipment in several departments, manager M92 based the decision on data and used the results as a justification when reasoning with departments that were not satisfied with the decision outcome:

> We had lots of [departments] that were disappointed. So then we walked them through the process and said: well, here's the numbers. So, it was the data that saved our decision making, because we could go back to it: 'well here is the fact. You're in or you're out'. (C922)

While this form of justification is the norm for data-driven companies, organizations in earlier stages of their data journey, as well as not-for-profits with an often more traditional organizational culture, can also benefit from using data analytics for justification. Not-for-profit organizations particularly require data in order to obtain and manage funding. As outlined in incident C612, data is an integral part of obtaining this grant money. Once grants have been won, organizations need further data to justify their decisions and performance, as executive M71 pointed out:

> Keeping our statistics and keeping our records and proving that we're doing a good job is actually really vital. A) for any potential to grow

> B) for survival. I think [the company] has lost contracts in the past for not reporting properly. (M71)

Data analytics in the role of justification is often included in business cases, when presenting decisions and key information for their reasoning to stakeholders or higher authorities for approval. Managers use data in this role to realize projects that do not have wide-spread support from the outset, as head of department M81 remarked. While upper management might support the general notion of a new project or decision, the backing of analytics is often needed to advance to the next stage, as head of department M82 confirmed when retelling incident C822 involving their team:

> We couldn’t have done it just by simply saying to the business: ‘Hey, it’s a good idea, it’s going to work – let’s move’. I’ve always had to push business cases up to the highest level within the company. And at that level people don’t just buy into emotive kind of thoughts. It has to be backed up by some kind of solid information/justification for doing it. (C822)

4.2.3.6. Challenger of Judgment

Corresponding to the human judgment role of sense-check and data challenging is the data analytics role of challenger of human judgment. Due to its objective nature, data is often seen as a neutral source of information that can challenge cognitive biases and initial assessments, which are based on subjective perceptions. Data analytics was found to function as a challenger of human judgment in three incidents. While the number of incidents is low, executive M31 still estimated that 20-30% of their initial intuitive judgments were contradicted by the data. Executive M10 added that the more available data, the more effective this role of data analytics is in preventing mistakes. This role was therefore seen as critical by head of department M85 in avoiding biased decisions and creating an opportunity for reflection:

> I think intuition is important to be able to just step back, make sure you've removed your biases: 'I know that was my intuition in the beginning, but having been presented with this other stuff, what I truly think is …' And be honest with yourself to challenge that. (M85)

Challenging one's own perception is not the only purpose of this role. It is also used by managers to change others' initial assessments and biases to carry out organizational change. As M85 emphasizes, data in this case can achieve immediate results: "And it was just great, because [the data] was able to move a mindset very quickly" (C851). Changing the mindset of senior management and executives also proved effective in incident C511. Executive M51 introduced a data-informed profitability analysis that allowed the company to re-evaluate their customer base and therefore increase their profit. The results of this analysis had contradicted the other executives' prior assumptions on the customers' value and was a valuable piece of evidence supporting M51's case.

In a similar incident C932, general manager M93 used data to challenge team leaders' assumptions on the capacity levels of their employees, rejecting the planned organizational change of adding further employees. When asked if the data revealed any surprises, M93 responded:

> Probably more for the managers of those teams. Where they thought that one person was flat stacked and one person wasn't. I think it gave them a few surprises. There is always a bit of push back. But once you

> could show and compare with others and even within their own teams, it was starting to make sense, and the data allowed for it to be a much more facts-based discussion rather than emotive. (C932)

The challenging of human judgment is often necessary, especially when this judgment is based on outdated experience that is applied to now-changed circumstances, leading to biased judgments (M81). As a result, managers particularly value the role of data analytics as a challenger in strategic and high-impact decisions, as general manager M12 highlighted: “I believe that you should look at the data, anytime you’re looking at changing policy or moving a customer demographic from your sweet spot” (C122).

4.2.3.7. No-Brainer

Data was seen as self-evident and the sole decision maker in its role as ‘no brainer’ in three incidents. The role is an in vivo code identified in the interview with executive M10, who pointed out the dominant role of data analytics in certain decisions: “Yes, sometimes intuition takes over data, and sometimes data is so black and white, that it’s a no-brainer” (M10). As described in this statement, data analytics’ role as a no-brainer can be understood as the other end of the spectrum from the human judgment role of ‘outweighing data analytics.’ Data used as a no-brainer can therefore similarly be the main or sole factor considered in selecting the best alternative.

As manager M92 remarked, the selection stage of the decision-making process can be rather simplistic: “If it’s inside the metrics – it’s obviously yes; if it’s outside the metrics – it’s obviously no” (M92). These decisions are often simple operational decisions that have limited consequences and follow a structured, predefined approach. An example was mentioned by manager M11 as the selection of suppliers, during which the cheapest provider is chosen. Similarly, in incident C822 data also took on the role of no-brainer for part of the alternative evaluation. For this decision, head of department M82 created several data-driven criteria for selecting one of three alternatives. One of these alternatives achieved a higher result than the other two, “so it was a no-brainer” (C822).

4.2.3.8. Relation between Data Analytics Role and Decision Trigger

As discussed in section 4.2.2.6. for human judgment roles, decision triggers influence the following decision-making process steps of development and selection. Correspondingly, this section investigates the relation between the data analytics roles and decision triggers as identified in the critical incidents. A summary of these relationships can be seen in Table 20.

Table 20. *Data Analytics Role in Identification Step*

Trigger	**Data (Analytics) Role**						
	Enabler of Judgment	Confirmation	Identification	Exploration	Justification	Challenger	No Brainer
	n=23	n=21	n=10	n=10	n=9	n=9	n=3
Anecdotal	4	3	1	1	1	3	0
External	6	5	0	0	2	0	1
Evaluation	**7**	**9**	3	**6**	**3**	2	**2**
Routine	6	4	**6**	3	**3**	**4**	0

Enabler of judgment was the most frequently used role of data analytics in decision making (n=23), and most often occurred in evaluation-triggered decisions (n=7). However, externally-triggered (n=6) and routine-based (n=6) decisions also regularly applied data analytics in the form of an enabler of judgment. This role is well-rounded and applicable to several scenarios, which explains its frequent occurrence. Evaluation decisions are usually large in scale, incorporating several analytics and human judgment roles. Data analytics provides an opportunity to objectively evaluate most considered factors. In externally-triggered decisions, internal data analytics can be used to assess external data, as well as the fit of offered opportunities within the organization. Routine-based decisions usually rely on sophisticated regular reports, which enable managers to judge the problem or opportunity at hand.

The role of data analytics as confirmation was most frequently used in evaluation decisions (n=9). Evaluations can be heavily informed by manager's experience and intuition. In these cases, data analytics takes on the important role of confirming initial theories and perceptions.

Identification most often occurred in routine-based decisions (n=6). As these decisions are mostly based on regular reports, data analytics' role of identifying problems and opportunities is an inherent quality.

The role of exploration was particularly relevant for evaluation decisions (n=6), as these are often rather complex and unstructured decisions with little available or familiar data. This consequently results in the exploration of wider datasets in order to identify patterns and discover relevant factors that might influence the decision outcome.

Justification is mostly used in evaluation (n=3) and routine-based (n=3) decisions. As evaluations are mostly impactful decisions that are quite commonly supported by business cases, data analytics is used as an objective form of validation to justify the selection of the decision alternative. Routine-based decisions are mostly triggered by data, which in turn can function as justification for beginning the decision-making process, as well as the selection outcome.

Data analytics was employed most commonly as a challenger of human judgment in routine-based decisions (n=4). When routine-based decisions are not triggered by internal data reports, but external data sources, or are the result of regular meetings, these decision initiatives can be biased. Data analytics can then be used to challenge biased assumptions or external views.

The role of ‘no-brainer’ was mostly used as part of evaluation decisions. While these decisions usually entail several data analytics roles, the eventual selection or later stages of the development step are often reduced to a small number of options that are evaluated by a metric composed of several data sources. This last-step evaluation of options is often seen as a no-brainer, purely based on the metric at hand.

The roles of human judgment and data analytics cannot be considered as negative or positive influences per se. The interviews with managers clearly showed that a certain role could be a contributor as well as a disrupter of successful decision making. While a certain influence was considered negative by one participant, another participant considered it a positive influence. An example of this was using human judgment to make an initial assessment. Most managers considered the formation of an initial assessment to be something positive, as discussed in section 4.2.2.1. However, in incident C122, this initial assessment was biased, leading to complications during the decision-making process. It was therefore considered to have had a negative effect on decision making by general manager M12.

These different perceptions of the roles are fleshed out in the following section reporting on the actual decisions, which were collected using CIT. Eventually, this exploration of the data led to the understanding that a categorization of the roles as contributors or disrupters additionally depended on further factors, which will be discussed in Chapters 5 and 6.

4.2.4. Actual Decision Making

During data collection, 43 incidents were captured with diverse impacts and contexts, a wide range of data analytics and human judgment roles, different outcomes, decision triggers and a varying extent of data and judgment use. Below, the findings regarding these differentiators highlight significant relationships between them. This section focuses solely on the insights gained from analyzing these incidents, incorporating the roles and decision-making process steps that were discussed in the previous sections of this chapter. The findings outlined here are structured according to the decision clusters that have been determined in section 4.1.2., namely balanced decisions (n=18), high-judgment decisions (n=13), and high-data decisions (n=12). The relationships between decision clusters and decision types can be seen in Table 21 and are additionally further discussed below.

Table 21. *Decision Types per Cluster*

Cluster		Decision Type						
		Complex/ Strategic	Complex/ Tactical	Complicated/ Strategic	Complicated/ Tactical	Complicated/ Operational	Simple/ Tactical	Simple/ Operational
		n=10	n=7	n=7	n=13	n=2	n=1	n=3
Balanced Decisions	n=18	**6**	1	**5**	**4**	1	0	1
High-Judgment Decisions	n=13	2	**5**	0	**4**	1	0	1
High-Data Decisions	n=12	2	1	2	**5**	1	1	0

Incidents in the balanced cluster were mostly found to be complex strategic decisions (n=6). These decisions are generally considered to be critical and have long-term consequences. Managers therefore gathered input from several–often difficult to access or acquire–data sources, even if the data could only be added in hindsight. This data was then balanced with the experience and judgment of senior management. The balanced cluster also contained several complicated strategic decisions (n=5). However, data acquisition was usually considered easier to acquire for these decisions, as they are not as complex and have more measurable components. Lastly, the balanced cluster had several complicated tactical decisions (n=4). However, these decisions were quite evenly spread throughout the different decision clusters. Their scope is limited, and the application of data often depended on the need and availability.

For the high-judgment cluster, most decisions were complex tactical (n=5). These decisions are similar to complex strategic ones, in that data might be scarce and difficult to apply. However, since tactical decisions are typically not as critical and smaller in scope, the effort to gather data was more limited than for strategic decisions. As a result, these complex tactical decisions relied highly on judgment. As mentioned above, complicated tactical decisions were also rather prominent in this cluster (n=4). The cluster of high-data decisions only had a majority of complicated tactical decisions (n=5). Otherwise, the decisions types were evenly spread out.

This following section facilitates a deeper understanding of actual managerial decision making, highlighting the impact and diverse influences of data analytics and human judgment on the different decision clusters. For each decision cluster, to analyze the specific impact of the data analytics and human judgment roles within the decision-making process, the frequency distribution of findings for each role between the different steps was compared. The frequency distribution determined whether the results indicated a relatively high, medium or low importance of analytics or human judgement for each step in the decision-making process. In contrast to the managers' general statements and perceptions of the balance between these two key influences, the following findings are informed by actual decisions, and represent a realistic sample of decision making in the age of big data.

4.2.4.1. Balanced Decisions

Most critical incidents were categorized as balanced decisions (n=18), which means that the managers involved displayed a high level of both data analytics and human judgment use. Seven of the decisions could be categorized as assessing opportunities, while the other 11 addressed problems. When looking at the distribution of strategic decisions, with 11 out of 18, the balanced decision cluster contained most strategic decisions. Balanced decisions were triggered externally (n=4), by routine checks (n=6), and most often in the context of evaluations (n=8). None of the balanced decisions had an anecdotal trigger.

Evaluation decisions were mostly identified in the balanced decision cluster. As these evaluations were usually large-scale, they demanded a balanced approach, that benefitted from data analytics, but also the experience and judgment of the managers. Another common trigger for the balanced decision cluster were routine checks. These decisions were mostly triggered by recurring reports providing a substantial amount of data. Furthermore, these routine checks could mostly follow established processes for the use of judgment, in the form of management or board meetings that ensured the input of human judgment. External triggers were also common in this cluster, as they were often based on external data and demanded business understanding and experience to evaluate that data or influences for organizational fit.

While balanced decisions benefitted from both, human judgment roles as well as data analytics roles, these roles were not evenly distributed among all three stages of the decision-making process. Figure 10 highlights the frequency of these roles in the different decision-making steps. Comparing the frequency distributions between the different steps of the decision-making process shows that human judgment roles were predominantly employed during the identification and development steps of the decision-making process, whereas data analytics was primarily used for the development and selection steps.

Decisions in the balanced cluster were often without precedent, and therefore initially relied on the managers' intuition, expertise and domain knowledge, because there was no familiar data or information available. However, data could be added in later stages and helped to shape and enrich the project (C123, C221). Data analytics enabled decision makers to reach more precise conclusions, to further explore certain aspects of their decisions, and to evaluate their initial assessments and impressions of those decisions.

A typical example of this cluster is incident C123, a complex strategic evaluation led by a new hire to assess the potential of a new line of business. The identification step and the initial phase of the development step were informed by the manager's prior experience with the potential line of business, which led to a pilot project. Data gathered during this pilot was then used for further stages in the development and selection steps to make a decision:

> So we launched the pilot. And it went better than expected for those first six weeks. So then we pulled the data of that six weeks. What was the score? Does it fit in with the assumption that we had in the business case? And then that data over that short period of time helped us to do the full nationwide launch. (C123)

	Identification	Development	Selection
Human Judgment Roles	N=9	N=14	N=4
Data Analytics Roles	N=5	N=22	N=18

Figure 10. *Roles in Balanced Decisions*

While this particular analysis provides an overview of the extent of data analytics and human judgment use in balanced decisions, not only the extent, but also the specific roles used during the decision-making steps, were found to vary according decision cluster. Table 22 summarizes the use of human judgment roles in the distinct decision-making steps of balanced decisions. During the identification step, the initial assessment role is the only frequently used role (n=6) and was often described by managers as a logical starting point (M11, M41, M81). It is also the most common role in the development step.

However, this development step also benefitted from human judgment in the form of the enrichment of analytics (n=4), and an identifier of need for analytics (n=3). After an initial assessment, managers used their judgment to provide additional insights to enrich the gathered data analytics results, and to identify further use cases for data analytics. The role of sense check and data challenging was used in equal amounts in the identification and development steps (n=2) and provided management with an opportunity to test the data involved in the decision.

Human judgment was less critical in the selection step of decision making, where it still mostly functioned as an initial assessment (n=2). It was additionally used once in the capacity of data challenging, and once to outweigh data analytics results.

Table 22. *Balanced DM-Steps - Human Judgment Roles*

Human Judgment Role		**Balanced DM Steps**		
		Identification	Development	Selection
		n=9	n=14	n=4
Initial Assessment	n=13	**6**	**5**	**2**
Sense Check and Data Challenging	n=5	2	2	1
Enrichment of Analytics	n=4	0	4	0
Identifier of Need for Analytics	n=4	1	3	0
Outweighing of Analytics	n=1	0	0	1

Table 23 focuses on the different data analytics roles managers employed during the various decision-making steps. As mentioned above, data analytics plays a limited part in the identification step of balanced decisions, while the only relevant role of analytics in this step was identification itself (n=4).

The roles of analytics became much more prominent in the development step, where it was used particularly often to enable judgment (n=9), for confirmation (n=5), and for justification (n=3). Once managers were provided with access to data, analytics was applied in this stage to assess the more complicated but measurable aspects of their decisions. Balanced decisions therefore benefited from the enabler of judgment role. In its second most common capacity, data was used to confirm the managers' initial assessment and judgments, providing them with more confidence in their decision. The role of justification had already been previously applied in the development step to move forward with certain alternatives and provide objective validation.

Data analytics' use during the selection step exhibited the same order and similar frequency; analytics was once again used to enable judgment and decide between different alternatives developed in the previous decision step (n=6), to confirm previous initial assessments (n=5), and to justify the manager's selection of alternative.

Table 23. *Balanced DM-Steps - Data Analytics Roles*

Data Analytics Role		**Balanced DM Steps**		
		Identification	Development	Selection
		n=5	n=22	n=18
Enabler of Judgement	n=16	1	**9**	**6**
Confirmation	n=10	0	5	5
Identification	n=7	**4**	2	1
Justification	n=6	0	3	3
Exploration	n=3	0	2	1
No Brainer	n=2	0	1	1
Challenger	n=1	0	0	1

Decisions in the balanced cluster applied human judgment to incorporate the managers' prior experience as a starting point to the decision-making process. In later stages of these balanced decisions, data analytics was added to provide managers with the opportunity to assess measurable aspects of decisions, and to confirm and justify their judgments.

Due to its balance and thorough nature, this holistic approach was therefore commonly used for complicated decisions involving decision parameters that could be calculated, as well as for complex strategic decisions that were crucial enough to warrant an often extensive effort to collect data. Both decision types provide an explanation for the common use of the data analytics role of enabler of judgment in this decision cluster.

Particularly strategic and tactical decisions were found to require this balanced approach to ensure that the selected decision alternative was the best choice. M91 emphasized this point, highlighting the amount of diverse inputs that go into these strategic decisions: "So you make a strategic call, which obviously has to be justified as strongly as it can be; for all the right reasons financially, let alone logically and taking people into account, and a whole lot of other things" (C912). M41 expressed a similar sentiment, saying that strategic and tactical decisions cannot be made purely based on numbers in a sterile environment, as even the most perfectly designed product might not get accepted by the market. He therefore concluded that there are “probably things outside your data analysis for strategic and tactical decisions” (M41).

4.2.4.2. High-Judgment Decisions

The second-most populated decision cluster was high-judgment decisions (n=13), which means that these decisions displayed a high level of human judgment use, and a limited or no use of data analytics. Eight decisions assessed opportunities, while only five decisions addressed problems. Only two of the 17 strategic decisions fall into this cluster. These decisions were most often triggered externally (n=5), but also in the context of evaluations (n=4), by anecdotes (n=2), and through routine checks (n=2).

As discussed in the balanced cluster, external triggers often required human judgment to assess external data or influences for their organizational fit. In contrast with the evaluations in the balanced cluster, the high-data evaluations were mostly tactical decisions (n=3). As tactical decisions are limited in their impact and resources, a lack of available data was substituted by human judgment instead of more elaborate and costly efforts to gather additional data. Anecdotes are mostly driven by human judgment, and therefore led to high-judgment decisions. Routine checks that trigger tactical or operational decisions were not seen as critical and were mostly resolved by relying on human judgment.

As is evident from Figure 11, in contrast to balanced decisions, human judgment roles are not predominantly applied during the earlier identification and development stage, but during the latter two stages: development and selection. Data analytics roles are very limited in the identification and selection step, and mostly find application during the development of alternatives. Due to the high number of external triggers, the relevance of both data and judgment roles in the identification step is limited.

	Identification	Development	Selection
Human Judgment Roles	N=2	N=6	N=6
Data Analytics Roles	N=2	N=13	N=3

Figure 11. *Roles in High-Judgment Decisions*

High-judgment decisions are often the result of limited access to data. Especially external and anecdotal triggers can lead to a lack of available or applicable data, as they are rooted in external sources that might not be applicable to the organization, and human judgment respectively. For the mostly tactical decisions in this cluster, the effort and resources to gather more data was considered not profitable (M01, M91). As the medium impact decisions did not warrant a more thorough gathering of data, managers relied solely on their judgment. This lack of data analytics, and therefore lack of objective inputs, was the root cause of the only negative outcome incidents (n=3) shared in this study. Two of these incidents referred to the same decision but were reported by two different managers.

These negative outcome decisions were categorized as high-judgment decisions, with the extent of data use having a value of three or less. All these decisions were business opportunities that were accepted due to the lack of relevant data but should have instead been rejected. All of them were complex tactical decisions. Additionally, the managers lacked relevant experience, as head of department M81 points out in a negative-outcome incident (C812) that led to the acceptance of external contract work. Their decision to accept had been based on limited internal data that did not match the conditions of the contract work, and limited experience with the subject: “And that didn’t turn out too well, because the work was a lot more significant than we thought it was going to be. So there was no real experience in doing it, so it was just a guess” (C812).

This decision led to considerably more work than estimated, which strained the company’s financial and human resources (C842). The managers learned from this that information must be relevant for the context of the decision, and their organization furthermore decided to include a standard into the planning process, which enabled them to more accurately assess the starting point of potential contract work (C842).

After outlining the extent of data analytics and human judgment use, determining their specific roles helped to further characterize the high-judgment cluster. As can be seen in Table 24, the human judgment roles employed are quite evenly distributed, with no clear majorities. During the identification stage, only the role of initial assessment (n=2) was used by the managers. The development and selection step show a rather equal application of all human judgment roles, except the identifier of need for analytics. This role, matching the characteristics of this cluster, was not relevant for high-judgment decisions, as analytics was not an integral part of these decision processes.

The human-judgment roles used in the negative-outcome decisions were also limited. One of the decisions (C113) used none of the defined roles, but only had external human judgment from a partner available when making the decision. The other decisions (C812, C842) were influenced by the role of initial assessment. This initial assessment, however, was impacted by limited experience.

Table 24. *High-Judgment DM-Steps - Human Judgment Roles*

Human Judgment Role		High-Judgment DM Steps		
		Identification	Development	Selection
		n=2	n=6	n=6
Initial Assessment	n=4	**2**	1	1
Outweighing of Analytics	n=4	0	**2**	**2**
Enrichment of Analytics	n=3	0	**2**	1
Sense Check and Data Challenging	n=3	0	1	**2**
Identifier of Need for Analytics	n=0	0	0	0

As Table 25 shows, data analytics was almost exclusively used during the development step, mainly in the roles of confirmation (n=5) and enabler of judgment (n=5). The role of confirmation was employed in this step to confirm the managers' judgment and initial assessment, which matches this cluster's characteristics. Data was employed as an enabler of judgment when managers reached the limits of their own experience or mental capacity but had already defined the key parameters of the decision. The roles of challenger of judgment, exploration, and no-brainer found no application in this high-judgment decision cluster. Its use in the roles of justification and identification was also limited, as these decisions were not data-centric, the value of data as identification or justification being limited.

The negative-outcome decisions applied the data analytics roles of enabler of judgment and confirmation. In decision C113, data was used as an enabler of judgment; however, only external data was available. While data analytics results deemed the selected alternative a good choice, this data did not reflect the organization's characteristics, which eventually led to a negative outcome. For incidents C812 and C842, the role of confirmation was used to confirm the managers' initial assessment. But while the data confirmed their assessment, both the data and the assessment were limited to a very specific context that did not apply to the actual decision parameters.

Table 25. *High-Judgment DM-Steps - Data Analytics Roles*

Data Analytics Role		High-Judgment DM Steps		
		Identification	Development	Selection
		n=2	n=13	n=3
Enabler of Judgement	n=9	**1**	**5**	**3**
Confirmation	n=6	**1**	**5**	0
Identification	n=2	0	2	0
Justification	n=1	0	1	0
Challenger	n=0	0	0	0
Exploration	n=0	0	0	0
No Brainer	n=0	0	0	0

Decisions in this cluster mostly relied on the managers' human judgment during the development and selection steps of the decision-making process. The roles of analytics were essentially only used for the development step to confirm managers' assessments or enable judgment. The overall use of data analytics for this cluster was thus relatively limited in scope and scale.

Managers attributed this to the decision types that mostly fell into this cluster. A lot of tactical decisions could be categorized as high-judgment decisions. These decisions tended to lack access to data, and due to the often digestible consequences of tactical decisions, managers decided to go with their intuition:

> You wonder about the consequences later. As long as you know that the consequences are not going to be that severe, then why not? But you know, the more severe the consequences, the more checking and double-checking you would have to do. (M01)

M91 echoes this sentiment by saying that the day-to-day decisions are mostly based on experience and the manager's professional background, and not on data analytics results, "but when you're getting into bigger strategic decisions, absolutely is where to me data does play a big part" (M91).

Also, several complex decisions could be attributed to this cluster. These decisions mostly lacked clearly definable parameters or, often, access to data. As general manager M91 phrased it, complex decisions "can go all over the place" (C911). For these kinds of decisions, managers could not follow a structured process, and human judgment became more relevant, as M91 added: "When you go outside of a standard process […] it does come often down to judgment, or experience. When we just make a call" (C911). Executive M31 summarized the importance of human judgment in complex decisions with one sentence: "Essentially the complex question is a talking one" (M31).

4.2.4.3. High-Data Decisions

The last identified decision cluster, high-data decisions (n=12), refers to decisions that displayed a high level of data analytics use, and limited to no use of human judgment. Three of the decisions were categorized as opportunities, whereas eight were considered problems. One decision could not be classified as either. While most high-data decisions were found to be solving problems (n=8), high-judgment decisions were mostly assessing opportunities (n=8). The support of data analytics was therefore seen as more significant for problem-solving than for the assessment of opportunities. High-data decisions were triggered to equal amounts by anecdotes (n=4), routine checks (n=4), and in the context of evaluations (n=4). None of these decisions were triggered externally.

As noted in the definition of externally triggered decisions, they often lack internal reference points and therefore require a fair amount of human judgment. The lack of external triggers in this high-data cluster therefore matches its characteristics. Most anecdotal decisions fell into the high-data cluster, as the trigger was purely based on human judgement, and the ensuing decision used data to assess this judgment. High-data decisions triggered by routine checks exclusively used the role of exploration for their decisions, with managers following established data-driven processes. The evaluation decisions in this cluster were either complicated or simple decisions for which the managers had measurable components to assess and enough data was accessible.

Figure 12 provides an overview of the frequency distribution of data analytics and human judgment roles across the different decision-making steps of high-data decisions. Human judgment roles can be seen to have had an equally light impact on all three steps of the process. Data analytics roles also only exhibited a light frequency in the identification step but became more important for the development and selection step.

While human judgment was employed throughout the decision-making process in a supporting capacity, data analytics was a significant influence on the development step of the most often complicated decisions. In these decisions, the alternatives were often rather clear and defined, and data analytics was used to judge the best option for management. In often predefined and structured data-driven decision-making processes, data analytics could not only be used to evaluate the best option when given a limited number of alternatives, but also to further explore the variables of the decision.

	Identification	Development	Selection
Human Judgment Roles	N=5	N=5	N=4
Data Analytics Roles	N=5	N=19	N=12

Figure 12. *Roles in High-Data Decisions*

In accordance with their data-driven nature and the well-organized application of analytics in the decision-making process, these high-data decisions were almost exclusively made by the two companies with the highest level of analytics maturity, Organizations 1 and 9. The consistently positive outcomes of the incidents in this cluster indicate that data-driven decisions can be successfully employed by organizations that are mature with respect to data analytics. More on the aspect of analytics maturity is discussed in Chapter 6.

A typical example of such a high-data decision by an organization with a high level of analytics maturity is decision C133. This decision was triggered by a routine check to evaluate a scorecard in use by the organization. In an established and highly structured process, data analytics was employed as an enabler of judgment to assess the impact of previously determined and recurring variables on the performance of their scorecard. The role of data analytics was very significant for the outcome of this decision, whereas human judgment functioned in a merely supporting capacity. Similar results can be found in most decisions in this cluster.

While the human judgment roles were evenly distributed across the three decision-making steps, the actual roles applied were limited, as demonstrated in Table 26. Judgment was almost exclusively used by managers in form of initial assessment, mostly during the identification (n=4) and development step (n=4). In these high-data decisions, the value of human judgment was noted primarily as providing a first assessment of the situation, which was then further evaluated by data analytics. In exceptional cases, human judgment was furthermore used as a sense-check (n=2) and to enrich data analytics results (n=1). The role of outweighing data analytics did not find application in this cluster, as the relevance of human judgment was limited in high-data decisions.

Table 26. *High-Data DM-Steps - Human Judgment Roles*

Human Judgment Role		High-Data DM Steps		
		Identification	Development	Selection
		n=5	n=5	n=4
Initial Assessment	n=10	**4**	**4**	**2**
Sense Check and Data Challenging	n=2	0	1	1
Identifier of Need for Analytics	n=1	1	0	0
Enrichment of Analytics	n=1	0	0	1
Outweighing of Analytics	n=0	0	0	0

Similar to decisions in the balanced cluster, data analytics roles were mostly employed in the development and selection step, as shown in Table 27. The most common analytics roles were enabler of judgment (n=10) and exploration (n=10). Enabler of judgment was primarily used for the development step (n=5), but also found application in the other steps, matching the results of the previous two decision clusters. The role of exploration mostly found application in this cluster, having had no influence on high-judgment decisions, and only limited impact on balanced decisions. Exploration was particularly significant for the development step (n=8), in which data analytics was applied to identify patterns and understand complex connections that were not evident to managers from the outset.

Justification (n=5) was also an important, if less frequent, role for high-data decisions, as a data-driven environment requires the support of data analytics to justify decision outcomes. Furthermore, the role of challenger (n=4) was employed to challenge the initial assessments of managers, the only relevant role of human judgment in this decision cluster. The role of confirmation, one of the main data analytics impacts in the other two decision clusters, barely influenced managerial decisions in the high-data cluster (n=2). This matches the characteristics of this cluster, in which data analytics took on leading instead of supporting roles in the decision-making process.

Table 27. *High-Data DM-Steps - Data Analytics Roles*

Data Analytics Role		High-Data DM Steps		
		Identification	Development	Selection
		n=5	n=19	n=12
Enabler of Judgement	n=10	**2**	5	**3**
Exploration	n=10	1	**8**	1
Justification	n=5	0	2	**3**
Challenger	n=4	0	2	2
Identification	n=3	**2**	1	0
No Brainer	n=2	0	0	2
Confirmation	n=2	0	1	1

The high-data cluster contains data-driven decisions by analytics-savvy organizations for which data analytics took the lead in the decision-making process. While the impact of human judgment was mostly limited to providing managers with an initial assessment of the situation, data analytics dominated the development and selection stage. In this cluster, data analytics was used to its fullest potential by applying it for exploration and using it as the main criterion in the selection process.

While all three clusters contain successful decisions, managers often voiced their discontent about their own or their organization's decision making; they were generally in favor of more balanced or data-driven decision-making approaches. These discrepancies between the managers' actual decisions and their general views on ideal decision making are further discussed in the next section.

4.2.5. Ideal Decision Making

The previous section focused on actual decisions that were shared by the managers during the critical incidents part of the interview. However, during the more general case study portion, it became apparent that the participants often had differing ideas about their ideal decision-making process. This idealized process often contrasted with the examples of actual decisions they had previously shared. Several participants were aware of this discrepancy and their current shortcomings, as executive M22 demonstrated when asked whether he follows a structured process or certain steps when making decisions: "Uhm, ideally or what we do?" (M22). Several managers expressed similar sentiments, using phrases such as "I would like/want it to be…". An example of this is manager M83 explaining his ideal balance of data and judgment use: "I'd like it to be 75% data-driven, 25% intuition. I'd like it to be like that" (M83).

In this section, the focus therefore lies on outlining findings that describe this 'ideal' decision-making process further, accumulating managers' perceptions on requirements to improve decision making, as well as lessons they learned from their previous decisions and from overcoming obstacles. The five key requirements managers identified were to find a balance between judgment and data in decision making; building trust in data analytics; transforming reactive into proactive decisions; and creating processes and guidelines around decision making.

4.2.5.1. Finding Balance in Decisions

Finding a balance between data and human judgment use was a key concern addressed by managers, and often seen as a shortcoming in their current decision making (M12). Both data input and judgment were often crucial for decision success, as incident C711 showcases. Executive M71, for example, had been approached by an external party for a business opportunity and had to decide whether to take or decline it. As M71 emphasized, both data and human judgment were critical to reach a positive decision outcome. Data in the form of financial information and judgment in the form of business understanding and experience were considered in assessing the opportunity for cultural fit. M71 remarks that in past decisions, neither of the components might have been considered, which would have led to a negative decision outcome:

> So again, if I think back: Once upon a time we might have just gone for it and found out later to our cost that a) it wouldn't have worked financially, and b) it wasn't going to work culturally either. (C711)

M10 confirmed this notion by saying that even if data yields a certain result, past experiences will always be mixed into the decision making as well. Maintaining this balance was important, as both human judgment and analytics have limitations. Analytics reached its limits at the point when the decision parameters were unclear or impossible to model. As executive M51 argued, intuition could then be an invaluable decision-making tool for managers, given the right experience:

> Quite often it's necessary to make decisions based on intuition. And intuition can be a powerful way of making the right decision, take it the practitioner has the experience or some knowledge or the ability to work in heuristics or they've got knowledge about lots of different things that are very hard to model. You can end up getting some quite good answers. (M51)

The roles of human judgment and individual knowledge were also limited and could be prone to biases. Managers' knowledge was found to be formed by their own experiences which might vastly differ from the organization's collective knowledge or procedures. Head of department M82 therefore advocated to reduce the influence of these factors in certain decisions to avoid inconsistent decision quality and work outputs:

> I think there are many roles within the business, where we should not necessarily rely on individual knowledge. Don't base it on your own personal knowledge. We have many people in this office next door

> that do things because they know better how to do it, and we get different products into my team because of that. (M82)

Participants generally spoke out for a balanced decision-making approach, advocating the use of both, human judgment and data analytics. A balanced approach, however, was also found to encounter the difficulty of contradicting results. If, for example, an initial assessment did not match the results of data analytics, managers were often conflicted about the selection of an alternative. Manager M92 pointed out this “clash” of intuition and data, referring also to the concept of developing sufficient understanding for analytics, which builds trust in data results.

4.2.5.2. Trust in Data Analytics

Trust in data analytics was a significant factor for successful data-driven decision making. Reasonable data quality and access to information were essential prerequisites. However, to build organization-wide trust in data demanded further steps, including a cultural shift. This shift and its importance were highlighted by head of department M85 in an incident:

> It’s not about presenting facts, it’s actually about effecting change. So the challenge now is we’ve got reasonably good information but flying that information out would get the change we need, and there’s a real cultural thing of building belief. But if you don’t have good information, you can’t build belief. Once you believe in the value, you get action.” (C851)

If this trust was not built, managers faced difficulties when using the data analytics results to justify their decisions, particularly when employing the results that contradicted the intuition of other parties involved in the decision. Executive M51 demonstrated the importance of this trust and understanding in an incident he shared. During this decision, analytics provided valuable insights, but not all involved decision makers were willing to accept the results:

> So suddenly you've got this breakthrough and either one will be in complete disbelief and denial: 'How could that be? That must be wrong. No, I'm not going to understand it or believe it.' And others would take their time to actually absorb that, and say: 'I had no idea', and it might change the whole range of things. (C511)

In order to facilitate this understanding of analytics' significance and to create trust in its results, it was therefore deemed a useful practice to share positive experiences with data-driven decisions. According to general manager M93, showing and comparing data results with coworkers obliged employees to make sense of the data. This facilitated more fact-based discussions than emotive ones (C932).

The topic of trust will be further discussed in Chapter 5. Data quality and access, as well as organizational change, are aspects discussed in Chapter 6.

4.2.5.3. Transforming Reactive into Proactive Decisions

Once managers had had their first successful experiences with data analytics, the lessons they learned from these decisions were often incorporated into further decision making. After a positive outcome decision that was informed by data analytics, analyst M86 applied a similar approach to an on ongoing decision:

> I think I'm trying to apply that thinking to my current project. I thought rather than being reactive, which is: 'oh I have an error…just

> solve it, get rid of it', we need to have a preventive approach. So I will make sure that I use more that kind of thinking by maybe tweaking the code, which will fix the root cause. (C861)

In this example, the analyst M86 used the lessons learned during the previous data-driven decision to define a more proactive decision-making process. This approach was then considered a guideline to prevent errors and avoid negative outcomes. In a similar example, general manager M14 used data that assisted a positive decision outcome to establish a regular report. This report enabled the organization to make more proactive decisions, and to identify negative developments early on: "And based on this one we started producing a regular report to see this coming sooner" (C142).

4.2.5.4. Decision-Making Processes and Guidelines

In their process to convert the lessons learned in the early stages of data-driven decision making into actionable insights for others, managers often saw the need to clearly define decision-making processes or guidelines. An example of this is an established case study process, as manager M41 explained during incident C411. Particularly in data-driven organizational cultures, structured decision-making and business cases were clearly valued. While organizational culture is further discussed in Chapter 6, its implications for decision-making processes and guidelines are made clear in an example by general manager M93. Discussing the company's decision-making approaches, he emphasized the role of business cases:

> We're very structured. You just can't go and say: 'I'd like to do this, because I think this is the right thing to do.' No, it's very much about that business case, the analytics is done, the recommendation is done, and you've assessed something properly, before you design it. (M93)

Executive M51, contrastingly, pointed out a limitation of business cases: as these cases are mostly used for strategic and complex decisions, the availability of suitable data and experiences is restricted. M51 therefore highlighted that structured business cases were a useful tool, but that their predictability was difficult to determine: "[when] you always deal with the future, you don't have a lot of knowledge about how it's likely to work" (M51).

In general, however, managers saw structured decision-making guidelines as a benefit. When asked if there was a defined process in place for strategic decisions, head of department M85 negated the question but expressed a need for a more structured approach:

> There should be. In my current role, I haven't got a good defined process. It's always: understand, validate, test, probe. But a really good decision-making process or analytical method that I use? No. (M85)

Analyst M86 also recognized the benefits of a long-term integration of lessons learned. She not only adapted her current decision-making approach according to a past positive outcome decision, but furthermore made "sure the policies are documented" (C861). The documentation was a vital contribution for future decisions in this field.

While the consensus among managers supported decision guidelines, executive M10 saw limited value in defined decision-making processes. He elaborated that decisions are not created equal, their results therefore not necessarily universally replicable: "I think each decision would have quite a different impact. So if you put that in a square box I don't think that would work in different areas of the business." (M10)

4.3. Discussion: Dual Process Theory in the Age of Big Data

The analysis in this chapter focused on the exploration of changes in management decision making in the age of big data on the level of individual decisions. It therefore contributes to the current understanding of management decision-making processes, and particularly to data-driven decision making, in the following ways:

- Decision-making processes incorporating managers' use of data analytics in addition to human judgment were introduced, extending extant literature on decision making. The comparison of managers' actual versus ideal decision making provided further supporting insights.
- Decision processes were categorized according to the extent of data analytics and human judgment in use, providing a new categorization of decisions for the age of big data.
- Distinct data analytics and human judgment roles were identified, highlighting the different facets of both in order to provide a contrast to the often one-sided representation in extant literature.

Overall, the findings provide insights into the balance of data analytics and human judgment that managers ultimately need to find in their decisions.

Clustering the decisions shared during data collection into balanced, high-judgment, and high-data decisions helps to develop a more detailed understanding of the specific processes the managers used. The clusters highlight the extent of data and judgment use, their specific roles, as well as the decision triggers, types and contexts that impacted managerial decisions.

This section discusses the findings, covering the embedded unit of analysis, i.e. the decision in the context of the two-system view of dual process theory. Distinguishing between the decision maker's intuition and reasoning, referring to System 1 and System 2 respectively, the theory is used as a lens for explaining the extent and specific applications of data analytics and human judgment.

Firstly, the extent of data and judgment use is discussed by placing the identified decision clusters into the context of decision types and decision contexts, as defined by current literature. Secondly, the specific roles data and human judgment played in decision making are discussed in the context of cognitive biases, heuristics, and expert decision making. Lastly, the impact of these data and judgment influences on decision-making processes on extant literature is discussed. This serves to highlight the extension of decision-making process steps in the age of big data.

4.3.1. Extent of Data Analytics and Human Judgment Use: Decision Clusters

The clustering of decisions as outlined in the findings is considered the first key contribution of this research. This clustering extends the understanding of decision categories beyond traditional decision types and contexts by incorporating the unique decision clusters of data and judgment use. Establishing these decision clusters furthers the academic understanding of increasingly data-driven decisions and will enable managers to better grasp the increasing number of impacts on their decisions.

Clustering decisions according to the extent of data analytics and human judgment used was a result of the analysis performed. The decisions gathered during data collection were initially categorized according to decision types as described by Ackoff (1990), and decision contexts as defined by Snowden and Boone (2007). In terms of decision types, the incidents were classified as strategic, tactical, or operational, according to their impact and longevity (Ackoff, 1990). These classifications are commonly accepted, with the decision types finding application in further extant literature (Drucker, 2006; Eisenhardt & Zbaracki, 1992; Mintzberg et al., 1976). The second dimension, decision context, assessed decisions as either complex, complicated, or simple, in an attempt to reflect the decision's complexity and circumstances. This classification is based on Snowden and Boone (2007). Further sources referencing complex, complicated, and simple decisions could be found in the decision-making literature (Dykstra & Orr, 2016; Wray, 2017).

However, these categorizations of decision types and contexts did not fully capture the two main components of this study, i.e. the use of data analytics and the use of human judgment. Therefore, as outlined in section 4.1.2., additional decision categories were created by assessing the extent of data and judgment use for every decision. Three main clusters ultimately emerged: balanced, high-judgment, and high-data decisions.

Most decisions were sorted into the *balanced cluster*. These decisions displayed high levels of both data analytics and human judgment use, reflecting a balanced approach by the managerial decision makers. Most strategic decisions could be categorized as balanced. This is in accordance with extant literature, which states that strategic decisions require an interplay of intuition and rational decision-making elements (Calabretta, Gemser, & Wijnberg, 2017; Elbanna, Child, & Dayan, 2013; Khatri & Ng, 2000). Indeed, decisions with considerable impact demand managerial experience, but also call for further validation and business case support to justify the decision to other stakeholders (Hanlon, 2011). Collecting information has been found to be a key success factor for decision-making performance and the gateway to more effective strategic decisions (Dean & Sharfman, 1996; Elgendy & Elragal, 2016; Kaufmann et al., 2017).

Strategic decisions are known to consume a considerable amount of time and resources, due to their complexity and long-term effects (Harrison, 1995; Intezari & Gressel, 2017; Shepherd & Rudd, 2014). This complexity was also confirmed by the findings of this thesis, as the decisions in this cluster were mostly complex and complicated. Both complex and complicated decisions were made by using human judgment and data analytics: while human judgment was mostly used during the identification and development steps of the decision-making process, data analytics was primarily utilized in the development and selection steps.

Complex decisions are seen as unpredictable and rely on probing and experiments (Snowden & Boone, 2007; Wray, 2017). The complex decisions captured during data collection therefore benefitted from an initial assessment that was based on experience and intuition, and subsequent data-driven piloting and experiments during the development and selection steps. This approach also served complicated decisions, as they often have a number of potential solutions and therefore require thorough analysis and expertise (Snowden & Boone, 2007).

Decisions in the *high-judgment cluster* displayed high levels of judgment use, and only low to moderate levels of data use. In these decisions, business understanding and domain experience were considered more relevant than the input of data. Mostly tactical decisions were sorted into this cluster, as well as a mix of complex and complicated decisions. The main differentiating factor between the decision in the balanced cluster, ultimately was the decision type. Managers making decisions in this cluster made extensive efforts to gain access to data for strategic decisions by, for example, running experiments and pilots. Tactical decisions in this case were considered to have fewer significant consequences, and the time and cost to gather relevant data was not deemed proportional to the decision impact. Instead, managers relied particularly heavily on human judgment.

Human judgment was mostly used during the development and selection step of the decision-making process, whereas data analytics was only used in a limited capacity. In several instances, data played no relevant role whatsoever. Here, human judgment was the driving force of the decision. The importance of business understanding and experience was also supported by the high number of complex decisions. The resulting novelty and open-endedness of these complex decisions often leads to unclear decision requirements, solutions, and difficulties in evaluating outcomes (Mintzberg et al., 1976). Managers referred to these decisions as, in essence, all over the place. As neither their process nor their outcomes could therefore be predicted by data, judgment was considered more relevant in these cases.

Such an intuitive approach is particularly more suitable for decisions that are characterized by incomplete information and knowledge, which is often the case in a dynamic business environment (Kathri, 2000). The factors and variables of these decisions might not always be quantifiable. The managers' experience thus becomes more valuable as a decision-making influence. This is supported by the Theory of Unconscious Thought, which postulates that more highly complex decisions benefit from the use of unconscious thought and lead to higher quality outcomes than conscious decisions (Dijksterhuis & Nordgren, 2006).

While this theory explains the successful judgment-driven complex decisions in this cluster, it is important to revisit the fact that the only negative outcome incidents of this study were also complex and judgment-driven. These incidents were made by managers who lacked both previous experience and relevant understanding of the decision background. As unconscious thought relies on these previous experiences (Dijksterhuis & Nordgren, 2006), their judgments were as a result not reliable.

High-data decisions were characterized by high levels of data analytics use and comparatively low levels of human judgment use. The influence of human judgment was therefore limited throughout all decision-making process steps in this cluster. Data analytics was considered much more significant for these decisions by managers and found application particularly in the development and selection steps. These findings match the representation of data and judgment use in extant literature regarding the cluster's decision contexts.

High-data decisions held a clear majority of complicated decisions, compared with complex or simple contexts. As complicated decisions require a high level of analysis and expertise to determine the best solution among a large number of possibilities (Snowden & Boone, 2007), data-driven decisions fit logically into this cluster. The expertise that managers required for these complicated decisions was merely supported by the role of human judgment. The required high level of analysis explains why decisions in this cluster were exclusively made by managers from organizations that showed very high levels of analytics maturity: managers in these cases were mostly able to simply follow established processes.

This justification matches literature on data-driven decision making that posits a readiness of organizations for big data and analytics-driven decisions (M. Gupta & George, 2016; Jagadish et al., 2014; N. Shah, Irani, & Sharif, 2017). The managers reporting the high-data decisions worked in data-ready environments, which also explains the positive outcomes of the four strategic decisions of this cluster. While strategic decisions usually also require high levels of human judgment, the organizations' level of maturity enabled the managers to benefit from sophisticated and tested data analytics methods that had already previously incorporated and synthesized expertise. In such a stable environment, data and an analytical approach are seen as more reliable and can lead to better outcomes than decisions based on judgment (Dijksterhuis & Nordgren, 2006; Khatri & Ng, 2000). The concept of analytics maturity will be further discussed in Chapter 6.

As outlined above, the characteristics of the decision clusters can be attributed to the composition of each cluster's decision types and contexts. While this provides a certain background explaining the extent of data and judgment use, a further investigation of the specific parts data and judgment played in the decision-making process added still more insights.

4.3.2. Roles of Data Analytics and Human Judgment Use

The second key contribution this research makes is the understanding of human judgment and data analytics as distinct roles in the decision-making process. Extant literature focuses on the importance and extent of intuition, judgment, and data in decision making, but not to the scale of differentiating between distinct roles. For an increased understanding of the identified roles and their place in the decision-making process, all identified human judgment and data analytics roles were assessed in the context of the dual process theory. This offered insights into the interaction of System 1 and 2, and therefore the interaction of the roles with one another. Therefore, this research contributes to the extension of the dual process theory by deepening the understanding of conscious and unconscious thought in managerial decision making in the age of big data.

System 1 is understood as a fast, effortless, automatic and intuitive response which is shaped by previous experiences (Evans, 2003; Gilhooly & Murphy, 2005; Kahneman, 2003). As data analytics roles require conscious thought and deliberate action, only human judgment roles of this research can be categorized as part of System 1. However, not all human judgment roles are automatic processes, some requiring similarly conscious, analytical thought to data analytics roles.

Looking more closely at differences among human judgment roles, initial assessment as well as sense check and data challenging can be understood as System 1 processes, as they are a manager's automatic response to being presented with either a new decision or new data results, respectively. In both cases, the response is an immediate assessment that is based on habits and experience with the decision subject or data. A negative gut feeling can therefore lead managers to further investigate or ignore certain data sources (Kaufmann et al., 2017). The aforementioned System 1 roles identified in this research are considered required skills for positive results when it comes to big data: "A proper understanding of the challenges to be addressed, plus critical thinking when it comes to turning data into insights, are probably more crucial success factors than using the latest Big Data analytics tools" (Wirth & Wirth, 2017).

System 1's role in the dual process theory is seen as providing shortcuts for System 2, so as to avoid lengthy analysis of potentially endless options (Betsch & Glöckner, 2010; Kaufmann et al., 2017; Stanovich & West, 2000). The roles of initial assessment as well as sense check and data challenging, match System 1's role in the case of this research, providing the analytical parts of the decision-making process with shortcuts and rapid feedback. In the age of big data, this proved useful to managers for narrowing the focus of the decision, minimizing required data analytics efforts, and evaluating analytics results.

These System 1 shortcuts or heuristics can also lead to cognitive biases (Bazerman & Moore, 2013; Betsch & Glöckner, 2010). Although cognitive biases did not play a prominent role in the collected data, several examples could still be identified. In the examples, relying on outdated or insufficient experiences led to misinformed judgments. Preventing negative outcomes from these biases is part of System 2's monitoring task, which is an essential component of the systems' interaction helping managers to avoid negative outcomes like those mentioned above. However, biases cannot be avoided completely, as not only System 1 is biased. Rational analysis is also biased, as quantitative approaches are based on assumptions and perceptions as well (Kathri, 2000). Managers need to be aware of the limited application of pre-defined approaches in unfamiliar environments (Dane & Pratt, 2007).

Intuition and judgment are therefore also inevitably part of System 2, which is generally understood to consist of systematic procedures that allow decision makers to deliberately gather and evaluate information, enabling hypothetical thinking (Dane & Pratt, 2007; Gilhooly & Murphy, 2005). Three of the identified human judgment roles could be attributed to System 2, namely identifier of need for analytics, enrichment of analytics, and outweighing of analytics. These roles are conscious processes that demand managers' attention and full analytical capabilities.

As an identifier of need for analytics, the manager's conscious assessment is that their judgment is not sufficient to reach a satisfactory decision outcome, and that data analytics is therefore required to further evaluate the situation (Kaufmann et al., 2017). In this role, judgment also determines the extent of and sources for the data analysis (Larreche &

Moinpour, 1983). This role is therefore used in early stages of the decision-making process.

In a sequential and rational process, following the identified analysis, managers can also use their judgment as an enrichment of analytics. Data has limitations which might not be able to represent all relevant aspects of a decision, and can be mitigated by human judgment (Pauleen, 2017). In the role of enriching analytics, judgment was used to incorporate experience and business understanding, and to provide further facets for the development of decision alternatives. Eventually, judgment could also outweigh the results of data analysis, when important components could not be captured by the data.

Data analytics also took on several roles identified as System 2 processes. As analytics always requires a certain extent of conscious thought and action, all data analytics roles were attributed to System 2. In the managers' decisions, data was able to identify situations that required decisions and enabled managers' judgment when the alternatives were too complicated to judge using merely previous experience and intuition. Data also fulfilled the roles of exploring decision factors and functioned as a 'no-brainer' in clear black and white situations that did not demand any further human judgment.

The data analytics and human judgment roles were found to interact in various ways, balancing their limitations; similarly, System 1 and System 2 complement one another. Interacting with System 1, data analytics contributed to the decision-making process by providing a justification for other stakeholders, or by confirming or challenging managers' initial assessments. Particularly in the role of challenger, analytics (and rational processes in general) can outweigh biased or misinformed initial assessments (Kaufmann et al., 2017).

These interactions and their effects on the decision-making processes depended on the decision types and the extent of data and judgment use, which will be outlined further in the next section.

4.3.3. Extension of Decision-Making Process

The increasing potential of data analytics and the availability of various data sources undoubtedly impacted the decision-making process of the interviewed managers. As indicated in the previous sections, these impacts were evident in the evolving roles of data and judgment, as well as in the extent of their use. All three steps of the decision-making process were affected when comparing the findings to extant literature on decision-making processes. This section focuses on the seminal work identified in the literature review. As the abductive approach applied in this study focuses on matching theory with findings and searching for explanations for phenomena, these seminal works provided sufficient explanations and a solid theoretical base. The number of steps identified in the data could be matched to the traditional three-step decision-making models introduced by Simon (1960) and followed by Mintzberg et al. (1972). Eisenhardt and Zbaracki (1992) also identified a three-step process as a result of their strategic decision-making literature review.

While Mintzberg et al.'s (1976) model concurs with Simon's (1960) trichotomy, it differs in its definition of the three decision steps, most significantly regarding development and selection activities. Mintzberg and colleagues' selection step consists of either an intuitive approach referred to as judgment, bargaining activities with other stakeholders, or an analysis of previously designed alternatives, which in turn also leads to judgment or bargaining. The development step is limited to search and design activities.

This contrasts with Simon's (1960) description of the decision steps, and the findings of this thesis. In Simon's model, the development step in the findings incorporated mostly alternative evaluation activities. The analysis taking place during the development step is a result of data demanding a more dynamic decision-making approach and increased System 1 and 2 interaction, which helps to avoid analysis paralysis (Harrison, 1995) or cognitive biases (Bazerman & Moore, 2013) during the development of alternatives.

Mintzberg et al. (1976) accounted for the dynamic nature of strategic decisions in a different way by postulating a non-sequential nature of the steps. They reasoned that the decision-making process "is subjected to interferences, feedback loops, dead ends, and other factors" (p.263). These dynamic factors can delay, speed up, stop, or restart the decision-making process, and cause cycles within a phase, or even the circling back to a prior phase. While the results of the critical incidents content analysis did exhibit dynamic elements, there were no processes that circled back into previous stages.

Simon's (1960) process understanding therefore matches the results of this study well, in that he outlined the development stage to contain most of the work regarding design and evaluation of alternatives, and the selection stage as a mere fragment of that time. Simon (1960) also said that the steps are mostly clearly distinct from each other, but that each step also contained a self-contained decision-making process, meaning that each step of the process might require its own intelligence, design, and choice, as he previously labeled the three steps.

The findings of this research would therefore fit the trichotomy's definition outlined in Simon (1960), and to some extent the dynamic spirit of Mintzberg et al. (1976). However, through the definition and use of roles of human judgment and data analytics, the dynamic of the process can be achieved within each phase, and does not require a recycling to previous phases, as Mintzberg et al. (1976) postulate. Neither does each step resemble a completely self-contained process, as Simon (1960) understands the three steps. From the findings and the application of roles, it is rather understood that the steps follow a clear path, and even within each step follow a sequence of roles. The sequence of roles per step can be repeated, for example, per decision alternative, but is limited to the specific step's tasks. 'Identification,' therefore, is limited to assessing the situation, 'development' to developing and evaluating different options using a combination of analytics and judgment, and 'selection' ultimately to choose one of the options in the final step of the process.

In order to clarify the gained understanding of the managerial decision-making process in the age of big data, the findings are discussed in the context of these models and further extant literature below. The distinct steps are reviewed and the effects of both the extent and most significant roles of human judgment and data analytics are outlined per decision cluster. This highlights the most common results and suggests an ideal decision-making process for each cluster.

4.3.3.1. Balanced Decisions

Decisions in this cluster followed a balanced approach between the use of human judgment and data analytics, which was reflected in a comprehensive and thorough decision-making process on the part of the managers. This process is illustrated in Figure 13 below, which illustrates the interaction of Systems 1 and 2, as well as the most commonly used data analytics and human judgment roles by managers, which were balanced in the case of these decisions.

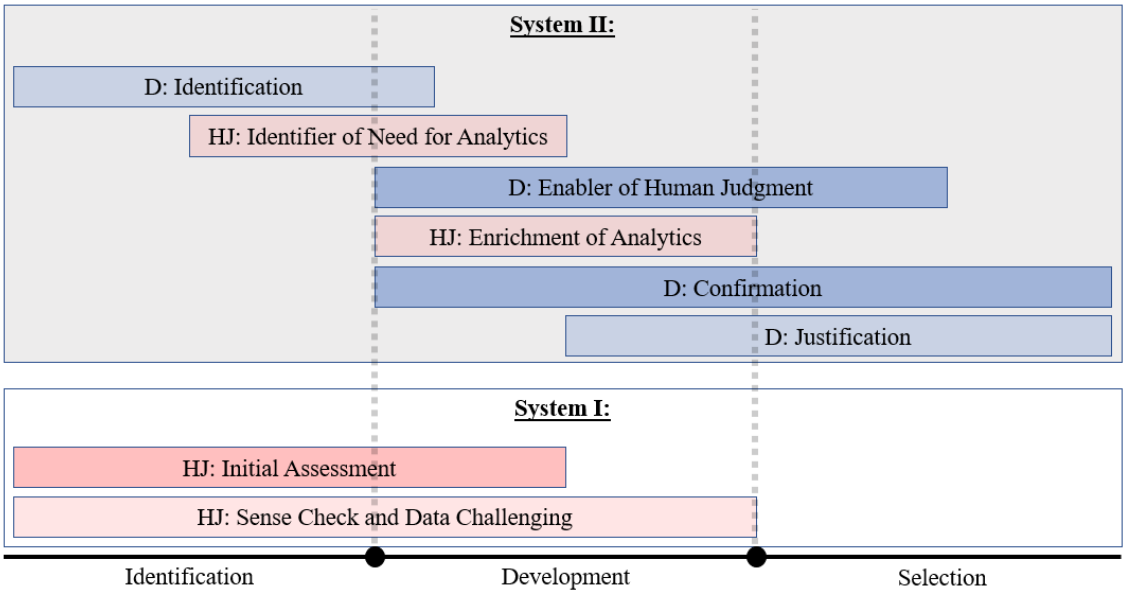

Figure 13. *Balanced Decision-Making Processes*

The first indication of the thoughtful approach behind these balanced decisions could be seen in the identification step. Only a very low number of decisions were initiated by the reactionary catalyst of external triggers, with most decisions being triggered by the active efforts of evaluations and routine checks. This matches Simon's (1960) depiction of managerial decision identification. He states that executives spend a considerable amount of time on identifying changes in their environment that require a decision action. Mintzberg et al. (1976) posit that a decision is triggered when a threshold of stimuli is crossed, meaning that either several stimuli or one severe stimulus leads the manager to take action. For this research, this threshold was not defined or considered a significant criterion. Rather, the identified decision triggers were categorized according to the nature of the stimuli. The different decision triggers were found to influence the ensuing decision-making process.

Following the identification, the development stage usually involved a significant amount of data in the form of reports, ad hoc analytics, experiments, and pilots. The involvement of data to this extent also inferred the inclusion of analytics-savvy employees in the decision-making process. This could be the managers themselves or, in many cases, additional business analysts. This contradicts Huber's (1990) proposition that advanced information technology tends to decrease the number of people involved in the decision-making process.

Furthermore, increased availability of data analytics provided the managers in this study with additional options to develop and assess alternatives during the development step. Including relatively new data sources and unfamiliar data types often led to loops in the development step, as data still had to be sense-checked. Analysis paralysis was more of a risk at this point than not considering enough alternatives (Harrison, 1995).

The selection stage was mostly based on data, as managers had already employed their and others' human judgment during the earlier decision-making steps. Considering most strategic decisions in the balanced cluster, managers used the data in this step to confirm their previous assessments, or to justify their choices to other stakeholders. As data analytics was an important part of this final decision-making step, several managers encountered related obstacles, such as a lack of trust in the data, misunderstandings of the results, and lingering biases that needed to be overcome.

The selection step modes of analysis, bargaining and judgment could be partially identified in the managers' decisions, and the roles managers applied in the process could be assigned accordingly. The analysis mode took place during the development step of the process and was executed by System 2 processes, i.e. the roles of enabler of human judgment and enrichment of analytics, as well as by System 1 processes in the form of initial assessment and a sense check of data analytics. The bargaining mode took place in the actual selection step in the form of System 2 processes and the data analytics roles of confirmation and justification. Intuitive judgments, which would require System 1 processes, could not be identified in the selection stage of balanced decisions. Intuitive processes were limited to the identification and development steps. This enabled the input of unconscious thought at the beginning of the decision-making process and an analytical and well-argued selection of evaluated alternatives at the end.

Calabretta et al. (2017) outline a similar logic in their paradoxical thinking work when describing the interplay between intuition and rationality: System 1 processes provide affective evaluations and make connections, while System 2 processes structure the information and form a cognitive evaluation. Similarly postulating the interaction of System 1 and 2, Shapiro and Spence (1997) furthermore suggest using intuition first and following up with a more rigorous analytical approach. This timing was reflected by the balanced decisions cluster. System 1 processes in form of the human judgment roles of initial assessment, as well as sense check and data challenger, were mostly applied during the identification and development steps. The more analytical System 2 processes in the form of the other human judgment and data analytics roles could be found in all decision steps, but particularly during development and selection.

The decision-making process displayed in Figure 13 and discussed above captured the actual findings of the critical incidents in this cluster. However, given the success of these decisions and the managers' satisfaction with their outcome, this process can also be understood overarchingly as an ideal process for important strategic decisions. The findings showed that long-term strategic decisions benefit strongly from the input of human judgment, i.e. business understanding, experience, intuition, and from the use of analytics as a tool for gaining insights from data. In most cases, strategic decisions had to be justified. Data offered the opportunity to go beyond the use of a rule of thumb or a mere gut feeling, delivering a solid validation of human judgment. The decisions in this cluster therefore relied highly on the knowledge of managers, but also required analytics to extract meaning from complex and often vast data sets–not only to confirm the managers' judgment, but also to help them discover finer nuances.

4.3.3.2. High-Judgment Decisions

Decisions in this cluster relied to a large extent on the use of human judgment, and only minimally on data analytics. This led to a mostly judgment-driven decision-making process which heavily relied on the manager's previous experience and intuition. This process is captured in Figure 14 below, which displays the interaction of Systems 1 and 2, as well as the most commonly used data analytics and human judgment roles in this cluster.

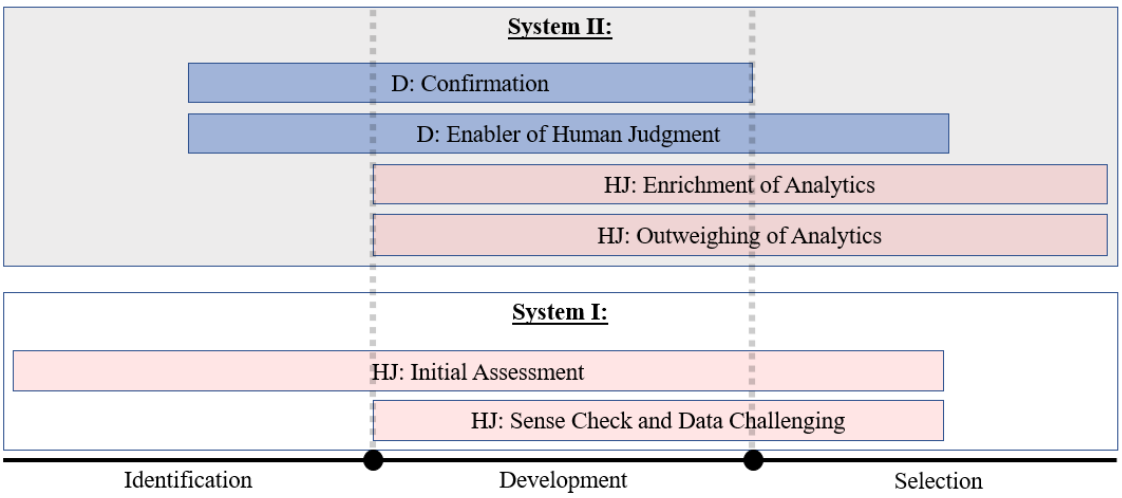

Figure 14. *High-Judgment Decision-Making Process*

Compared to the balanced decision cluster, System 1 is more prominent in high-judgment decisions, and spans across all three decision-making steps. Human judgment roles also outweigh the number of analytics roles managers applied during the process. An early indication of this judgment-driven approach is found in the identification step: most decisions were triggered externally. External triggers often led to the problem of a lack of internal reference points, which impeded the managers' capabilities to assess the external data for organizational fit. This corresponds to the veracity criterion of big data, which posits that big data needs to be checked for credibility and for target audience suitability (Jagadish et al., 2014; Sathi, 2012). Due to the managers' inexperience with data, or simply the lack thereof, decisions often had to be made based on incomplete information, which led to the high emphasis on human judgment in this cluster.

This high reliance on human judgment was also noticeable during the development and evaluation of alternatives. Data analytics was only used to confirm judgments, or to take on minor parts in enabling judgment for more complicated scenarios. Most of these development and selection steps relied on the managers' experience, business understanding, and intuition. These judgments, however, were error-prone, as the use of System 1 processes is particularly prone to resulting in cognitive biases (Bazerman & Moore, 2013; Stanovich & West, 2000). Furthermore, more heavily analytical System 2 processes that relied to a large extent on human judgment led to incomplete assessments, demonstrated by the fact that in several incidents, the managers' lack of experience negatively impacted the decision outcome. Experience is a critical contributor to decision making, particularly for impacting human judgments (Dreyfus & Dreyfus, 1980). As managers required experience in the decision matter as well as the assessment of internal and sometimes external data sources, any lack thereof led to the only reported negative-outcome incidents.

The three basic decision-making steps of identification, development, and selection, as outlined by Simon (1960), could also be recognized in decisions from this cluster. However, as described above, the identification step was less of an active scanning of the environment, and rather more so triggered by external sources. The development step was also not as rigorous as in balanced decisions. While Systems 1 and 2 interacted during what Mintzberg et al. (1976) refer to as analysis, the contribution of data analytics was kept to a minimum. System 1 affected this step through the initial assessment of alternatives and sense check of data analytics results. System 2 processes provided these data results through the role of enabler of judgment and used further human judgment to enrich these results.

Similar to balanced decisions, the analysis mode began and ended during development, while the two modes of judgment and bargaining took place during the selection step, as originally defined by Mintzberg et al. (1976). The only role that could be assigned to the bargaining mode is the outweighing of analytics, once again emphasizing the dominance of human judgment in this cluster. The mode of intuitive judgment requires System 1 processes and could in this cluster be assigned as the role of sense check and data challenging. However, in contrast to Mintzberg and colleagues (1976), this intuitive judgment would not mark the endpoint of the selection step. While the challenging of data results could be identified as an important part in the development and selection step, the endpoint would in this case be the managers' use of the roles of outweighing analytics, or enriching analytics with additional business expertise. System 1 processes therefore did not end the decision-making process; instead, conscious System 2 processes informed by human judgment served as the final step.

Data analytics only found application in a very limited capacity during the development and selection steps of the decision-making process in this cluster. Data merely functioned as a confirmation for intuition or managerial judgment, or enabler of judgment for more complicated aspects, if sufficient data input was available. These roles were then succeeded by the human judgment roles of enrichment of analytics or were outweighed by judgment. This corresponds to the work of Agor (1986), who suggests following up rational analysis of information with an intuitive synthesis.

Due to the susceptibility of high-judgment decisions to cognitive biases and their limited potential for justifying decision outcomes, managers preferred the balanced decision-making approach. However, the high-judgment approach was still often applied and seen as suitable for tactical or complex decisions.

4.3.3.3. High-Data Decisions

Decisions in this cluster relied mostly on data analytics, leading to a data-driven decision-making process that was only marginally influenced by intuitive judgment. This process is captured in Figure 15 below, which displays the interaction of Systems 1 and 2, as well as the most commonly used data analytics and human judgment roles by managers in this cluster of decisions.

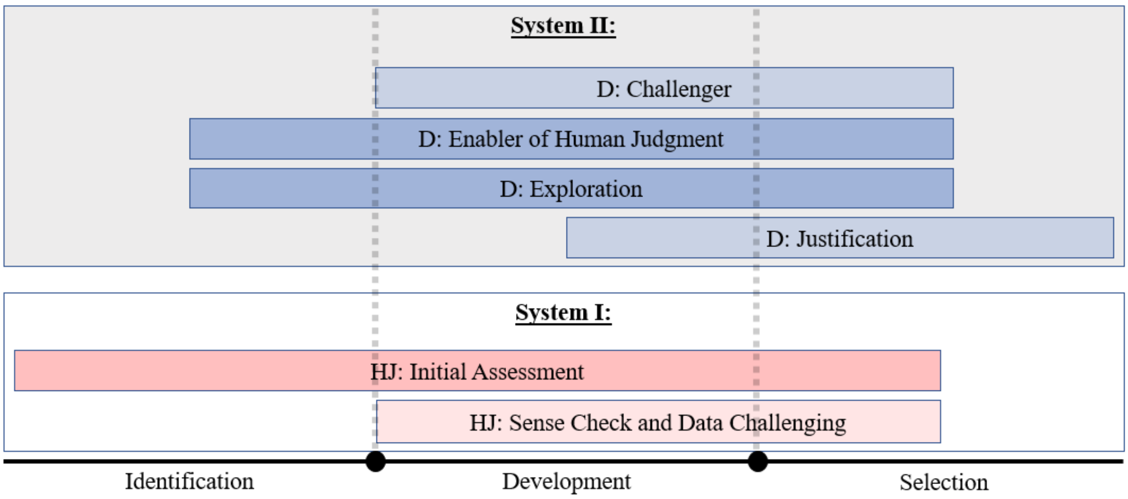

Figure 15. *High-Data Decision-Making Process*

In contrast to balanced and high-judgment decisions, high-data decisions' System 2 processes are only comprised of significant data analytics roles. Human judgment roles were limited to System 1 processes. While this means a significant reduction in the variety of human judgment applications, System 1 processes were still relevant during all three stages to some extent, which exceeds their relevance in balanced decisions.

This contrary use of data and judgment roles compared to the high-judgment cluster is immediately evident in the identification step. The decision triggers of this high-judgment cluster were equally distributed between anecdotes, routine checks, and evaluations. No externally triggered decisions were assigned to this cluster, in contrast to most external triggers found in the high-judgment cluster. As data-driven decisions highly rely on the analysis of various internal and external data sources, external triggers do not provide a beneficial starting point, as discussed in the previous section. The triggers identified in this cluster, similarly to balanced decisions, match Simon's (1960) definition of this step, which characterizes it as time-consuming scanning of the environment.

During the development and selection steps, data was often the driver in these decisions, since the decisions often involved various variables and data sources that made the use of judgment impractical and insufficient to grasp their complexity. Human judgment was restricted to initial assessment and consideration of the analysis results' validity during development and selection. Its active impact on the creation of alternatives was limited. This corresponds to findings by Kaufman et al. (2016), who see the most valuable contribution of intuition as a 'complement/supplement to rationality' (p.9).

Data, on the other hand, had a significant and diverse impact on the decision-making process. The role of exploration was used particularly extensively, after having played no significant role in the other two clusters. Data in the role of exploration was also employed, as judgment was not sufficient to identify all, or even the best, alternatives for the decisions. Data in these cases was used to identify all the relevant possibilities, as well as to discover more in-depth insights. This approach was solely used by the organizations with the highest analytics maturity. Particularly for top-performing organizations, analytics is preferred to intuition in decision making, independent of the decision type (LaValle et al., 2011). In their study, LaValle et al. (2011) found a clear correlation between performance and analytics-driven management. The analytics maturity of an organization was an important factor for their decision making, which is further discussed in Chapter 6.

The high-judgment decision-making process corresponds to Simon's (1960) depiction of the decision steps. The identification was driven by management, development was an elaborate effort of creating and assessing all relevant alternatives, and the selection step was a brief moment of choice after the already-completed analysis, followed by a justification of this choice.

As with the other three decision clusters, Mintzberg et al.'s (1976) model mostly fit the findings, except for the analysis mode taking place during the development step instead of the selection step. This analysis consisted of interactions between the System 1 processes of initial assessment and sense-check, as well as the System 2 processes of enabler of human judgment and exploration. Intuitive judgments were possible in this cluster, as the System 1 processes were still applied in the selection step. However, these intuitive judgments did not mark the end point of the decision, as characterized by Mintzberg et al. (1976). They were furthermore corroborated by data, which took place in the bargaining mode. The bargaining mode consisted of System 2 processes in the form of justification and challenger roles. Intuitive judgment was therefore still justified or challenged with the means of data analytics.

High-data decisions resulted in positive outcomes and were valued by managers. However, all managers agreed that data-driven decisions were mostly applicable to operational and tactical decisions. Managers emphasized that a high reliance on data analytics requires a familiarity with the decision. If established processes were followed, data could lead to successful decisions with minimal human judgment input, as they had already incorporated human judgment in the form of previous experiences and organizational knowledge. Key requirements for the success of these decisions were believed to be access to quality data and analytics maturity. This maturity was postulated on an organizational level, but also on an individual level in the form of analytics understanding and trust.

Both managerial characteristics and organizational factors are further discussed in later chapters, managerial characteristics in the following Chapter 5, and organizational factors in Chapter 6.

4.4. Summary of Findings and Discussion: Chapter 4

This chapter focused on the embedded unit of analysis, the individual decisions, and specifically which processes the managers employed to make their decision. The steps of these decision-making processes could ultimately be categorized as 'identification', 'development of alternatives', and 'selection'.

The identification step refers to the recognition of a problem or situation that requires a decision. Four distinct triggers that start this decision-making process were identified: ‘Evaluation’, ‘Routine Check’, ‘External Trigger’, and ‘Anecdotal’. ‘Evaluation’ refers to an internally triggered and intentional review of current practices or future opportunities. ‘Routine Check’ refers to an ad-hoc problem that is identified during a routine check or review. ‘External Trigger’ refers to an external impulse, usually originating from outside the organization. Lastly, ‘Anecdotal’ refers to concerns that are based on employees’ perceptions.

In the development of alternatives step of the decision-making process, the managers focus on determining the different possible decision alternatives from which a choice needs to be made. During this step, the availability of additional data sources and ubiquitous information enable a more thorough development and evaluation of alternatives, which can lead to this step requiring an extended period of time. If the amount of available data becomes too large, it can even lead to analysis paralysis. During the selection step of the decision-making process, the manager chooses one of the alternatives. In this step, data analytics is found to be an enrichment, as it allows management to justify their decision in a more objective manner, rather than solely basing it on subjective human judgment.

Within the decision-making process, data analytics and human judgment were found to play very distinctive roles. For human judgment, five roles could be identified. Human judgment was used as an initial assessment of the problem, as an enrichment of analytics, as a sense-check and way to challenge the data, as identifier of the need for analytics, and to outweigh analytics. To make an initial assessment of the problem the managers were facing, they relied on their previous experiences, intuition, and business understanding. This experience and business understanding often added different nuances, aspects, and context that could not be captured by data analysis alone. As it is important to understand and trust the data, managers used human judgment to doublecheck data instead of just relying on the results. After the initial context of the situation was created, human judgment helped managers to identify the need for additional information and data analytics. Finally, in the situations where factors that could not be captured by data analytics but played an important role, human judgment could outweigh the results put forward by analytics.

For the use of data analytics in the decision-making process, seven distinct roles could be identified: as an enabler of judgment, for confirmation, identification, exploration, justification, as a challenger of judgment, and as a 'no-brainer'. Data as an enabler of judgment assisted managers in making decisions that their human judgment could not fully evaluate. Data analytics could also provide valuable support to confirm the initial assessment of the manager. In the form of identification, data analytics was used to identify problems or opportunities that may have gone unnoticed otherwise. Data analytics also served as an exploratory tool to assess complex factors and their impact on the decision through correlation and dependencies. To enable a more objective form of reasoning, data analytics was used to justify the decision. Due to this objective nature, data is often seen as a neutral source of information that can challenge cognitive biases without factoring in subjective perceptions. In the role of 'no-brainer,' data analytics can best be understood as outweighing human judgment. For those scenarios, this application functions as the sole factor for determining the best alternative.

The roles of human judgment and data analytics cannot be considered as negative or positive influences, per se. A certain role could just as easily be a contributor or a disrupter of successful decision making. Three distinct decision-making process clusters could be identified as using the human judgment and data analytics roles in different capacities. The first cluster contained the balanced decision-making processes. Here, human judgment was used to incorporate the managers' prior experience as a starting point to the decision-making process. In the following stages, data analytics enabled the managers to assess the measurable aspects of decisions, and to confirm and justify their judgments.

The second cluster contained the high-judgment decision-making processes. These processes favored human judgment roles, mostly as the result of limited access to data, or because the effort and resources needed to gather more data was considered not profitable. The third cluster was comprised of high-data decision-making processes. This cluster focused primarily on problem-solving. The data analytics roles were found to play an important part, as often the alternatives were clear and well-defined.

Overall, most managers agreed that the 'ideal' decision-making process involved the following five key requirements: finding a balance between judgment and data in decision making; building trust in data analytics; transforming reactive into proactive decisions; and creating processes and guidelines around decision making.

CHAPTER 5: TYPES OF MANAGERIAL DECISION MAKERS

This second of three findings and discussion chapters focuses on the main unit of analysis: the managerial decision maker. The chapter contributes to the current understanding of decision making using (big) data analytics in two ways:

- It provides an empirical, in-depth view of managers' awareness and perception of analytics in decision making.
- It distinguishes between four different managerial decision maker types, accounting for differences in experience, skills and preferences.

The exploration of the decision maker's understanding and perception of human judgment and data analytics, as well as their impact on decision making, is the focus of this chapter. It primarily draws on the collected case study data, with supporting data included from the critical incidents. Comparative case study analysis allowed for a thorough within-case analysis of each manager and offered the benefit of further cross-case analysis among all participants. This provided valuable in-depth insights into the characteristics of each managerial decision maker and enabled the clustering of all participants into distinct manager types.

The chapter is structured as follows: first, a brief overview is provided of the analysis techniques employed in this chapter, describing the utilization of thematic analysis to highlight the managers' varying understanding and perceptions of analytics and human judgment. Furthermore, the use of comparative case study analysis for the identification of distinct types of managerial decision makers is outlined.

In the findings section, the definitions and the perceptions of big data and analytics are described using descriptions provided by the participating managers themselves.

Correspondingly, the managers' understanding of human judgment is explored. This is followed by a categorization of four distinct management types, focusing on how their characteristics, including experience, skills, and preferences, impact their decision making.

The discussion section then compares the managers' understanding of big data and analytics as well as human judgment with the extant literature, identifying gaps in practitioners' knowledge. In response to these gaps and the varying preferences of managers, different training options and tools are also discussed. Lastly, the identified managerial decision maker types are compared to existing frameworks differentiating managers from one another by their characteristics.

5.1. Data Analysis

In contrast to the previous findings and discussion Chapter 4, which focused on the content analysis of decisions, this chapter is driven by the thematic analysis of the main unit of analysis, the managerial decision maker. This thematic analysis enables the exploration of the different levels of managerial understanding for analytics and human judgement in the decision-making process. While revealing significant gaps in some managers' knowledge of (big) data analytics, the analysis also uncovers commonalities regarding these deficiencies, insecurities, or reasons for rejection of data-driven decision making.

When questioned about their decision making, the managers highlighted that their approaches did not only depend on decision context, but also referred to their decision-making style as something personal and subjective. The within-case analysis of each manager, including the analysis of their shared decisions, highlighted the influence of managerial characteristics on their decision making. After identifying several seemingly significant and frequent managerial characteristics, the cases were cross-analyzed to compare different managers and their decision making.

While the subjective differences in the managers' approaches to decision making could vary from person to person, four distinct themes emerged that characterized managerial decision maker types. This typology was created to "synthesize meaningful characteristic aspects of individual phenomena in order to explain the occurrence of social events" (Hekman, 1983, p. 121). Typologies have been used frequently in extant business and MIS literature in the past. A typology of employees based on their ability to find and analyze information can be found in Shah et al. (2012); a framework created by Eckerson (2011) categorizes analytics users into casual and power users; several studies can be found on managerial characteristics influencing effectiveness, company performance, and decision making (Elbanna et al., 2013; A. K. Gupta & Govindarajan, 1984; Papadakis, Lioukas, & Chambers, 1998). These and further examples are outlined in the discussion section of this chapter.

After the cross-case analysis and the identification of the four distinct types, these types were furthermore compared to the insights gained from the content analysis: Managerial decision maker types were matched with their respective decisions, to see if their characteristics influenced their decision-making processes. The analysis in this chapter followed a variable-oriented strategy (Miles et al., 2014). Utilizing this strategy, in contrast to a case-based one, the analysis of the dataset focuses on variables and themes, instead of isolated cases. As discussed in Miles and Huberman (2014), a similar study with 25 participants was analyzed this way when recurring themes were located after inductive coding. The participants of the study were then sorted into 6 different types, matching the approach of this chapter.

This multi-case study focuses on the identified cross-case issues, and not on single cases as such. In this reporting format, individual cases do not have to be reported at all, but can be included in abbreviated form, or simply dispersed throughout the different chapters when discussing cross-case themes and findings (Yin, 2014). In the following sections, one selected case per managerial decision maker type was summarized to provide an example of each type. Following this format, each of the four identified manager types outlined below begins with such a case summary highlighting all relevant characteristics of the respective manager type. The sections are then complemented by findings from the other managers of this type.

5.2. Findings

The findings of this chapter are structured in a way that initially highlights the diverse understandings of the underlying topics of this research. The terms of ‘analytics’ and ‘big data’ were interpreted and perceived differently by the interviewed managers, who exhibited varying levels of awareness and knowledge of them. The constructs combined under the umbrella term of ‘human judgment’, such as intuition and wisdom, were also varied in how they were perceived and defined by the participants. This understanding of human judgment and data was found to be one of the primary indicators for the managers’ decision-making behavior.

Therefore, the chapter builds on these fundamental discrepancies, while adding additional significant factors that contributed to the diverse decision-making processes of the managers. The types of managers that emerged from this analysis are then displayed in a matrix and more thoroughly discussed to exemplify the implications of their decision-making approaches.

5.2.1. Managerial Understanding of Analytics and Big Data

An exploration of managerial decision making in the age of big data then begins with the exploration of managers' understanding of big data and analytics. The participants were as a result asked in the beginning of their interviews about their definition of these terms before answering specific and general questions about their decision making. This was done not only to ensure a mutual understanding of these terms for the duration of the interview, but also to capture the current impressions and perspectives that managers had of these terms, particularly in relation to decision making.

Their general perception of analytics and big data also often emerged at various points throughout the interview, when the managers reflected upon the roles of data and judgment in their decision making. These perceptions, as well as their understanding of the terminology, were expected to influence their decision making. Managers with a deep understanding of analytics and big data were presumed to be more aware of their potential benefits and pitfalls. Novices would likely be either hesitant in their use of analytics or trust its results blindly. These differing levels of understanding were expected to significantly impact the managers' decision making and are therefore outlined in the findings below.

5.2.1.1. Defining Analytics and Big Data

The common understanding of the term 'analytics' equates to the computational analysis of data. The participants' answers mostly exceeded the scope of this common definition. From the participants' answers, three main components of analytics could be identified. They are displayed in Table 28.

Table 28. *Components of Analytics*

Component 1	Component 2	Component 3
Define/Ask Question	Computational Analysis of Data	Gain Insights/Make Sense
n=8	n=14	n=17

All three components of this definition could be found in the head of department M94's answer, when he outlined an ideal approach to applying analytics in managerial decision making:

> Start with the question, not with the data. Where do you believe value could be in your business? And then, what's the fastest, cheapest way for you to demonstrate a test of where that value could be? Do you need to develop an analytical model, or can you simply create a set of simple hypotheses to test? If you don't even know where to start, you probably want to do some analysis, and some interpretation of insights. (M94)

The first component, asking the right question and defining the requirements, was referenced eight times by participants when defining analytics. These questions referred to the metrics that would need to be defined, the cause or reason for the analysis for the decisions, or benefits that were sought out. Asking the right question was seen as a required starting point of the analytics process, and also as a critical skill for decision making: "Where I pride myself is: I know what questions to ask, I have a sixth sense in being able to understand if the data is accurate from my questions and from what I hypothesize in my head" (M92).

The second component matches the common understanding of the term, as reflected in analyst M01's answer: "I gather the data from the information data sources that we have, and then I combine it all, and have analytical software perform calculations and computations." Several managers also used a simplified formulation for this computational analysis component: head of department M85, for example, answered that he always referred to it as "turning pixels into pictures" when talking to his team. He considered this component to be a challenge that eventually led to important insights. This step was therefore seen as a significant prerequisite to the acceptance of data in decision making, as "with information people make decisions; with data, they get annoyed" (M85).

The third component of analytics refers to gained insights and was considered essential by the majority of participants. Managers specifically addressed the outcomes and making sense of computational analysis results. It therefore exceeds the scope of the second component, aiming at transforming data results into intelligence, as manager M83 highlighted: "Analytics to me is looking at what the data tells us and it's really turning raw data into intelligence and information and giving insights." Analytics was therefore seen as "part of a [bigger overarching] process, as opposed to just one function on its own," as general manager M91 summarized.

The three components of the analytics definition provided by the participants describe a contemporary view and expectation of analytics that goes beyond the traditional scope of analytics definition, or the mere computational analysis of data.

While managers were confident about their understanding of analytics, big data proved a more difficult term for managers to define. Most participants had less than one year of experience with big data, or none. Only six participants had over one year of experience with the topic. This was an indication of the limited use of big data in organizations. In general, big data was perceived as a rather subjective term that was often met with confusion. This subjective perception was demonstrated by several participants who began their responses with “For me/us…” or “My interpretation/understanding…”.

From these varying perceptions, four thematically distinct definitions could be identified. Several of these thematic definitions were mentioned by each participant. Definitions from well-informed participants covered (parts of) the academic and practitioners’ 3 V definition. Others with less familiarity with it focused on the term in relation to the outcomes they were expecting of big data, or the lack thereof. Some informed but disillusioned managers saw big data merely as a buzzword. More traditional managers tended to provide incorrect answers or described different concepts. These definitions are all displayed in Table 29 and are further discussed below.

Table 29. *Definitions of Big Data*

Definition 1	**Definition 2**	**Definition 3**	**Definition 4**
(Part of) 3 V’s	‘Buzzword’	(Lack of) Outcomes	Confusion
n=17	n=4	n=9	n=6

Participants answering according to definition 1 referred at least partially to the definition as outlined in the literature review (n=17). The full definition was mostly used by participants in analytics teams or departments (n=4), as can be seen in analyst M01’s response: “Big data is basically the same as regular data, but then on a larger scale, so you would have large data sources with millions of records, you have multiple data sources combined into one, and you have access to it in real-time.” Other participants mostly focused on the criteria Volume or Variety (or both), like general manager M13 emphasized: “For me, I think that it is just about volume” (M13). This observation indicates a rudimentary understanding, but also highlights the gaps present among the definition 1 users when it came to grasping the full extent of big data.

Four participants had a critical view of big data, having picked up on the hype surrounding the term, and referring to it as a ‘buzzword’, resulting in definition 2. This definition was an in vivo code, coined by executive M31: “Big data I would define as a buzzword to sell stuff to corporates right now. And the interesting thing about data today: it’s fashion. And a lot of people talk about it. But they don’t really understand it.” Head of department M81 echoed this sentiment, when asked about his definition of big data: “people don’t actually know what to do with it, they just talk about it a great deal. It is more talked about than done I think.” Participants answering in accordance with definition 2 were extremely knowledgeable and reflective when it came to big data and were therefore critical of its potential.

When answering in line with definition 3, participants focused on defining big data in terms of its outcomes or promised value propositions and expectations (n=9). When talking about big data’s applications and use cases, several participants also added that these solutions were not yet available to them, or that they had not seen any solutions that followed up on these promises. This is highlighted in head of department M21’s definition: “We’re starting to get on top of that. But big data trends, like buying trends and behaviors and that sort of stuff, through third party means – no, I really haven’t had exposure or usage of that.” Similarly, managers see the lack of outcomes as defining the effectiveness or usability big data, as mentioned by head of department M81: “In theory, somewhere in there is an interesting thought or concern or solution…I don’t see brilliant solutions popping out.”

Lastly, in definition 4, participants were either not familiar with the term big data or defined it incorrectly by referring to other analytics concepts or components (n=6). Several managers referred to different or specific analytics concepts, such as KPIs or behavioral analytics when defining big data (e.g. M11). While these could be considered examples, their answers demonstrated that some managers' understanding of big data was too narrow. Several managers were also not familiar with the meaning or concept of big data (e.g. M82, M84, M91).

A detailed understanding of big data, ultimately, was not seen as a key requirement for all managers, as executive M10 mentioned. While he thought that his employees were not aware of the amount of data that flowed into the information they used for their decisions, he also added that they did not need to know: "No, they [my employees] won't be aware. But they don't need to be. I mean everyone is doing their job" (M10). Managers can still be using big data without knowing specifics, as can be seen in general manager M91's answer to the question of whether he had previous experience with big data: "Definitely yes, without calling it that."

Understanding and knowledge of big data was significantly lower in comparison with the term analytics. Still, participants familiar with big data showed at least a rudimentary understanding of the term, but also exhibited critical views. Doubts about big data and an unfamiliarity with it could both be traced back to a lack of exposure to success stories. The reason for this could be, as M11 hypothesized, that even in companies that are rather far on their data journey, big data is not something that is used on a weekly basis.

<u>5.2.1.2. Perceptions of Analytics and Big Data</u>

In addition to being asked to define the terms, participants were also asked how analytics and big data were involved in their positions as part of their day-to-day activities. Their answers to this question, as well as the notions they expressed during the interviews, often revealed both positive and negative aspects of big data and analytics. Ultimately, the managers recognized drawbacks as well as benefits resulting from their use of data-driven decision making.

Their positive perceptions can be categorized into two main themes: Objective validation and enrichment. Trust is seen in this case as a neutral factor, as it was perceived as positive for managers who had trust in data. However, managers that were not familiar with data, or saw the pitfalls of subjective data interpretation, perceived it negatively. Negative perceptions resulted in four themes: the lack of skills, data access and speed of analysis, limitations of analytics, and misunderstanding or manipulation of data. These positive and negative aspects understandably contributed to the managers' perceptions, and thus ultimately to their willingness to use analytics and big data in their decision making.

Positive perceptions were influenced by analytics' potential to objectively validate and therefore justify their decisions (n=27). Confronting the doubt of other stakeholders with hard data and facts provided managers with additional bargaining power, as was pointed out by manager M83: "If [the argument] is data based, it's easier to convince the other stakeholders that look: 'it's not just that I want to do it, I've actually got facts and data which back it up.'" Manager M11 extended this argument, by saying that the additional security data analytics provides, is not only beneficial in arguments with other stakeholders, but also for the decision makers themselves: "It's quite important to have data to back up your reports and your results. Otherwise you're a little bit in the blind."

Analytics was therefore considered an enrichment to the decision-making process (n=29), as it enabled managers like M41 to explore causes and connections that were previously not accessible to them: “When I’m in a meeting trying to understand and explain our result–we’re actually able to do that now. So, it’s definitely changed for the better.” Particularly for small organizations that traditionally had limited access to data, ubiquitous data sources are more and more facilitating informed decision making. This was highlighted by executive M71: “I think small organizations like this in the past have really just done it by guesswork and hope.”

Although data analytics was in this context considered to be making a positive impact on the decision-making process, the actual impact of data can certainly vary. Data can simply function as a source of confirmation, supporting managers’ ideas and intuitions, as manager M83 pointed out. Head of department M21 conceded that data might not necessarily change the outcome, but it could regulate expectations towards the outcome, leading to a more realistic planning process. On the other hand, executive M22 mentioned that data had on another occasion actually changed their business strategy for the forthcoming year. Data can therefore be an enrichment, independent of its impact’s reach.

Trust in data analytics was seen as a critical aspect of relying on it (n=17) but was categorized by managers in different ways. The theme incorporated doubts in the credibility of the data itself, as well as the interpretation and analysis of it. However, managers generally perceived analytics positively and trusted in its results. They saw building trust in data as a key prerequisite to changing organizational culture. Asked about how data contributed to decision making, head of department M85 said: “I think the outcome is that we have a new philosophy embedded…that people believe now what the system is telling you, because now it is backed up by robust data that has been tested and proven.” However, several managers were also aware of the drawbacks of analytics use and had a critical view of it. They particularly lacked trust in other employees’ interpretations of data. This concern was voiced by executive M10: “data is one thing, but the way you interpret the data might give you the wrong impression and [lead to] the wrong decisions.”

Organizations were frequently found to struggle with the lack of required analytics skills in the beginning of their data journey. While there might be interest in more data-driven decision making, not all organizations have access to enough business analysts to explore data analytics’ full potential. Managers therefore often brought up the lack of skills when speaking about their negative perceptions of big data and analytics (n=18). Executive M22 referred to this obstacle directly, mentioning that the organization was planning to hire more technically oriented analysts that would also have the necessary skills to understand the required tools.

The complexity of analytics for processing big data often exceeds the skills of current employees. However, new hires might not always be an option for organizations, due to a shortage of available talent and often limited budgets. Executive M51 emphasized this problem: “If you have to have a dedicated highly qualified data scientist between you and that solution, it won’t work. One, because they’re scarce, and two, the scale of the organization won’t justify the hiring of someone with that capability.” Without the required skills, organizations might have access to big data, but have limited options to get value out of it (M41).

Even if sufficiently skilled employees are available, organizations can still encounter problems, which contribute to a negative perception of big data and analytics. These problems were mostly related to the delays in decision making due to time-consuming data analysis (n=21). Manager M92 pointed out that even though he and his team have access to high-quality data, the analysis of it can be too complicated and time consuming, which in turn deters them from using it. Head of department M81 echoed this sentiment about analyzing data: “It takes so long and I’m thinking: ‘I’m not going to bother doing that. I’ve got access to SAP, but I’m not going to sit there for hours and hours trying to figure out how to get information out.’”

A related problem is the gathering of the necessary data input for analysis, which was pointed out by manager M41. Data can have internal restrictions, as various departments might have information silos due to the different interpretations of data in different contexts. Particularly the availability of near-real-time data (or lack thereof) can hinder the decision making of managers as analyst M01 highlighted:

> Speed sometimes hinders you. For example, one of the systems we have, the data does not come real-time, but we only get that a day later, which means that it’s always after-the-fact. So if you need to make a decision based on what happened today, I wouldn’t be able to get the information, because it’s not available. (M01)

If data is not available at all or not in a timely manner, managers may simply decide to solely rely on human judgment instead of incorporating the data in their decision-making process. For head of department M84 this depended on the decision circumstances:

> The effort that will go into that is based on the size of the decision to be made. And by effort, I mean if the data is not readily available, how much effort would I put in going and finding that data? Or would I just be starting then to call on my experience and instinct? (M84)

Given the right skills and access to data, analytics can enrich managerial decision making. However, it still must be considered that even big data has limitations, which led to negative perceptions for some managers (n=12). Particularly in complex decision contexts, data was not considered to be able to cover all relevant decision aspects. These decisions still required the input of human judgment, as manager M41 pointed out: “You’re not going to know everything, and your data is not going to show you everything. So you always got to have some reliance on your own judgment and experiences.”

Similar limitations were noted for strategic decisions, as applicable data is often not available, and the impact of analytics was therefore considered limited. Particularly, when it comes to forecasting, data has limitations as “it’s not a mystic with a crystal ball” (M52). These strategic decisions often addressed future and hypothetical high-impact actions, as executive M51 highlighted: “It’s more of a business case. It’s a relatively high-level analysis, usually because there isn’t any better information. You always deal with the future; you don’t have a lot of knowledge about how it’s likely to work.”

In addition to the clear limitations of data analytics, the risk of misunderstanding, misinterpreting, or intentionally manipulating data also contributed to several managers’ negative perception of it (n=15). As referenced in connection with the aspect of trust, misinterpretations of data were considered an especially significant pitfall of data analytics (M52). However, these misinterpretations were not always attributed to a lack of experience and skills with analytics, but as head of department M84 pointed out, could also be due to a manipulation of data to benefit the decision maker: “You could make data mean anything you want it to.” The consequences of this might ultimately be detrimental to the organization, as manipulated data can be “totally destructive and manipulative” (M85).

5.2.2. Managerial Understanding of Human Judgment

Throughout this thesis, human judgment has been used as an umbrella term for different experience-based human influences on the decision-making process, namely intuition, wisdom, and experience. These factors are outlined as distinct constructs in the literature. They were also treated as such at the beginning of this study, when asking participants about their definition of human judgment constructs and how they perceived their importance. What became clear throughout the interviews was that managers often saw these factors as closely related, or even interchangeable. At times, the naming conventions would switch repeatedly during their answer, beginning with 'intuition', then referenced as 'wisdom', and so forth – all referring to the same umbrella term 'human judgment'.

The use of this umbrella term was sufficient to portray the general balance in decision-making processes as outlined in the previous chapter. However, considering the context of this chapter focusing on decision makers and their characteristics, their understanding and perception of the different human judgment constructs provided interesting insights. Intuition and wisdom were the two main factors to distinguish between, as there was a consensus on the meaning and value of experience. Their views on intuition and wisdom, however, could often reveal clues about their overall decision-making approach.

Intuition was perceived by participants as having both a negative and a positive influence on the decision-making process. General manager M91 highlighted one of the risks of employing intuition in decision making as the connection to cognitive biases: "The most dangerous thing, and this is part of intuition, of course, is around assumptions. And intuition is full of assumptions." These assumptions were seen as contributing to erroneous judgments, as they might be based on the agendas of managers or their personal biases.

Another perceived risk affecting intuition as well as cognitive biases was a lack of experience. As intuition relies on heuristics and shortcuts, a limited range of experience might be applied to inapt situations and lead to biased or misinformed decisions. This risk was seen as decreasing with an increase in experience. More experience was understood to provide managers with a richer portfolio of different scenarios and an eye for recognizing nuances. Experience in this context was equated to an additional source of data or facts, as head of department M84 elaborated: “experience can be the things that you’ve seen, and that’s almost factual, and adds to the dataset.” This experience can assist managers in improving their ability to assess current situations in comparison to past experiences. As a result, it was considered important to distinguish past decision scenarios from current situations, and to apply the ‘facts’ of experience only to situations that matched those experiences (M10).

For managers to trust in their intuition, they therefore require sufficient experience, an understanding for spotting differences in current situations, but also an unbiased motivation as a starting point. M85 highlighted this as another key component to intuition being a valuable contributor to the decision-making process: “If your motivation is right, and you’re looking out for others, not self, then I think you can really use intuition” (M85).

Intuition was mentioned repeatedly by participants, and there was a consensus on its definition. The concept was readily available in the managers’ vocabulary and was comfortably used throughout the interviews. Only the managers’ perception of it and therefore their trust in it varied, which in turn influenced the extent of their intuition use in decision-making situations. Wisdom, on the other hand, was not brought up by the managers proactively, only referred to when questioned about their understanding of it and its role in decision making.

Wisdom seemed to be a rather abstract concept for most participants (e.g. M86, M91). Managers often did not see wisdom as an active part of the decision-making process, as they focused particularly on the aspect of hindsight when talking about wisdom. Asked for a definition of a wise decision, analyst M01 highlighted that he would only be able to refer to a decision as wise after knowing its outcome: "You don't know if it's a wise decision until you see the result of the decision, whether it was wise or not." General manager M91 echoed this sentiment by adding that "the degree of success will determine how wise the decision was."

Wisdom was therefore often related to reflection on past decisions and incorporating these as lessons learned into future decisions (M85). It is closely connected to and reliant on experience (M93), to some extent 'replacing' intuition and the mere use of gut feel with a more holistic approach (M13). This holistic approach was particularly important in an incident shared by manager M92. During this incident, M92 was confronted with a straight-forward operational decision to replace outdated machines with newer models. However, he examined a wider context and considered the more holistic question of: Were those outdated machines actually used, and are new ones required? The operational decision therefore became a strategic one, which led to a restructuring and reconsideration of parts of the company's business model.

A definition of wisdom as this holistic approach was offered by manager M83:

> For me, wisdom is a capability which some individuals have, who are able to combine experience with insights into the current situation,

> and also look what it means for the future. It's looking at a wide horizon, so taking various factors into account and optimizing the situation. It's also something that is sustainable in the longer term. So that we're not looking at short-term gains without building on the longer term. (M83)

Several participants saw data as an important component of this holistic approach, and as a contributor to wise decisions (e.g. M01, M14, M22, M41). Analyst M14 emphasized that while experience was essential to making wise decisions, this experience could also be provided by data and function as a substitute for a lack of personal experience: "wisdom is about experience, but it doesn't have to be your own. So, you can learn from the experience of many others, if you use data. We do that systemically through a lot of our processes." M22 added that simply deciding to use data in the decision-making process could be considered a 'wise choice'.

While data was described as having the potential to diminish the importance of wisdom (M93), its relevance particularly for the human judgment role of sense checking and challenging data was emphasized by general manager M93: "We've got to be protective of it, that's all. And the numbers aren't always right; I think it would be very important to have that sort of knowledge to just maybe question things" (M93).

5.2.3. Types of Managerial Decision Makers

While the findings outlined in Chapter 4 and above have already answered the research questions of this study asking how big data and analytics are perceived by managers and how they are balanced with human judgment in decision making, the answers given thus far fail to provide a truly holistic picture. As reported in the previous two sections, the participants had diverse understandings and perceptions of data analytics as well as human judgment. However, these perceptions were not entirely unique, and several managers expressed similar notions. When grouping these managers according to their use of analytics and judgment, four distinct types of managerial decision makers emerged. These types not only shared similar views, but also certain characteristics and comparable decision-making behaviors.

As these different manager types share characteristics, views, and preferences that influence their decision making, their distinction from another establishes an important prerequisite for organizations in understanding individual managers' needs. In order to build a data-driven workforce, all managers need to be comfortable with the use of data, and therefore share an informed understanding of data analytics. The typology of managerial decision makers thus will enable organizations to cater to their employees' needs with customized approaches that match their characteristics and preferences.

The quadrant below in Table 30 provides an overview of the characteristics and requirements of the four different managerial decision maker types, arranged according to their use of intuition and data analytics in decision making. All four types emerged as themes during the coding process:

- Type A consists of managers that have an 'analytics-bent' and are therefore quite adapt at and experienced with using data and analytics. They often hold business analyst or related positions and tend to have more faith in data than in human judgment, which leads to mainly high-data decisions.
- Type B managers are 'all-rounders', who usually hold higher management roles. They are comfortable with the use of analytics and have accumulated a significant amount of domain experience, which enables them to make balanced decisions.

- Type C managers can be characterized as ‘insecure’ about data-driven decision making. They are mostly lacking analytics training and experience, which leads to skepticism and avoidance. Their decisions tend to be spread across all clusters.
- Type D managers can be considered ‘old-fashioned’ decision makers. They mostly trust in their own experience and judgment and hold positions in companies that are not very data-driven. They have either not been exposed to data or are data-averse.

The following sections introduce the different manager types and explore their shared characteristics, such as experience, skills, and preferences in more detail. Additionally, how these characteristics impact their decision-making behavior is also examined. Each type of managerial decision maker is described in more detail below. One abbreviated case summary per manager type was selected in order to provide an example and showcase their features.

Table 30. *Types of Managerial Decision Makers*

Data-driven

<table>
<tr>
<td>Type A “Analytics-Bent”

<u>Characteristics:</u>
• data-driven
• analytics experience
• trust in data
• critical of judgment

<u>Requirements:</u>
• access to high quality data
• coworkers open to analytics
• skills to relay data to others

<u>Participants:</u> M01, M11, M14, M52, M85, M86</td>
<td>Type B “All-Rounder”

<u>Characteristics:</u>
• senior management positions
• business understanding and domain experience
• trust in data
• good communication skills

<u>Requirements:</u>
• access to quality data and personnel
• data-driven environment
• visualization tools

<u>Participants:</u> M10, M12, M13, M21, M22, M51, M91, M92, M93, M94</td>
</tr>
<tr>
<td colspan="2">Type C “Insecure”

<u>Characteristics:</u>
• judgment-based decision making
• sceptic towards data
• no analytics training
• no exposure to analytics successes

<u>Requirements:</u>
• leadership encouragement
• sharing of analytics successes
• analytics training

<u>Participants:</u> M41, M81, M82, M83, M84</td>
</tr>
<tr>
<td></td>
<td>Type D “Old-Fashioned”

<u>Characteristics:</u>
• non data-driven industries
• data-averse or lack of exposure
• rich domain experience
• requirement for high-judgment decisions

<u>Requirements:</u>
• leadership guidance
• analytics training and peer support
• communication of culture change

<u>Participants:</u> M31, M61, M71, M72</td>
</tr>
</table>

Intuition-driven

5.2.3.1. Type A: Analytics-Bent

Type A managerial decision makers are referred to as being 'Analytics-Bent', which is an in vivo code identified in the transcripts of M83 and M84, and describes the mindset of data-driven decision makers: "Some of them have the analytics bent, that kind of thinking" (M83). Further participants used similar terms to describe the same theme of having an analytics-oriented mindset, being a numbers person, or similar expressions. Managers with the analytics bent are characterized by their extensive experience with analytics and their trust in data. Type A managers mostly follow high-data decision-making processes, and value data as decision input more than judgment. They see analytics as an enrichment, a source of accumulated experiences, and a chance for objective validation. Intuition is perceived to be burdened by assumptions, biases, and limited applicability.

Due to their reliance on data for decision making, these managers require access to high quality data sources and coworkers that are open to data analytics results, as their decisions are often based on them. Therefore, these managers also need the necessary skills to relay data and analytics results to others in an easily understandable manner.

One key example of Type A managerial decision makers is analyst M14. This analyst shared that his analytical thinking had been strongly influenced by his Bachelor studies in mathematics. Further classes in statistics during his master's degree in business supported his analytical foundation. In a professional capacity, he had about five to six years of experience with data and analytics in decision making. He had never received any formal analytics training until he took on his most recent role as business analytics manager in a financial services organization four years ago. In this position, his role was to manage the small analytics team and to report directly to the CEO, contributing to strategic decision making: “That oversees all the reporting; that’s the business performance on a day-today, week-to-week, and month-to-month basis, that guides that kind of understanding where the business is at” (M14).

The decisions he recalled for the CIT part of the study were categorized as two high-data decisions (C141, C142) and one balanced decision (C143), all with a very high extent of data use. This high-data decision-making process, as outlined in Chapter 4, could also be identified in the description of M14’s general decision-making process, which begins with using judgment as an initial assessment: “I definitely have that information-gathering step; find out as much information as I can. First, it would be intuition, kind of like, think about it: what am I trying to find out? What data could help me?”

As a next step, M14 critically examines this initial assessment for any potential biases he might bring to the decision-making process and challenges them before beginning his analysis of the problem using data analytics:

> What’s my preconceived idea about something? But then I’m not afraid to recognize that, challenge it. I think a lot of people use data this way: “Oh yes, I know what the answer is, let’s find some data to support what I already believe.” I think that’s how people misuse it. But I am going to gather this data to be completely unbiased and then make a quality observation and analysis, then go through with it. So, I’m sure I do follow that almost like an experimental methodology every time I do make a big data decision anyway. (M14)

He furthermore added that using data is a balancing act and that even decision makers with the analytics bent have to be mindful of their extent of data use, as there is “always a danger of dismissing it or over-relying on it” (M14). As a last step of the decision-making process, he also uses a sense-check: “I usually bounce it off other people as well” (M14).

After learning about M14’s decision-making process, the influences of his position, his company’s organizational culture, and the company’s industry were also explored. However, M14 emphasized that he has always had the analytics bent. When asked about the influence of the company culture on his decision-making approach, he described it as a good fit, rather than an influence: “I’m not sure if it’s influenced as much as the culture supports how I already would have been. That’s why it fits. I wouldn’t think it influenced. I already was like that” (M14). When asked about the influence of the industry, he provided a similar answer, saying the industry indeed relied heavily on data analytics, but that it simply matched his analytical personality.

Besides M14, further managers categorized as Type A were M01, M11, M52, M85, and M86. These managers shared key characteristics and levels of experience with analytics, resulting in similar analytical mindsets. While the majority held analytics positions, other Type A managers were also found to have a very analytical mindset and data-driven decision-making approach (M11, M85). Head of department M85 described himself as “a bit of a data freak–not compared to some real data people, but–I like to have the facts and understanding it for making a decision.” He reasoned that his affinity to high-data decisions stems from having held ‘fairly data-centric roles’. According to M85, using data analytics for decision making enabled him to better understand situations instead of solely trusting in intuition and ‘jumping to confusions’ – a behavior he often observed with colleagues.

While the analytics bent of Type A managers provided them with valuable insights from data, these managers have certain prerequisites to make successful high-data decisions, namely access to high quality data, colleagues who are open to data results, and the skills to relay analytics results to others.

Access to quality data is a key requirement for Type A managers to make successful decisions. If an organization's IT infrastructure does not support their preferred way of making decisions and required data is not available, managers must solely rely on their judgment, which can lead to negative decision outcomes (C113). As analyst M86 highlighted, getting access to the right data can be challenging, due to budget and time restraints. Particularly in large organizations, the ownership of different data sources can also be spread across several departments or units. This complicates the analysis, as M86 pointed out: "If you have 6 or 7 databases for one piece of input–some of them are controlled by [unit A], some of them are looked after by [unit B], some of them we look after–it's just my time and people's time."

The other two requirements for Type A decision makers are closely related: Managers with the analytics bent require coworkers that are open to data-driven decision making, and need to have the necessary skills to relay data analytics results to their colleagues, particularly ones that are hesitant about using data for decision making. Analyst M14 highlighted this connection when asked about how he reacts to others challenging his data analytics results:

> It depends where the doubt is coming from. I have to maybe take it as, is this coming from someone who has a fear, and is it just mistrust or misunderstanding of what this data actually represents? And in that case, I may need to reemphasize or sell the point a little bit better and maybe do a better job at explaining, what this represents. (M14)

While keeping a certain balance when using data has been mentioned by M14 above regarding the decision-making approach, the same goes for keeping a balance when relaying data analytics results to others. Depending on the audience, e.g. levels of seniority or the organizational culture, the amount and details of presented data should be adjusted so as not to overwhelm others with too much information. Head of department M85 had to learn this after starting his current position:

> The way I have related what data has told me, has probably hindered sometimes: because I've presented the data to people when they don't need the data, they just need your opinion or your decision. (M85)

Type A managers can be summarized as very data-driven and data-savvy decision makers whose experience is centered around analytics and not domain knowledge. They require a fitting organizational environment for successful decision making.

5.2.3.2. Type B: All-Rounder

Type B managerial decision makers are considered all-rounders, as they not only have an excellent grasp of data analytics but also extensive domain experience, which allows them to make balanced decisions. Their skill set also enables them to make high-data and high-judgment decisions successfully, although their preferred decision-making process is balanced. Type B decision makers mostly hold senior management positions, which is the reason for their extensive business understanding and domain experience. Like Type A managers, they have a good grasp on analytics and trust in data, albeit not to the same extent. What also characterizes Type B managers are their excellent communication skills, which enable them to communicate their judgments and analytics results to others.

All-rounders mostly see equal value in data and judgment as decision-making inputs. Analytics is considered an enrichment, or a chance for objective validation, and they generally trust in data. Therefore, they require an organizational culture and environment that is supportive of data-driven decision making. This extends to the need for access to quality data and analytics personnel who can support managers with more sophisticated data needs. As they are aware of the need to communicate analytics results to others, they also value visualization tools, which bring data into a more accessible format and facilitate the communication of analytics results.

Type B decision makers also recognize the limitations of analytics, which leads to the mostly followed balanced decision approach. They challenge data and use their judgment according to decision contexts and data availability. While they recognize the value of intuition and experience, they also understand their limitations, such as the risk of cognitive biases, assumptions, and potentially limited applicability.

M92 is an example of a Type B managerial decision maker. He had been with the same financial services organization for 20 years, which provided him with extensive business understanding and domain experience in his current position. Since starting out in this data-driven company, he had been using data and analytics in his decisions, which provided him with an appreciation for its value. While he never received any formal analytics training, he completed several management trainings, which taught him to analyze problems from different angles using various techniques. M92’s most recent role consisted of evaluating the operational model of his organization, which he considered a very data-driven task.

In this role, M92 was part of several tactical and strategic decisions, two of which he shared in form of the high-data decision C921 and the balanced decision C922. Both decisions relied to a high extent on data, but also incorporated a significant amount of human judgment. This matched his general decision-making process, as M92 rated the influence of data on his decisions at 80%. However, he elaborated that the data itself was already full of assumptions, and therefore contained human judgment to a significant extent: “You could even have a 100% data-driven decision, but it’s 50% based on assumptions.” This led M92 to generally follow an overall balanced decision-making approach.

For manager M92, this general process begins with a thorough initial assessment, matching Type A decision makers. However, once the development of alternatives step of the decision-making process is reached, Type B manager M92 follows a different approach. While he relies on data experts during this stage for conducting the actual analysis of the data, he engages his judgment to sense check and challenge the data results. His business understanding and experience play a significant part in this step of the decision-making process. For the selection step, M92 then takes advantage of his communication skills to convey the analytics results to other stakeholders:

> I know how to kind of format or present data so that it helps to tell a story. So, I have people that drive and create data. I have people that then turn data into insights, and then I have people that create insights to business cases and presentations. So, I can work with all levels or areas, but I particularly like to work on the presentation end, in the sense of: ‘show me meaningful insights and then we’ll tell a story.’ (M92)

This well-rounded and balanced decision-making approach incorporates M92’s analytics skills and his judgment. The data-driven environment provided by the industry and company, in combination with the management training courses he attended, certainly supported M92 in becoming an all-rounder. After 20 years with the company, he identified with their values and approaches. He showed a high appreciation for data, especially in its capacity to challenge biases: “Yea, [data] beats the gut” (M92). While he said that everyone in the organization understood the value of data and appreciated its potential, the access to it and the often time-consuming analytics process were still considered deterrents for data-driven decision making by many. The manager recognized this and other limitations of data analytics and therefore valued the balance provided by human judgment.

In addition to M92, other participants categorized as Type B managerial decision makers were M10, M12, M13, M21, M22, M51, M91, M92, M93, and M94. Type B managers therefore made up the largest group of this sample. Most of them were part of the two organizations leading this sample in analytics maturity (Organizations 1 and 9). All these managers made decisions based on data analytics as well as their previous experience by using their judgment. Executive M10 highlighted the importance of this balanced approach by referring to the limitations of data analytics. He elaborated that while data is a valuable decision input, managers still require intuition to “reconfirm and check that the data’s integrity, quality and the way it’s been presented is impartial” (M10). The importance of this role of human judgment, namely the sense-check of data, was confirmed by general manager M91.

As all-rounder managerial decision makers rely on both data analytics and human judgment, their requirements are similar to managers that have an analytics bent. Type B decision makers require an environment that supports and is open to data-driven decision making. Several of Type B managers have made their careers in data-driven environments, which influenced their method of decision making. Head of department M21 explained this by referring to M22’s and his own past in the finance industry: “It’s easy I suppose for the likes of myself and the CFO to basically say 'show us the money', because that's what we've grown up with" (M21).

All-rounders also require access to quality data, but furthermore to the right personnel that has sufficient analytics skills to support the managers with their more complex data needs. Type B managers have a good understanding of data, but mostly still require specialists for the data analysis (M12). As Type B managers might not have the extensive analytics experience of most Type A decision makers, they benefit from visualization tools that facilitate easier access to data analytics results. Part of their role is to relay their decisions and therefore data analytics results to other stakeholders. Visualization tools are of particular use for these scenarios, as they have the potential to reach a broad audience with varying analytics skills and understanding. Head of department M21 and general manager M93 brought this requirement up. Particularly M93 highlighted the benefits of visualization:

> What I'm trying to do is get everything that I feel that I need into sort of one main dashboard–productionalized information. At the moment I go to all those different areas to find the information I want; just trying to make it a bit easier for me to have that information there, and then I can quickly deal with insights I see from there. I want something that's very, very visual, not just numbers based. It's going to make that a lot easier. (#9.3)

While Type B managers were described as benefitting from visualization, insecure Type C decision makers shared mixed views on this. Head of department M82 also mentioned the need for visualization tools. However, head of department M81 did not see the need for it himself, as he preferred to interact with hard data, which had not been previously interpreted or manipulated. This signifies the varying needs among the different decision maker types, but also highlights how insecurity can manifest in different ways in the decision-making process. This is further explored in the next section on insecure managerial decision makers.

5.2.3.3. Type C: Insecure

Type C managerial decision makers exhibit insecurity around the topic of big data and analytics, being more used to a judgment-based decision-making environment. Often, they are part of organizations that have a traditional decision-making culture and have only recently embarked on the journey to a more data-driven approach. Type C managers are skeptical towards data, as they have usually not received any formal analytics training, and have not had sufficient exposure to analytics successes. They lack the understanding of analytics' potential and are unsure about gaining related skills. In terms of decision-making approaches, Type C cannot be assigned to a specific decision cluster. These decision makers might avoid using data all together, or experiment with it to some degree, often making their exact decision-making process rather unpredictable.

Insecure decision makers might generally be open to the use of analytics, but lack several prerequisites, effectively preventing them from data-driven decision making. They lack trust, analytics skills, access to quality data, and are not satisfied with the time commitment data analytics requires. As they mostly rely on their own experience and intuition, Type C managers will require leadership encouragement and analytics training in order to engage in data-driven approaches. Sharing positive results and use cases related to data-driven decision making can also be a helpful tool in creating more trust in data and demonstrating its value.

An example of insecure managerial decision makers is M83. The manager had been making decisions in a professional capacity for nine years, with partial support from analytics. Through his previous work engagements and the past five years at transport organization 8, he also acquired a vast repository of experiences and domain knowledge. His decisions tend to be influenced by both, depending on the decision context and circumstances. M83 had received several management trainings, as well as two short introductions to specific software tools in his previous company. His current company had not provided such training.

For the past two years, in his role as manager of the support and services team, M83 had been involved in several strategic and tactical decisions. During the CIT part of the interview, he shared balanced decision C831. He had selected the decision with the highest amount of data use to share for the context of this study. For this decision, M83 employed a very structured decision framework that he had acquired during one of his management courses. This decision does an excellent job of highlighting what was required for a Type C manager to make a successful decision.

While M83 was used to well-organized and structured decision making, the use of data was not a common component. The input of data analytics was provided by members of his team that were familiar with processing the data. M83 highlighted the support of these team members, as well as the leadership support and encouragement he and the cooperating teams received. The role of leadership was deemed particularly crucial for the positive outcome of this decision, as previous efforts had not been successful:

> I found that the leadership role in the organization is really the key. So, I had tried some elements of that approach with a previous manager, but then that wasn't successful, because he wasn't engaged

> and not communicating the expectation back to his staff and not explaining the value. But then, two years ago, when there was a new manager who started, I just saw a change overnight in the team's attitude and support, and basically wanting to work together to improve our business. (M83)

M83's decision-making process matched the organizational culture, which resulted in high-judgment decisions predominantly influenced by extensive domain experience. However, as the organization aimed for a more data-driven approach, manager M83 also began to incorporate data into his decision making; that is to say, he saw the organizational culture as a definitive influence on his own decision making.

In addition to M83, further Type C decision makers were M41, M81, M82, and M84. These managers are characterized by their insecurity around the topic of big data analytics. When faced with the need to use data analytics in their decision making, this insecurity could lead to negative decision outcomes, as seen in the incidents C812 and C842. These particular decisions were based on misjudgments related to data efforts and a lack of familiarity with analytics. On an individual level, Type C managers could therefore benefit from general exposure to data and analytics training.

Another contributing factor to this insecurity was the analytics maturity of the manager's organization. If the systems in place were not easy to use and trainings were not provided, even managers interested in data-driven decision making faced difficulties. Essentially, the organizational environment contributed to managers being categorized as Type C, even if they might otherwise be very capable of becoming Type B decision makers. Manager M83 and head of department M81 are examples of this: organization 8 was at the time of data collection going through a major shift from traditional to data-driven decision making. M81 had already realized there might be potential for data analytics to outweigh his judgment, but simply had not seen it happen yet:

> I think you'd soon learn that your guesses and intuition aren't necessarily right. You would question yourself more. At the moment, I have no reason to. I'm going to believe I'm right. But once the information comes, there will be turning points and changes. (M81)

Once their data use journey was further along, managers like M83 might be classified as all-rounders. A more detailed discussion of the effects of organizational analytics maturity can be found in Chapter 6.

Current Type C managerial decision makers require organizational support to avoid negative outcome decisions. These requirements include leadership support and encouragement and, at a minimum, basic analytics training. They also benefit from the sharing of positive data analytics results or cases.

In incident C831, leadership support was provided in the form of introducing the element of gamification and competition. The team leader of the cooperating department introduced a leaderboard using traffic light color coding to track error-free data entries and related activities. This led to a healthy and playful competition among team members, which led to more engagement with data analytics and peer support, as manager M83 elaborated:

> What we were able to do was to create almost like a competitive environment among the different stages: where did we get the best improvement? So once I got that going, it became almost like a game.

> So, it was like the monthly ranking of who was performing well. (C831)

Executive M71 encouraged insecure decision makers by presenting analytics results related to performance during team and company meetings. When seeing the results and receiving explanations around it, employees saw the reason for their expected contribution to data analytics and saw the value of the results. M83 echoed this sentiment by mentioning the need for use cases to foster a more wide-spread understanding of data analytics and for demonstrating its value. The sharing of use cases is expected to foster understanding, as manager M83 highlighted: “I think there is just that kind of opportunity for some quick wins, that you would be able to demonstrate.”

A further requirement for Type C managers is the access to analytics training. As discussed in section 5.2.3.1., Type A decision makers require an openness to data-driven decision making. Type C colleagues are therefore a hinderance for Type A decision makers, as their insecurity often leads to disbelief of results provided by Type A. Given the right skills, Type A managers can relay not only their analytics results, but also the basics of analytics to insecure managers, and encourage their use of information systems. This was explained by head of department M84, who himself was categorized as Type C. A Type A team member had been able to demonstrate the value of data analytics to him: “I’ve just lost a guy who had a real a) bent, and b) passion for analytics. And actually, until he came along, I didn’t appreciate what we could be getting if we get it right” (M84).

Helping managerial decision makers to understand the basics of data analytics was seen as a necessary approach to address Type C’s insecurities, as it reduced the impression of complexity and inaccessibility. This was emphasized by executive M51:

> That's [use cases] one way of helping to persuade people that this is a good approach. But once you start putting it in a black box, no one understands what the black box is, and no one's going to believe it. (C511)

This understanding is a key prerequisite for successful data-driven decision making, as it demands that managers sense-check and challenge analytics results. Manager M41 emphasized the importance of analytics understanding for the effective use of intuition in data-driven decision making:

> If you don't understand the data yourself, you're probably not going to question it. You should be able to understand what's going on in the data. It shouldn't be from a point that I just solely rely on the data and nothing else. (M41)

While Type C managers often avoid data-driven decision making because of their insecurity around the topics of big data and analytics, other managers outright reject data in favor of their own experience and judgment. These managers are further discussed in the next section.

5.2.3.4. Type D: Old-Fashioned

Type D managerial decision makers are characterized as 'old-fashioned', an in vivo code that was extracted from the interview with head of department M81 when describing the decision-making style prevalent in his organization: "Particularly in this part of the company, it's quite old-fashioned, if you like." Managerial decision makers classified as Type D shared certain characteristics. All of them were with companies in non-data-driven industries that required high-judgment decision making and therefore rich domain experience. Old-fashioned managers also shared a lack of exposure to data analytics or were averse to data use due to their negative perceptions of it. The decision-making process followed for high-judgment decisions is therefore their preferred method.

Old-fashioned decision makers that lack exposure to data analytics can be found in organizations that are in very early stages of their data journey. Their current high-judgment decision making could therefore still evolve with the progression of the organization towards a more data-driven environment. There are, however, also Type D managers that consciously avoid using data in their decision-making process. This can be a result of the managers being in an environment that demands creativity and has very little, if any, use for data analytics.

Another reason for avoiding high-data decisions are negative experiences with analytics. Managers that fall into this category understand the limitations and often unattainable requirements of data-driven decision making. Main data use deterrents for Type D managers are a lack of analytics skills, low quality data, and the time consumed by data analysis. Therefore, old-fashioned decision makers require additional organizational support in order to engage in high-data or balanced decision making. Essential components of this support are leadership guidance and the communication of the cultural change to a more data-driven environment. Furthermore, they benefit from analytics training, and particularly from peer support.

One example of an old-fashioned managerial decision maker is M31. For the past five years, the executive had been the last stop on the line of decision making as the owner and founder of his company. He was therefore involved in all strategic decisions, but also in more tactical and operational ones. Over the past two years, analytics had become more relevant in this context. As he had never had any formal management or analytics training, M31 mostly relied on his ‘gut feeling’ for his decision making. Success in the decisions he had made since founding his company gave him confidence and trust in his own judgment.

M31's decisions followed a high-judgment decision-making approach: "Basically all of those [decisions] are made on experience. I can pull reports and I use those to an extent, but I essentially use gut feel over the top of them." The role of data analytics was limited to exploration or enabler of judgment, and only of relevance for profitability analysis regarding employees and customers. These results often had little impact on the decision outcome, as the executive's judgment took on the roles of enrichment and outweighing of analytics: "So I sort of overwrite the analytics with common sense" (M31).

In addition to common sense, his own experience and domain knowledge, the executive also considered the perspectives of colleagues and peers as a decision input, as noted in his quote above. A valuable part of M31's decision-making process was therefore collaboration with others: "I talk to a lot of people and I get different opinions on what they would do in that situation."

Further 'old-fashioned' decision makers were M31, M61, M71, and M72. These managers are particularly apt at making very successful high-judgment decisions, as they rely heavily on their typically vast domain experience. Even though the role of analytics in these decisions might be minimal, the managers still incorporate facts into their process, as manager M72 clarified: "But nothing that I do is without having factual information" (M72). This information is usually not vast or diverse data, but still provides objective validation for the assessments.

Type D managers are often data-averse due to a general resistance to change, or more specifically, a lack in computer literacy. These managers therefore have certain prerequisites for engaging in data-driven decision making. Particularly beneficial are leadership guidance, clear communication of the change to a more data-driven decision-making culture, and at least basic analytics training and peer support.

A particularly key prerequisite for old-fashioned managers adopting a more data-driven decision-making style is leadership guidance. These Type D managers often display a general resistance to change. This was highlighted by analyst M86, who described the difficulties posed by introducing data-driven decisions to old-fashioned managers: “I mean you have mixed feelings, because people don’t like changes. So, you have people that were sitting and murmuring that ‘this idea sucks and I like doing it the original way, because I’ve been doing it for 35 years’” (C861). This sentiment was further echoed by manager M92 referring to Type D managers in his organization maintaining their original way of decision making.

Leadership support in these cases is crucial, as the reluctance from superiors who are not behind data-driven decision making can spread to their employees. Executive M71 shared such a difficult transition in one of their company’s offices. This office was led by a Type D manager who was not willing to change current processes. All employees reporting to this manager followed suit, which resulted in both offices following different decision-making processes.

Clear and consistent communication of the change in decision-making culture is therefore a key requirement for reliable decision-making success. The sharing of positive results was described as a valuable technique to not only communicate the change itself but also its benefits. This communication and sharing of positive results were instrumental in changing the organizational culture as part of the data journey by head of department M85:

> Once we had a philosophy, which took some time to educate people on the value of doing this extra step–sometimes it was just sheer ‘this is the way it will be’. Because until they take data for a certain amount of time, they don’t see the value in it. As soon as we would start to draw pictures and say: ‘this is what it’s telling us’, then believe grew in the system. (C851)

Another factor with the potential to contribute to the resistance of old-fashioned managers is a deficit in computer-literacy, which was addressed by executive M71. In these cases, peer support was seen as particularly effective, as the managers displayed less hesitation in approaching peers for help than when asking superiors:

> Some of the older ones weren’t particularly computer-literate; and it’s just a matter of giving them the training. And also, the peer support: so quite often they’ll be reluctant to ask me for help, but they’ll ask each other. So people have really helped each other to get more used to it. (M71)

If managers are not familiar with data analytics and lack essential training, their avoidance of it can be due to fear, as manager M92 pointed out: “And then, it won’t win, because some people are just afraid of it. They don’t understand it. So therefore, if you’re afraid, you avoid.” This insecurity is a commonality between Type C and Type D managers. While Type D managers make a more conscious choice to rely on judgment-driven decision making, both types benefit from basic data analytics training, which removes the unknown component about data and analytics, and therefore some of the trepidation. Analyst M86 identified this lack of training as the root cause of numerous processing errors, which led to incident C861. Insufficient training and missing processing policies led to managers using their own processes, which lacked consistency.

Training, as well as access to data, must be adjusted to the level of the respective manager and their data needs. As executive M22 emphasized, not every manager requires the same level of data access and analytics skills, as their needs depend on their positions and decisions:

> So yes, I think users need to be trained, and they need to have the right level of access. And sometimes the right level of access actually means that they have a piece of paper that turns up on their desk or a report that's generated to their inbox on a weekly basis. (M22)

Organizations will therefore benefit from determining the types of managerial decision makers in their midst, in order to adjust for their varying skills and preferences. Differing requirements must be met for the specific decision maker types to optimize decision outcomes organization-wide.

5.3. Discussion

The findings of this chapter contribute to extant literature in two major ways. Firstly, managers' perception of analytics is explored in the context of decision making and in contrast to the more traditional use of human judgment. Secondly, managers are identified as heterogeneous decision makers, with varying characteristics and, thus, requirements and preferences. Both key findings are discussed in the following sections in the context of the extant literature.

5.3.1. Understanding of Analytics and Human Judgement

This section explores the first key contribution of this chapter, and discusses the managers' understanding of data analytics as well as human judgment. The participants' definitions and perceptions of both concepts are further explored in the context of extant literature. Common views portrayed in academic and practitioner literature are compared to the insights gained from this study. Finally, addressing the identified shortcomings regarding the managers' understanding of big data and analytics, trainings and tools are suggested to facilitate the transition to more data-driven decision making.

5.3.1.1. Analytics and Big Data – Understanding and Perception

Gaining an overview of the managers' understanding and perception of analytics and big data was the foundation for exploring their decision making. During the interviews, the managerial decision makers shared their definitions of the terms 'analytics' and 'big data', displaying different degrees of their understanding of the concepts. They furthermore presented varying perceptions of the use of data-driven decision making. Examining the managers' answers in the context of definitions provided by extant literature exposed an often significant lack of analytics understanding. Unsurprisingly, these gaps in the managers' knowledge often corresponded to the extent of data and judgment use in their decision-making processes.

While managers displayed a high level of insecurity around the topic of big data, most participants showed a sufficient understanding of analytics. The answers provided could be categorized into three components, namely the definition of a question, the computational analysis of data, and the gaining of insights from the analytics results. These components signified a very contemporary view and expectation of data analytics. In this regard, managers went beyond the traditional scope of the analytics definition provided by extant literature, which refers to mere computational analysis to extract meaning and patterns from data (Analytics, n.d.). The extended definition provided by most participants additionally shows their awareness of analytics' increasing potential.

The concept of big data, however, proved to be unfamiliar territory for most decision makers. As even most academic and practitioner literature does not concur on one clear definition of the term, this was not an entirely unexpected result. While the 3 Vs (Laney, 2001)–volume, velocity, and variety–are commonly accepted as the defining dimensions of big data (Mishra et al., 2017), other dimensions have been suggested more recently, such as veracity (Abbasi et al., 2016; Jagadish et al., 2014; Wamba et al., 2017), and value (Bumblauskas et al., 2017; Colombo & Ferrari, 2015; Mishra et al., 2017; Sivarajah et al., 2017). Next to the specific dimensions of big data, its use and the sources for data also lead to discord. Big data might be understood as structured and/or unstructured data, as information dumps, web searches, or innovation (Richey Jr, Morgan, Lindsey-Hall, & Adams, 2016).

This insecurity around defining the term of big data was reflected in the participants' answers, which were divided into four thematically distinct definitions. Only one of these definitions was focused on actual characteristics of big data and entailed the 3 V dimensions outlined by extant literature. Out of the 17 participants referring to these dimensions, merely four referred to all 3 Vs, with most others focusing on the volume and/or variety of big data in contrast to regular datasets. Participants additionally referred to big data as a mere buzzword or hype, defined it by referring to big data's outcomes or a lack of use cases, or simply displayed confusion when explaining the term.

Misunderstanding the term 'big data' could also be considered an indicator for a general lack of understanding of big data sources, the context of big data collection, and its meaning. As Janssen et al. (2017) points out, this (lack of) knowledge has an effect on the managers' decision making quality. A thorough understanding of big data and data analytics in general is also a key requirement for a positive perception of these concepts.

Managers' perceptions of big data and analytics were found to have a clear impact on the extent of data use in their decision making. Positive perceptions led managers to rely on high-data or balanced decision-making processes. As these managers saw data as a form of objective validation or an enrichment of their decisions, the extent of their data use was rather high. Managers that had negative perceptions of data analytics referred to a lack of skills, data access and speed of analysis, the limitations of analytics, and the misunderstanding or manipulation of data. Data access and speed of analysis are factors that are managed on an organizational level and will therefore be discussed in Chapter 6. The limitations of data analytics have been discussed in the literature review and must be understood by managers for them to prudently use data-driven decision making.

The misunderstanding or manipulation of data, on the other hand, is related to an overall lack of trust in data analytics. Trust is an important factor for managers in order for them to rely on data analytics for their decision making, as confirmed by Moore (2017). Executives need the assurance that the data used for their decisions is of good quality. Distrust can be caused by "discrepancies between the data source and data store, over or understated data values, inconsistent or inaccurate data calculations, inconsistent data formats, data unavailability, and a lack of infrastructure to fulfil new requirements" (Moore, 2017, p. 130).

To avoid this distrust, it is considered essential to have a single source of truth, as was highlighted by several of the participants. This was confirmed by Ross, Beath, and Quaadgras (2013) and their research on the creation of business value from data. They found that managers consulting different sources to determine the same measures is not uncommon in organizations and can lead to differing and often widely inaccurate results. This highlights the value of determining a single system for each use case for providing data. As a result, managers are obligated to use this single source of data that is regularly maintained, therefore ensure the best possible data quality and consistency throughout the organization (Ross et al., 2013). As a result, the decision makers can thus recognize the value of data analytics and develop a habit of relying on data-driven decisions.

5.3.1.2. Human Judgement Perception and Understanding

In this study, human judgment was used as an umbrella term to capture the influence of human factors such as intuition, experience, and wisdom on managerial decision making. Managers were often found to use these concepts interchangeably during their interviews. This has already been stated by Simon (1960), who reported that managers were often not able to determine which of their abilities or skills were applied to their decisions, expressing that they simply used their judgment. To arrive at such a judgment, managers combine past experiences with facts and use their own imagination (Bhidé, 2010).

Decision makers were found to especially benefit from experience, with more senior managers making successful high-judgment decisions. This is confirmed by Dreyfus and Dreyfus (1980) as well as Dijkstra, Pligt, and Kleef (2013). Participants considered experience to be an essential component for discerning between past situations and current decision-making conditions, aiding their ability to recognize fine nuances. They furthermore perceived their past experiences as personal data, and therefore as another set of facts that could be included in the decision-making process.

Particularly for more complex and strategic decisions, the participants relied on high-judgment decisions, as these decision types often lacked applicable data. This is reflected in the Unconscious Thought Theory discussed in the literature review (Dijksterhuis & Nordgren, 2006). The theory states that the quality of decisions made based on conscious thought declines with increasing complexity, therefore increasing the value of unconscious thought. Human judgment, both conscious and unconscious, was therefore seen as a valuable part of managerial decision making.

Focusing on the different components of human judgment, experience was unanimously seen as a positive contribution to decision making and recognized as the foundation of intuition and wisdom. The managers' understanding of intuition matched extant literature. They displayed positive as well negative perceptions towards it. The concept of wisdom, on the other hand, was not very well understood by most, but the decision makers' definitions matched the characteristics of wisdom outlined in the literature to some extent.

Intuition provided managers with a rich portfolio of experiences for their decision making; however, the participants shared concerns regarding its limitations. Managers worried that the gained experience might lead to preconceived ideas and incorrect assumptions, often informed by cognitive biases. While intuition serves as a rapid decision-making tool by employing expertise, the use of heuristics incurs several risks. Heuristics enable managers to reduce the number of potential solutions (Busenitz & Barney, 1997; Tversky & Kahneman, 1973), but they are also based on previous experiences that might not reflect current circumstances. Particularly when decision makers are unaware of their use of heuristics, the results can be biased (Bazerman & Moore, 2013). Depending on the framing of the presented alternatives, managers might make misinformed decisions (Reyna et al., 2014). Participants shared these concerns and highlighted that managers' motivations can contribute to biased intuitive judgments.

Unlike intuition and its associated risks, wisdom was perceived solely as a positive impact on the decision-making process. It was seen as a more holistic approach compared to using one's gut feel, therefore enabling the mitigation of risks from other factors. Wisdom goes beyond mere intuition and knowledge, as it adds prudency and values to the manager's decision-making process (Intezari & Pauleen, 2013). Human judgment's role of sense check and challenging particularly benefitted from the wisdom of the managers in this study.

When elaborating on wisdom and wise decisions, managers particularly focused on the aspects of hindsight and reflection. The outcome of a decision and whether a decision was wise according to participants, could only be judged in hindsight. It provided managers with an opportunity to reflect on their decision-making processes. Wisdom was also mentioned by managers when speaking about collaboration with other parties during the decision-making process. Consulting others and considering different opinions and experiences was considered an important aspect of wise decision making. This open-mindedness and embracing of diverse experiences are characteristic of wise managers (Rooney et al., 2013; Yaniv & Choshen-Hillel, 2012), and assists in avoiding biases (Yaniv & Choshen-Hillel, 2012). Collaboration is especially valuable in the case of uncertain strategic decisions, which demand the forming of coalitions and bargaining to reach an agreement (Shepherd & Rudd, 2014).

Considering the benefits provided by intuition and wisdom, managers perceived human judgment as a valuable contribution to their decision-making process. While they saw risks in solely applying System 1 thinking, they recognized the benefits of incorporating judgment into the more structured and analytical System 2 processes. Participants highlighted the fact that human judgment delivered important contributions to all stages of the decision-making process, which confirms extant literature, as captured in section 2.2.4.

5.3.1.3. Training

Biased human judgments, lack of data, or misinterpretations of analytics results were the main reasons for negative decision outcomes and delays in the decision-making process. To reduce these negative occurrences, managers could benefit from further training. This was mentioned by managers in the case study portion of their interviews and its value is confirmed by extant literature. The following section outlines the specific training needs identified in this study that might alleviate common decision-making problems.

The managers' understanding and perception of human judgment was mostly sufficient; they displayed a general awareness of its value and drawbacks. Traditional Type D managers, for example, might overuse their human judgment–setting aside data insights–but they were aware of the one-sidedness of their approach. They understood the implicated risks and potential biases, but still preferred their own judgment over data analytics.

However, the often significant lack of understanding regarding analytics and big data displayed by several the participants is considered detrimental to prudent decision making. As pointed out in the literature review, an understanding of the meaning, context and collection of data is required for managerial decision makers. If this understanding is lacking, and the manager possesses insufficient skills, big data can have a negative effect on the manager's decision-making quality (Janssen et al., 2017).

As a result, Phillips-Wren et al. (2015) see the provision of big data and analytics training for decision makers as part of an effective governance structure. Through training, managers cannot only learn to grasp the concept of big data itself, but they can also be exposed to the various legal, ethical and regulatory challenges surrounding the use of big data (Phillips-Wren et al., 2015). Watson and Marjanovic (2013) confirm this need for training, highlighting its role in addressing existing skills gaps in the current workforce. While some organizations might attempt to address these gaps by hiring qualified graduates, this approach is not future-proof (Carillo, 2017): Closing these skills gaps demands ongoing training, as the subject of big data and analytics is considered very complex and constantly developing at a rapid pace. Furthermore, research suggests that standardized training for big data analytics may not suffice, as individuals benefit more from customized training programs (Motamarri et al., 2017).

Managerial decision makers are therefore expected to benefit not only from general analytics training, but from experimentation and in-house advice from analysts and peers who work with the same data and use cases. Gamification and competition, as mentioned in section 5.2.3., can in the same vein be effective tools enabling insecure or traditional managers to become more acquainted with data analytics in a decision-making capacity (C831). Serious games or simulations are also recommended in the extant literature as an effective pedagogical strategy, as they offer managers a chance to experiment with data analytics (Carillo, 2017).

Another important component that should be addressed in the training of managerial decision makers is data literacy (S. Shah et al., 2012; Wirth & Wirth, 2017): Managers should be made aware that not all data is reliable. They should therefore develop a basic understanding of the factors and calculations that lead to the analytics results that will later be used in their decision making. As a next step, managers then need to develop and engage their critical faculties to evaluate their data sources on their level of accuracy, biases, quality, and sample sizes.

While these contents can be covered in workshops, another (and often more effective) approach is coaching (N. Shah et al., 2017; S. Shah et al., 2012). Organizations can therefore benefit considerably from hiring analysts who can provide continuous training and support to data-driven decision makers. These analysts-as-coaches cannot only provide analytics expertise, but also influence decision-making behavior and create trust in analytics (N. Shah et al., 2017). This was particularly mentioned by M82, who acknowledged the analytics support his organization received from the now centralized BI department. This support enabled them to build trust in analytics, to make more reliable data-based decisions, and to uncover complex insights.

Another training tool related to the more informal training approach of coaching is the concept of peer support. The value of peer support was highlighted by executive M71, who emphasized its impact on insecure and old-fashioned managers who struggled with computer literacy. This lack of skills was the main factor leading to the managers' resistance to adopt a more data-driven decision-making approach. Particularly insecure Type C and old-fashioned Type D managers are affected by their lack of analytics skills. While in executive M71's organization managers had proved hesitant or reluctant in asking superiors for help, they were more comfortable consulting their peers. This relates to the concept of computer self-efficacy (CSE).

In order to accept the use of analytics as a complement to their intuition, experienced decision makers need to trust their capabilities regarding the use and interpretation of analytics. The theory of self-efficacy describes the psychological phenomenon of a person's belief in his ability to achieve success in a given situation or when confronted with a certain task. In connection with observational learning, this theory postulates that external factors and the behavior of others influence an individual's attitudes and confidence in their own abilities (Bandura, 1978).

Compeau and Higgins (1995) transfer this theory into the field of information systems and define an adjusted construct of self-efficacy: "Computer self-efficacy…refers to a judgment of one's capability to use a computer. It is not concerned with what one has done in the past, but rather with judgments of what could be done in the future" (p.192). CSE is therefore an important factor and determinant of technology use, and subsequently affects the individual's outcome expectations and use of that technology (Compeau & Higgins, 1995). Besides the use of technology, CSE also has an impact on the user's effectiveness and therefore his performance using the system in question (Marakas, Mun, & Johnson, 1998).

Training can also go beyond the imparting of technological understanding and big data knowledge. Type D managers, for example, could benefit from 'training in orderly thinking', extending their often rapid and unstructured System I approach to decision making (Simon, 1960, p. 11). As Simon (1960) points out, managers can be trained to apply a more structured approach to nonprogrammed decisions. This can be achieved by facilitating the formation of habits, such as beginning the decision-making process by asking: 'What is the problem?'

This study focused on exploring managerial decision making, and highlighted the managers' understanding of human judgment and (big) data analytics. Several shortcomings and the potential for more effective and efficient decision making were identified in the process. Training seems ultimately to be at the core of addressing these shortcomings and improving managerial decision making. Further action-based research on the outcomes of training methods might therefore be a valuable extension of the insights provided in this study.

5.3.2. Categorization of Managerial Decision Makers

This section explores the second key contribution of this chapter and discusses significant findings that began to emerge in the early stages of data collection. These findings highlighted that not only could the decisions be sorted into different types, but the managers themselves. While there are other categorizations of managerial traits explored in extant literature, this study managed to identify four distinct manager types based on their decision making with analytics.

The insights that emerged in this chapter present a significant contribution to the field's understanding of analytics-based decision making. The theoretical contribution of highlighting the importance of analytics understanding and the different types of managers can inform further research exploring the effects of customized training on these different types of decision makers. The practical implications of this chapter are twofold: Managers who aim to improve their decision making can benefit from categorization by identifying which decision maker type they are and taking the respective action to further develop their skills. Second, organizations that are interested in becoming more data-driven can tailor their change management approach to the respective managers in their current workforce, instead of solely focusing on hiring external talent.

Initially, individual characteristics were not considered in the setup of the study, and managerial characteristics were only included to the extent of the questions covered in the demographics section of the interview (see section 3.3.2.1). However, throughout the data collection phase it became clear that distinct types of managers could be characterized by factors such as their domain experience, familiarity with analytics, but also based on more abstract factors such as affinity for numbers or visualization. Therefore, Chapter 5 was used to elaborate on these different types of managers.

In extant literature, managers and their characteristics have been researched in several contexts related to organizational performance. Examples of these studies report on the influence of experience, tolerance for ambiguity and risk on the building of strategic business units (A. K. Gupta & Govindarajan, 1984), or the influence of managerial characteristics on the implementation of strategic change (Boeker, 1997). Furthermore, there are psychological assessments for practitioners, such as the Myers-Briggs Type Indicator, that allow managers to recognize the impact their personality and preferences have on their decision-making style (Cristofaro, 2017; Hirsh & Hirsh, 2010).

More relevant for the findings of this chapter are previous studies that have reported on the influence of managerial characteristics on decision making (Hensman & Sadler-Smith, 2011; S. Shah et al., 2012; Shepherd & Rudd, 2014). These studies cover a wide range of factors as their specific contexts informed the researchers' selection of potentially relevant managerial characteristics.

In their conceptual review, Shepherd and Rudd (2014) look at top management team characteristics as one of the influences on strategic decision making. These team characteristics capture demographic information (tenure, education, diversity, age) as well as diversity in cognitive style and personality. The factors are understood to influence the use of rationality, intuition, financial reporting and several other components of the decision-making process (Shepherd & Rudd, 2014). While the findings of Shepherd and Rudd (2014) focus on group decision making, the relevance of the identified characteristics offers reasonable confirmation for the findings of this study on individual decision making.

Hensman and Sadler-Smith (2011) conducted a qualitative study exploring intuitive decision making in the banking and finance industry. Their results showed that experienced executives' reliance on intuition depended on the task at hand, individual factors (such as the executives' experience and confidence), and on the organizational context. This confirms the results of this study, which relayed the influence of decision types and contexts on managerial decision making (Chapter 4) and discussed the influence of the managers' decision-making environment (Chapter 6). Regarding individual characteristics, the results captured in this Chapter 5 corroborate Hensman and Sadler-Smith's (2011) findings in that experience was found to impact the use of intuition in decision making. However, the findings in this chapter extend beyond intuition to the use of data analytics to capture all factors influencing decision making specifically in the age of big data.

Closely related to this approach is an expansive research project evaluating 5,000 employees by S. Shah and colleagues (2012). The researchers grouped decision makers and the results show commonalities with the types of managerial decision makers identified in section 5.2.3. S. Shah et al. differentiate between three different groups, first of which are 'unquestioning empiricists', who trust analysis over judgment and value consensus. This group can therefore be broadly compared to Type A managers, although Type A decision makers were mostly focused on data results without needing too much input from other parties. Secondly, 'visceral decision makers,' who distrust analysis and prefer to make decisions unilaterally. This group also exhibits similarities to a type of decision makers identified in this study, namely Type D managers. However, these traditional managers mostly valued collaboration and the exchange of opinions with other parties. The closest match among the two studies can be found between S. Shah et al.'s 'informed skeptics' and Type B managers. These informed skeptics are characterized as balancing judgment and analysis with solid analytics skills and a willingness to consider differing opinions.

While S. Shah et al.'s (2012) results offer confirmation for key insights of this study, the findings outlined here deliver more in-depth insights that account for different decision types and contexts as well as the decision makers' environments. Furthermore, this study identified a fourth category of managerial decision makers, Type C, to account for insecure managers that are in a transition phase–a significant group representing a large proportion of managers today.

5.4. Summary of Findings and Discussion: Chapter 5

Different managerial decision maker types were identified in this findings chapter, which highlight the varying requirements, strengths and weaknesses that should be considered by organizations. The manager types were furthermore matched with their respective decisions to see if their characteristics influenced their decision-making processes. This matching showed that managerial characteristics indeed significantly influenced their decision-making process. Examining the decision makers' characteristics and preferences enabled the identification of a set of prerequisites per manager type. Determining which decision maker types can be found in their workforce enables organizations to recognize and understand key differences among their employees. To foster a data-driven environment, organizations need to be aware of these varying prerequisites and must provide their managers with customized approaches for decision making based on this information.

Managerial decision makers could be divided into four different types, as summarized in section 5.2.3., Table 30. Type A managers with an analytics-bent display a thorough understanding and positive perceptions of data analytics. As they are critical of human judgment and its limitations, they prefer high-data decision-making processes. These managers require access to quality data and the skills to relay analytics results to their open-minded coworkers. All-rounder Type B managers are comfortable with the use of data analytics, but also have rich domain experience that can influence their decisions. Even though these managers prefer balanced decision-making processes, they can also make successful high-data or high-judgment decisions. These managers thrive in a data-driven environment that grants them access to quality data and skilled analysts. They also value the aid of visualization tools.

Type C managers are categorized as insecure and skeptical regarding data-driven decision making. Their decision-making processes are not exclusive to one cluster, as their insecurity leads them to follow the processes that are most convenient. Insecure managers strongly benefit from leadership encouragement and analytics training, which provides them with sufficient skills and support to embark on data-driven decision making. A further helpful tool is the sharing of positive analytics experiences and use cases to demonstrate the value and basic mechanisms of data analytics. Old-fashioned Type D managers have not had significant exposure to analytics or are data-averse. These decision makers mostly trust in their experience and rely on high-judgment decision-making processes. In order to change their decision-making behavior, these managers require leadership guidance and clear communication of the change in decision-making culture. They furthermore require analytics training as well as the support and encouragement from peers also relying on data-driven approaches.

Even though these managerial characteristics and the resulting decision maker types determined decision-making processes to some extent, environmental factors still had a significant influence. This influence is further discussed in the following chapter, which examine the managerial decision-making environment.

CHAPTER 6: MANAGERIAL DECISION-MAKING ENVIRONMENT

This last of three findings and discussion chapters focuses on the context of the main unit of analysis, i.e. the decision-making environment of managers. In the previous chapters, the decision types and circumstances were discussed as embedded units of analysis, along with the personal characteristics of managers that influence their decision making as the main unit of analysis. This chapter focuses on the third level of analysis, and therefore the context of these cases. Its aim is to assess the managers' environment and how it enables (or possibly hinders) the successful use of analytics in their decision making. The chapter contributes to current knowledge of decision making with (big) data analytics in two ways:

- The identification and relation of key influences on managerial decision making, namely:
    - Analyst support on the team level
    - Traditional versus data-driven organizational culture
    - Industry-specific access to data
    - The organization's analytics maturity
- The creation of a managerial decision-making environment in the age of big data, capturing the managers' environmental influences on their decision-making processes, and therefore the context of this study's main unit of analysis

The environment of managerial decision making was not addressed in the research questions at the outset of this study; it is an outcome that emerged entirely as a result of the data collection. The influence of environmental factors became apparent in the early stages of data collection. Participants reported on factors influencing their decision-making processes that exceeded decision types and contexts, as well as their personal preferences. Themes emerged from these reported factors that could be sorted into four categories, using the ecological systems framework as a lens. Bronfenbrenner's ecological framework postulates the influence of an individual's environment on their development (1977, 1979). Applying this ecological framework as a lens allowed for the holistic examination of the context of managerial decision making, not only identifying influences but also accounting for the influences' interaction. While individual factors emerged during the data analysis, the application of the ecological framework enabled the creation of a more holistic foundation for the results that depicts managerial decision making in the age of big data as a multi-factorial issue.

Through this lens, relevant external factors were assessed on the team, organization, and industry level, corresponding with the findings during data analysis. In addition to these hierarchical levels, an overarching influence on individual decision making was identified: analytics maturity. Organizational maturity in terms of analytics capabilities was found to be a critical component determining the power and prevalence of data-driven decision making, and was highly affected by the team-, organization- and industry-level influences.

This chapter follows the structure of the previous chapters by first outlining the specific approach to data analysis that was applied in this chapter. The thematic cross-case analysis mainly draws on the insights from the case study interviews with the participants, with additional data from the CIT lessons learned. This approach enabled the identification of various hindering and conducive factors within the different impact-levels of the decision makers' environment. In the findings section, these team-, organization-, and industry-level influences are discussed in detail, highlighting their impacts on decision-making processes. Furthermore, the construct of analytics maturity is identified and discussed as the most prominent environmental factor and is in turn observed to be significantly impacted by the other environmental factors.

In the discussion section, diverse frameworks and theories are evaluated to establish a theoretical basis for the significant factors that were found to determine the decision-making environment for managers in this study. These findings support and expand on certain factors of the extant literature, as well as extend our understanding of the managerial decision-making environment.

6.1. Data Analysis

Following a similar approach to the previous findings and discussion Chapter 5, which focused on the main level of analysis, this chapter is driven by the thematic cross-case analysis of the environmental context of managerial decision makers. This third level of analysis primarily draws on the case study data, which facilitated the exploration of obstacles found in organizations' data journeys and in managers' decision making using (big) data analytics. Furthermore, the thematic analysis extended to the critical incidents data. The lessons learned shared by managers in the CIT part of the interview were found to provide particularly interesting additional insights into their decision-making contexts.

As in Chapter 5, a variable-oriented approach focusing on the emerging themes of the managers' industry, analytics maturity, organizational culture, and colleagues was applied. Within each of these themes, several sub-themes could be identified, and are discussed in the findings below. These sub-themes elaborate on the diverse effects of the identified factors on decision making. As soon as external factors were identified as having significant impact on the managerial decision-making process, different theoretical models were used to assess and explain these findings. These theoretical models are further discussed in section 6.3. Ultimately the ecological systems framework was used as lens to interpret the findings and to further understand the relationship between different environmental factors.

Bronfenbrenner originally created the ecological framework when he suggested that individuals are influenced in their development by their environment, which consists of hierarchical levels (Bronfenbrenner, 1977, 1979). The model has since been used in different contexts, such as in research on bullying (Blackwood, 2015; Hong & Garbarino, 2012), immigration assimilation (Paat, 2013), and in the context of decision making (Harrison, 1995), to name a few examples. It is further discussed in section 6.3.1.

The hierarchical levels of the framework are the macrosystem, exosystem, mesosystem, and microsystem, with the individual at its center (Bronfenbrenner, 1977). For the scope of this research project, the framework was adapted to ensure the analyzed levels would align with the findings reported during data collection, which can be seen in Figure 16.

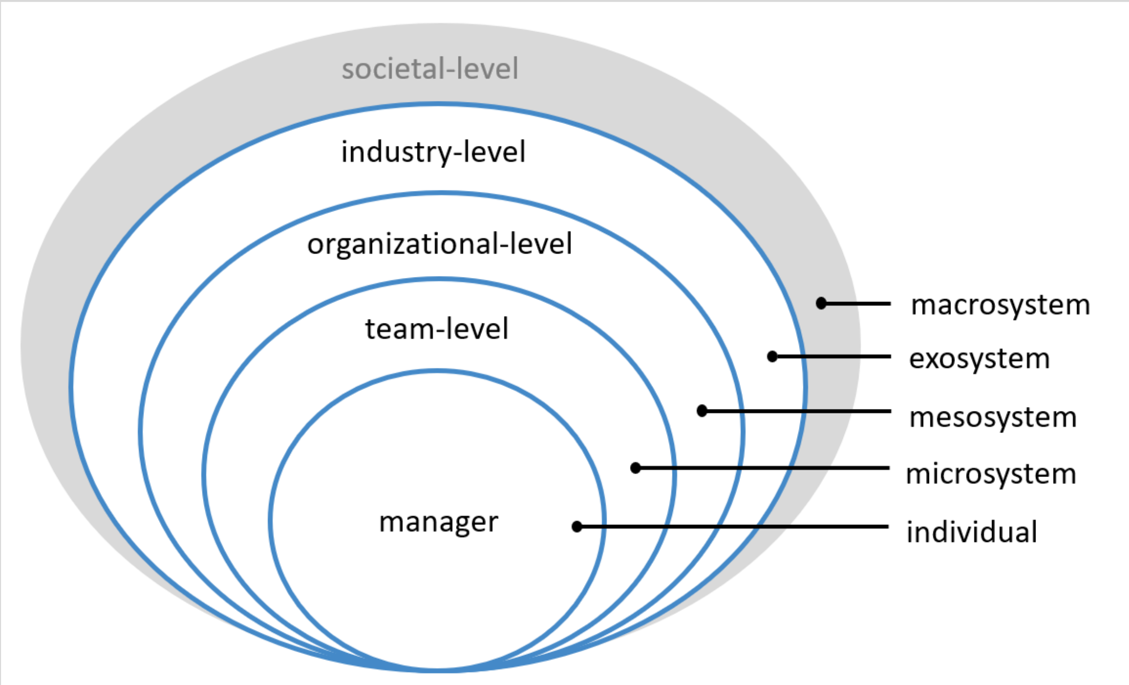

Figure 16. *Ecological Framework - Managerial Decision Making (deducted from Bronfenbrenner, 1977, 1979)*

The individual at the center of the framework is the managerial decision maker. The microsystem, described as peers or immediate contacts, are in this context team-level influences, such as colleagues. The mesosystem consists of interactions among microsystem factors, therefore extending to the workplace, i.e. organization-level influences in this research. The exosystem expands on those influences and forms the broader social system, encompassing further environmental aspects such as ‘the world of work’ (Bronfenbrenner, 1977, p. 515). The individual manager is not involved at this level but is indirectly affected by it. For the sake of this study, these influences are seen as industry-level and are considered the final layer of influences that had significant impact on the decision making of the participants. The macrosystem, containing factors such as economic, legal, social, and political systems, did not emerge as a relevant factor for the participants’ individual decision-making processes in this study.

The organizational environment types were most clearly reflected in the analytics maturity that the organization displayed. This concept allowed for organizations to be divided into different groups, matching the variable-oriented approach used in Chapter 5 to determine the different managerial decision maker types. As analytics maturity had the most significant effect on decision makers and decision process types, section 6.2.5. has been used to build on the insights from the previous two findings and discussion chapters. Chapter 5 utilized the insights gained from the content analysis in Chapter 4 to match decision makers with their respective decisions. In section 6.2.5., those insights were extended by determining a fit between the actual decisions, managers, and the environmental context. Managerial decision-making types and decision types are additionally outlined for each stage of analytics maturity.

6.2. Findings

This section begins by providing a high-level overview of an ecological framework outlining all significant factors that were found to influence managerial decision making. This framework is the first key contribution of this chapter, building the foundation of the findings section. By hierarchically organizing the levels of the participants' environment, the diverse influences of their environmental context, as well as the influences' relations, become apparent.

This is followed by the second key finding of this chapter: the identification and examination of the relationship of environmental influences on managerial decision making. Each of the four sections following the framework focuses on one of the influencing factors in the managers' respective environments. The key influence at the team level is identified as the access to analysts during the decision-making process. On the organizational level, the prevalent organizational culture, whether data-driven or more traditional, is found to be a significant factor. The industry-level factors highlighted by managers were primarily access, exposure and prevalence of data. The last of the influences discussed in this chapter is analytics maturity, which extends over all hierarchical levels.

6.2.1. Managerial Decision-Making Environment in the Age of Big Data

Analyzing the data on the decision makers' environment through the lens of the ecological framework provided insights into the examined hierarchical levels and the interactions between those levels. This allowed for the incorporation of findings from the previous two chapters, namely the different types of decisions as well as managers. The adapted framework outlined in section 6.1. was therefore extended by the embedded unit of analysis: the decision types. Furthermore, the framework was also extended by another component: analytics maturity. This was an additional environmental factor that spanned across the three hierarchical levels defined before the data analysis and shown in Figure 16. This resulted in a holistic managerial decision-making framework accounting not only for the environment, but also for individual and decision criteria that influence the decision-making processes, as seen in Figure 17.

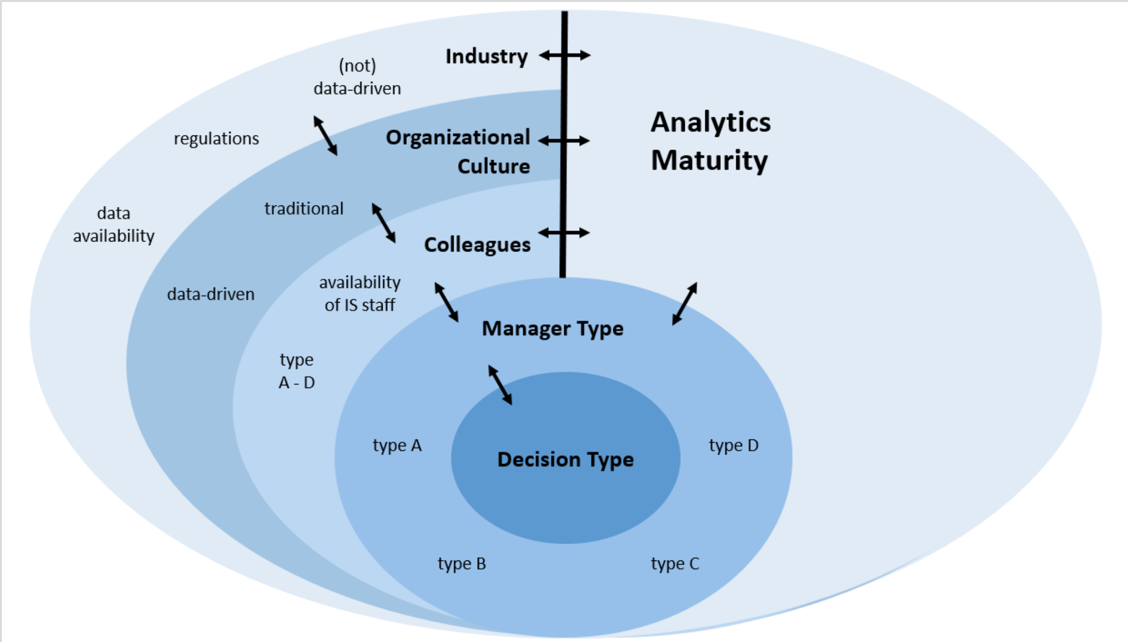

Figure 17. *Managerial Decision-Making Environment*

At the center of the model is the embedded unit of analysis: the decision types as identified in Chapter 4. The decision types, namely balanced, high-judgment, and high-data decisions, determine the decision-making process that is followed by the manager. Which of the decision types is chosen depends to some extent on the decision factors, such as the context and impact of the decision. The process, however, also depends on the manager type (Type A-D), as outlined in Chapter 5. Each individual manager's propensity to use data-driven or a more traditional decision-making process is therefore reliant on several personal characteristics.

Managers do not act in a vacuum. Their use of data-driven decision-making approaches is influenced by their environment, as the findings of this chapter show. As can be seen illustrated in Figure 17, managers are directly influenced by their colleagues, who in turn are influenced by the organizational culture. In the context of this research, the findings showed that on the team level, access to analysts was a significant prerequisite to using data analytics in decision making. The availability and dispersion of analysts throughout the organization depends on the organizational culture, i.e. whether data-driven decision making is valued and prioritized. In turn, organizational culture in terms of data-driven decision making depends to some extent on the industry the company is part of. Several industries tend to have access to data and have a long history of using it for decision making, while others are more traditional. Organizations that belong to data-rich industries often follow suit and have a more data-driven culture.

These influences are reciprocal, as will be further outlined in the following sections elaborating on the environmental factors and concrete findings. This reciprocity becomes particularly clear through the last significant factor identified as part of the managers' decision-making environment: analytics maturity. Analytics maturity represents any given organization's readiness to employ data-driven decision making. This factor has a direct influence on managers but is also highly dependent on the factors of colleagues, organizational culture and industry. Analytics maturity is therefore shown as spanning across multiple levels in the ecological managerial decision-making environment above.

In addition to incorporating the findings from the previous two chapters, the framework above identifies the various factors in the managerial decision-making environment that influence individual decision processes, which could be categorized into four main themes: team, organization, industry, and analytics maturity. These themes were arranged according to the ecological framework in Figure 16. Team-level factors include colleagues and supervisors, and most importantly access to analysts. Organizational factors include the perceived organizational culture, identified as a spectrum ranging from traditional to data-driven. Industry-level factors were defined as the availability of data sources and industry regulations. Societal factors, the macrosystem depicted in Figure 16, were considered to be things such as privacy and legal factors. Societal factors, however, were not mentioned by managers in this study as having significant impact on their decision making and have therefore not been considered in the final framework depicted in Figure 17.

As previously mentioned, one factor that spans across the other layers of the ecological framework is analytics maturity, as it is complemented by all the other factors in the managers' environment. The industry, organizational culture, and colleagues are key determinants of an organization's analytics maturity, affecting the organization's data journey, IT and IS infrastructure, and ultimately analytics capabilities, availability and acceptance.

The following sections focus on the influences that were found in the managers' decision-making environments, highlight their significance, and further discuss their impact and relationship to one another.

6.2.2. Team-Level Influences: Analyst Support

The team level of the decision-making environment represents the most immediate influence on a manager's decision-making process, as it encompasses direct working relationships with colleagues and coworkers. Considering the concept of Computer Self-Efficacy (CSE) (Compeau & Higgins, 1995), a general influence of team members and colleagues on decision making was expected, as was found and discussed in Chapter 5. However, the most significant finding of the team-level environmental influences on managerial decision making went beyond general coworker influences: access to data and business analysts was found to have a particularly significant impact on the managers' decision-making processes. This section focuses on this phenomenon and its impact.

Analysts, and specifically BI and data analytics departments, were valued by the participants for a variety of reasons. For one, they contributed to the decision-making process by challenging managers, asking hard questions about their motivation and the reasoning behind their data analysis efforts. This encouraged managers to further define the problem and decision requirements to better understand the decision context. Furthermore, access to analysts provided managers with a learning opportunity that allowed them to improve their own data and analytics skills. This gave managers a better understanding for the decision inputs and, as a result, more confidence in their decisions. Lastly, centralized BI units granted all departments in an organization access to well-maintained, high-quality data sources, as well as skilled analysts who could support their decision-making processes.

Analysts were mentioned as frequently contributing to managers' decision making simply by challenging them. This 'challenging' led managers to more clearly define the purpose of the data collection and to refine the initial question, as well as the expected results, before the analysts engaged in actual data collection and analysis. This particularly supported the definition and identification step of the decision-making process, enabling participants to avoid oversights and redundancies in the development and selection steps.

Skilled and experienced business analysts often take on the 'challenging' role when they are approached by business managers for data input. In response, analysts ask managers why they require certain information (M14, M94). With this practice, analysts want to ensure that managers have thoroughly defined the problem and requirements. Managers value the challenge, as head of department M85 pointed out: "The team challenges me. I've got a data analyst now who challenges me. I say, 'This is what I want to know', and he'll ask me, 'Why, why, why?'". A challenge at this point in the decision-making process prevents the misspent use of human and financial resources by avoiding the collection and processing of potentially irrelevant data.

While analysts are responsible for the actual data collection, analysis, and reporting, the manager, is responsible for the content of the queries, as executive M10 explained. Therefore, managers need to be precise when they request data input:

> The business sponsor or management person would drive the 'what' resort, so: 'I'm trying to understand this, can you please give me a summary of how that looks, what are the behaviors in that, are there any clusters or otherwise that we need to be aware of that may be risks or opportunities?' (M10)

While this relationship between managers and analysts needs to be established as part of the course of an organization's data journey, companies that are mature in terms of analytics capabilities can take advantage of this dynamic. As general manager M13 of one such mature organization pointed out, he used to approach analysts with requests for data input through a requirements document that outlined the purpose of the data collection. The analysts in turn would provide him with "some raw data and summary data and then I need to make conclusions and all that stuff myself" (M13). At the time of the interview, that process had evolved, and analysts had become more proactive, as M13 elaborated:

> If these people [analysts] are actively engaged in the business, of course, they will see things and hear things themselves. And when you're asking for data and putting criteria around it, much more engagement happens around that now. And when they're presenting

> data back, you know conclusions should be made and even recommendations for the business. And I think that is that next step in where the real power is. (M13)

This shows the potential benefit that close access and a working relationship with analysts can have on managerial decision making. It furthermore supports that analytics maturity is in a reciprocal relationship with team-level influences, which is indicated in the managerial decision-making environment in Figure 17.

Besides challenging managers in their decision making, analysts also ‘educate managers’ in using analytics tools for themselves, which has several benefits. For one, it saves managers time in their decision making, as they are not as reliant on coworkers for their data analysis. It also improves the managers’ understanding of the data that is incorporated into their decisions. As understanding is an important prerequisite of decision-making quality, analysts, in their educational capacity, are an important component for facilitating positive decision outcomes. Managers who interact with analysts, or coworkers who are responsible for data analysis, have a better understanding of the data, which in turn improves their decision making.

Manager M92 described this collaboration in the form of two analysts that work in his team and support him on a regular basis to create business cases and work insights from data into presentations. For in-depth reporting, both the manager and analysts approached the company’s central business intelligence team for more detailed data. As a team, they would then work on analyzing that data together, with the manager being heavily involved himself. This enabled him to have a basic understanding of which data is used in his decision making, and ultimately led to more confidence in the decision itself.

Both for analysts in central business intelligence departments, and those within the teams of managers, this means a shift in their role. Analysts are not solely responsible for the collection and analysis of data; rather, they take on an educational role, as head of the analytics department, as M94 confirmed: "what my job has evolved to is showing the business that that stuff is really easy."

While working closely with individual analysts enriched the managers' decision making, the participants benefitted particularly significantly from centralized BI and analytics departments. These departments had access to consolidated high-quality data that in turn enabled managers to gain access to well-maintained databases and the specialized individuals who have the skills to analyze them. While managers require a basic understanding of analytics to ensure high decision quality, dedicated analysts have superior skills and experience in analyzing data that benefit managers in their decision-making process. The centralized nature of these teams enables all departments of an organization to access required data and human resources instead of having skilled individuals divided across the departments in uneven quantities. Several participants even advocated for the existence of a centralized role or department for data analytics, depending on the size of the organization (e.g. M12, M84, M92, M94).

Key points that these managers mentioned were the integrated and shared service that these analytics departments offered, which gave managers access to a larger team (M82, M93). This provided managers with the advantage of "shared information and shared knowledge of business" (M82). As general manager M12 emphasized:

> If we didn't have that access to the Business Analytics team and the data they provided, it would have just been a thumbs up. But because

> we've got this data, we now feel as though we have made an informed decision to increase our risk appetite for the right customers. (C121)

When analysts and data are dispersed across the organization, managers perceive this as hurdles for data-driven decision making (M41, M92). While they might still be able to find the needed information, the search is effortful and time-consuming (M41). According to Manager M92, internal and political issues are particularly to blame for the problems with accessing data sources. As data analytics departments take on an internal supporting role in organizations, they are generally not revenue-generating, which often leads to underfunding and resulting shortages of resources, as M92 explained:

> The reality is: data makes no profit for the company–it's the decisions from data that make profit. So, these teams are potentially underfunded, and under-resourced, and yet everyone…you go through this horrible circle of wanting more data, but no one is able to get it. So, then you avoid it. (M92)

This explanation depicts access to analysts as a critical requirement for organization-wide data-driven decision making. However, general lack of acceptance of data-driven decision making, leadership support, or funding, as well as a shortage of skilled talent, are key problems that organizations face when setting up analytics departments.

Once managers have been exposed to a data-driven environment and access to analytics departments, they often advocate for this type of environment when switching to other departments or companies. Coworkers were therefore found to not only have a significant impact on the decision making of managers and other employees, but also on the overall organizational culture. Coming from a very data-driven environment in his previous role, head of department M85 recognized the potential of analytics for decision making, and in his new position supported coworkers in employing a more data-driven decision approach themselves. Taking on this advocating role had a transformative effect on his environment. Managers can therefore not only have an immediate impact on their coworkers, but also change the decision-making culture at an organizational level. The organizational culture and its influence on the managers' decision-making environment is further explored in the following section.

6.2.3. Organization-Level Influences: Data-Driven or Traditional Culture

The organizational level is the second tier in the hierarchy of environmental influences on managerial decision making. On this level, in term of analytics use and acceptance, the most significant influencing factor was the organizational culture. Managers addressed the organizational culture from two different vantage points. They reported on their current organizational culture, but also expressed their thoughts and plans for changing or influencing it. The prevalent culture was often described as an influence on their individual decision-making process. On several occasions, the participants spoke about changing the culture to facilitate more data-driven decision making on an organizational level.

Organizational culture was perceived as the key to achieving company-wide acceptance and use of data-driven decision making. In this regard, organizational culture was seen as even more crucial than overcoming technological challenges or mastering analytics techniques. This was highlighted by executive M51 when asked what his priorities were in their data journey: "Ultimately changing the culture, because the culture is far, far, far more important than any technique."

Having a consistent decision-making culture across the whole organization is therefore a key component for successful decisions. As head of department M82 pointed out, team-level as well as individual factors influence decision-making processes, particularly if an organization-wide approach is not accepted: “Culture does come into it a lot. Culture, personalities–people have their own way of doing things. And as I said, one of our teams receives information from many different teams within the business–it’s all different” (M82).

The data collection and analysis revealed several differences in organizational culture. The findings suggest that the organizational cultures affecting managers and their decisions can largely be described as either traditional or data-driven. These two types of cultures could further be considered diametric opposites, with most organizations falling somewhere in between the two. This led to the conclusion that this theme is not binary, but rather a spectrum ranging from traditional to data-driven organizational culture.

Organizations that prioritized or used human judgment, intuition, and experience for decision making were found to espouse a more traditional culture. The term traditional is an in vivo code recorded in interviews with the executive M71, who outlined the organizational culture as very traditional. For him, this meant that their employees were generally rejecting the use of data, having previously always relied on their judgment and experience, and had to get acquainted with basic data use in their day-to-day tasks. Head of department M81 outlined an example of this when describing the company’s culture:

> It’s quite old-fashioned, if you like. That’s the culture that we live in: very conservative. They base it on years and years of knowing, ‘this thing will lead to this thing’. We’re still back, like in the 70s, we behave like that. And we are in an industry like that. (M81)

His description illustrates the perceived effects of the industrial environment on the prevalent organizational culture. However, he also added that there were other departments in the organization that were further along in changing their culture, particularly accelerated by several younger new hires. This highlights the fragmentation of organizational culture due to team-level and individual factors, as well as the close relationship between the different environmental factors.

On the other end of the spectrum, data-driven culture describes an organization that values data and often requires analytics as a form of objective validation when justifying decisions. Mere judgments are usually not accepted without some form of data backing. This point was made by head of department M81, who was experiencing the shift to a more data-driven culture, and therefore the changing expectations of manager: “people ask you, why haven’t you got that information. They won’t accept, ‘Oh it’s too difficult, I’ll have to make a guess.’ They will expect that you want to go out and find it.”

Organizational culture might therefore not necessarily change the way individuals make their decisions, but nevertheless affects how these decisions are relayed to superiors (M85). This was confirmed by head of department M85, who elaborated:

> Organizational culture can make it very hard to present your decisions. And it does have an influence, because it helps you to be broader based, or it can make you very defensive. So it can influence your decision, but personally because I think of who I am, what I stand for, the values that I present: The decisions I make are not going to change too much, but it will definitely influence how I present them. (M85)

This shows that organizational culture is an important component in the managerial decision-making environment, and that managers recognize its significance. Several participants mentioned evolving into a more data-driven culture as an objective, albeit for different underlying reasons. Executive M22 favored informed data-driven decisions, as from his perspective, the current (more traditional) culture leads to 'average decisions based on what people have historically thought about something'. Several managers particularly highlighted the customer focus that data-based decisions enabled, allowing for improved customer insights and an improved ability to meet the customers' expectations (M41, M92, M93).

Overall, managers from organizations with mature analytics capabilities advocated a data-driven culture that employed balanced decision-making processes. Analyst M01 summarized the prevalent culture of his organization as using both human judgment and data analytics to reach the best possible decision outcome:

> What does your gut tell you what it's going to be, what is analytics telling you what it's going to be and really question the sanity of both, and really go from that. So, the culture is really to involve at least some analytics and use experience – best of both worlds kind of approach. (M01)

Changing the organizational culture to a more data-driven approach requires employee buy-in, which itself requires time and commitment. Therefore, organizations need to ensure that users understand the value of data-backed decisions (M21). Objective validation and the sharing of positive results are critical drivers of organizational change. Head of department M85 confirmed this by saying that a critical part of achieving this culture was building belief in the system by showing results to the management team over a timeframe of 12-18 months.

During this process of slow cultural change, leadership support and governance are critical. Certain guidelines and restrictions need to be provided by the organization, to ensure consistent, safe, and structured use of data analytics in decision making. As a manager herself, M72 emphasized that ‘management is the culture’, meaning that it is ultimately the management of a company that dictates the organizational culture. In their capacity, therefore, managers should be promoting the culture that benefits the organization most.

While changing the organizational culture facilitates long-term benefits, obstacles can be encountered along the journey. One inherent challenge is selecting the right approach to change management; that is, facilitating a smooth transition to a more data-driven culture that gain organization-wide acceptance (M85, M94). Experienced employees might be especially resistant to changing their often decades-old decision-making behavior, or they might be overwhelmed by the technology. Challenges also arise in organizations that are driven by the intrinsic motivation of their employees, as is often the case in not-for-profit organizations (M21). These organizations can still rely on traditional, experience-based decision making and the best judgment of their employees, as their decisions are often affected by emotions and intangible factors. Changing this culture to a more rational, objective and data-based approach was seen as especially challenging by head of department M21, as will be described and explored in the next section.

6.2.4. Industry-Level Influences: Access to Data

As outlined in the previous section, managerial decision making is influenced by the organizational culture. In turn, this culture is affected by industrial influences. The industry-level is the outer-most layer of the environmental framework, as shown in Figure 17 above. Organizations are experiencing these industrial influences in the form of restrictions on their business processes, imposed by industry standards or regulations, for example. Safety regulations or financial legislation might affect the organizations' freedom to make decisions and limit their options significantly. This was highlighted by head of department M82: "We can work out how we're going to do it within our own business–but to a larger extent we're managed pretty strictly by outside influences."

The participants of this study perceived the influence of their industry on decision making to a varying extent. This depended on the level of restrictions of the respective industry's regulations. Several organizations included in this study were limited by legal restrictions imposed on the financial services industry (i.e. organizations 1 and 9), or safety regulations imposed on the transportation industry (i.e. organization 8).

While the relevance and extent of these restrictions varied among the participants, all managers agreed on the influence of their industries' rising demands for and access to data. Manager M41, for example, did not consider the effect of industry characteristics as significant for his decision making, but emphasized the component of data availability: "So I wouldn't say the insurance industry influences me much. It's the data available that probably changes your approach to different things." For certain industries, the increasing appetite for data analytics simply resulted in an extension of their tools and capabilities. For other more traditional industries, the demand for data meant a complete overhaul of their decision-making culture and the beginning of a journey to data-driven decisions. The effects of these different industrial backgrounds and their access to data is further discussed in this section to explore the significance of the industry-level component on the managerial decision-making environment.

Organizations within the sample that had sufficient access to data were primarily in the industries of financial services (organizations 1, 4 and 9), the IT industry (organization

5), and transportation (organization 8). The financial services industry has a particularly data-rich history, as head of department M21 pointed out. While M21's most recent position was within a non-profit organization, he and his colleague M22 had both come from a financial background. M21 elaborated that he had in fact taken this previously instilled data-driven culture and thinking, and applied it to their current, more traditional environment: "that's worked well here. Back in the banking days, definitely the value is toward the data and the analytics. I suppose because of that rigor, people were accustomed to using data to make decisions" (C212).

Due to strict guidelines and regulations, companies in the financial services industry had long been accustomed to data-driven decision making (M21). Additionally, customers and competitors expected data-derived insights in the age of big data, which further increased the relevance of data in this industry, as head of department M94 remarked: "Nowadays, I think there's an expectation from the customer as much as competition from our peers around using data for an even more powerful conversation."

Not all organizations were used to relying on data to inform their decision making; certain industries tend to have less access to data, and therefore adopt a more traditional approach. This low access to relevant data mostly led to high-judgment decisions, which were identified particularly in the creative (organizations 3 and 6) and non-profit organizations (organizations 2, 6, and 7) of this study. These organizations displayed rather traditional cultures and were therefore not very reliant on data when making decisions.

In these industries, managers were more prone to relying on the importance of relationships and values in their decision making. This was brought to attention by executive M61, who relayed his process on deciding which grants to apply for. Grants are required sources of funding for non-profits that cover key portions of their expenses. However, being an established organization by now, M61 often reflects on their early days and forgoes certain grants so younger, less renowned organizations have higher chances: “Why take that scholarship? I guess, it’s because when we first used to get grants, we were the largest grants in the pool” (M61).

In these situations, decision makers preferred their judgment over objective data. Outweighing data with judgment was not always based on benevolence or ulterior motives. Often, simply a lack of relevant data was the cause of these judgment-driven decisions. More recently, these rather traditional organizations have also become more data-driven as data becomes more ubiquitous. Non-profit organizations’ dependence on funding requires a change in decision-making cultures, as funders become more and more data-oriented. Therefore, all decisions that relate to funding applications or reporting to funders are highly data-driven, as executive M61 emphasized: “Funding, finding new sponsors and partners is data-driven. We have to prove the benefits of our organization and the service to the community. That is full quantitative data.”

Executive M71 confirmed this sentiment and described it as a rather new development that can be attributed to the evolution of big data analytics. Funders are more aware of the relevance and the insights provided by data, and therefore require objective data results supporting non-profit decisions:

> What we are seeing is that traditional NGOs like ourselves having to be a lot more responsive to what funders expect of us, and properly measuring and evaluating what we do. But it’s a very recent, very new thing. And it’s not something we’re afraid of. Because eventually, in my view, it helps build our case for saying we should be allowed to

> do more instead of funding other organizations who aren't as effective as us. (M71)

Non-profit organizations ultimately are also still businesses that require data to justify their decisions. In this aspect, non-profit organizations resemble for-profit businesses that need to justify their actions to their stakeholders. Head of department M21 compared his experience in the financial services industry with his current work in non-profit organization 2:

> There [in financial services] it's about predictive: what are the customers wanting to actually do? What behaviors are we seeing and see if we can sell a product. Whereas here [at this non-profit], it's basically the same thing: what are our supporters doing? So we can identify what drives certain behavior to give. (M21)

This growing importance of data access and analytics reliance among traditional organizations exemplifies a gradual evolution. However, organizations' access to data did not automatically correspond in this study with the capability of those organizations to exploit insights from it. The tendencies towards data-driven cultures are represented across almost all industries, with many organizations struggling to achieve the necessary cultural change. This organizational journey to more data-driven decision making is further discussed in the next section, which outlines the different stages and obstacles of this journey.

6.2.5. Analytics Maturity

Early on during the data collection process, it became clear that most managers' understanding of analytics and big data did not cover the full extent of these concepts (section 5.2.1). Furthermore, the findings suggested that big data and even basic analytics were not as ubiquitously used by organizations as the impressions of current literature and vendors suggested. While vendors are found to sell big data as an omni-present solution, most participants were struggling with rather basic analytics tools, and were not ready to adopt big data. However, most organizations were aware of the growing availability and relevance of data, and therefore aimed at becoming more data-driven.

On their journey to more data-driven decision making, the participating organizations were facing similar problems, or had just recently overcome them. This pointed to the concept of adopting data-driven decision making as a key indicator of organizational maturity. The findings were therefore more closely analyzed for characteristics of this ‘analytics’ maturity. This in turn led to analytics maturity being considered as an additional component of the managers’ decision-making environment. Analytics maturity refers to an organization’s analytics capabilities, but also to what extent these capabilities are exploited for decision making and anchored in the organizational culture. The concept of maturity outlined in these findings therefore adds to the understanding of extant literature on analytics capabilities covered in Chapter 2.

Analytics maturity was considered so far-reaching and symbiotic regarding the other environmental factors that it was not added as another hierarchical level, but rather as a parallel influence on the decision maker in addition to the other factors of the ecological framework. Manager M92 confirmed this influence of the managerial decision-making environment when discussing the maturity of his organization: “I think the maturity of data has increased, the importance of data has increased. That might be driven by my role as much as the environment.”

Mapping the participating organizations’ data journey, three themes emerged that could be understood as distinct stages of analytics maturity. This is displayed in Figure 18 below, along with the positioning of the organizations in this study. The numbering of organizations is based on Appendix B.

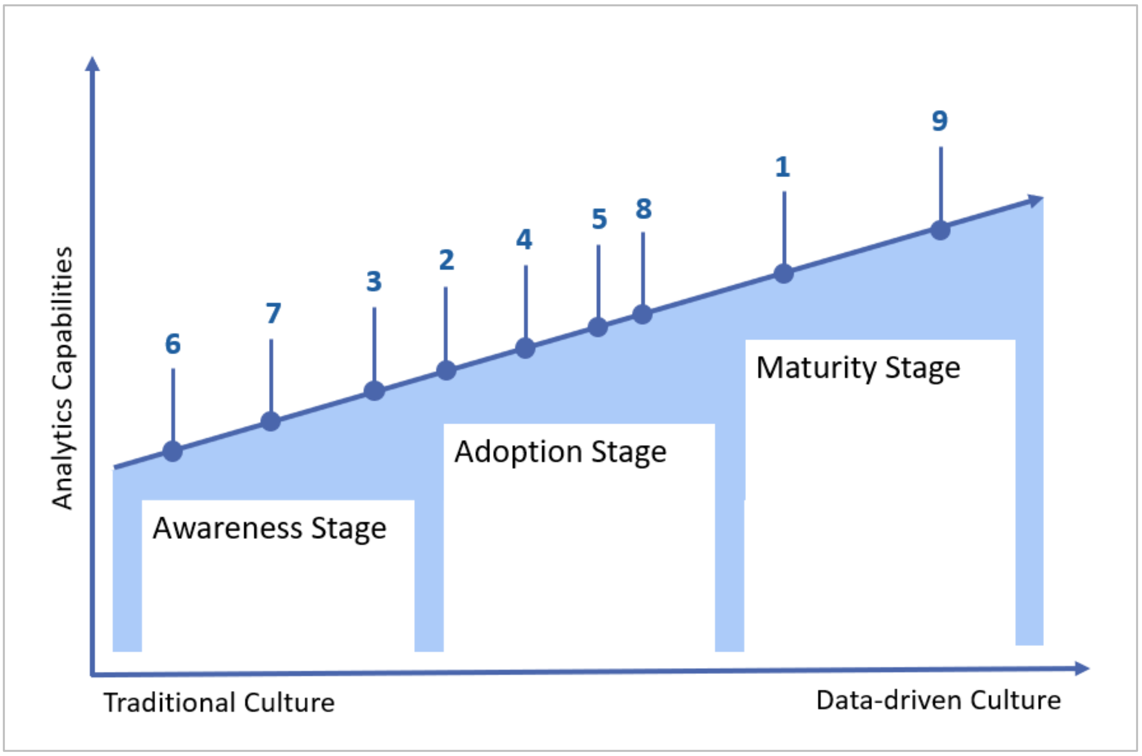

Figure 18. *Data Journey to Analytics Maturity*

The figure indicates the positioning of each stage in relation to the organization's analytics capabilities and its organizational culture. The stages reflect the organization's current relationship with analytics, namely the 'awareness', 'adoption', and 'maturity' stage.

The first stage of the data journey refers to the organization's awareness and recognition of data analytics. All organizations within this sample were to some degree aware of the potential of data analytics and its value for decision making. However, awareness did not equal actual use of data analytics. Organizations in the awareness stage had just recently embarked on their data journey. This pursuit of analytics maturity was not always a conscious decision, but often triggered by the organizational environment. When reflecting on his company's data journey, manager M83 described their trigger as a new external data source, that was giving the organization "access to much more data than we used to have." Being confronted with significant additional amounts of data, the organization started thinking about ways to harvest these sources.

In these early stages of the data journey, it is considered important to get buy-in from leadership, develop ideas for first use cases, and put together a team of skilled analysts (M21). Organizations generally rely on several factors in order to create a data-driven environment that leads to good decision making with the help of analytics. In terms of culture, organizations are advised to focus on showing employees that there is value to be gained from using data, and therefore require easy wins that demonstrate this value (M22, M94). From a technological point of view, the best starting point for this part of the data journey is good data quality, as negative decision outcomes are often attributed to it (M21, M51, M83).

Insufficient data quality is often discovered early in the awareness stage, when organizations delve deeper into their readily available data. This can also unearth errors in previous projects that relied on data, as executive M51 pointed out:

> It's not until you actually strike doing some of these things, that you start cleaning up, because there hasn't been a reason. So, we looked at the data, and actually some of the things that we did in that project last year–we recognized that the data that was more than four years old, was almost useless, for various reasons. (M51)

Organizations observed as being in this stage are 3, 6, and 7. Taking into consideration the insights gained from Chapter 4 and Chapter 5, the allocation of these organizations to the awareness stage matches the decision maker types and decision-making processes chosen by the participants: The managers of these three companies almost exclusively made high-judgment decisions, and belonged to Type D, i.e. the old-fashioned decision makers. Agency 3 was used to advising their customers on their data use and was thus able to work with big data on behalf of their clients. However, the agency itself barely used data, and executive M31 almost exclusively relied on his judgment for decision making. Not-for-profit organizations 6 and 7 were also considered to be in this stage. Characteristically for their industry, these organizations had not had extensive exposure to data that was useful for their purposes. However, with funders interest in data-backed reports and decisions growing, these organizations had to embark on their journeys to a more data-driven culture as well.

After passing the awareness stage, executive M22 reflected upon early projects in this stage and referred to these beginnings as a discovery: "For me this project was a discovery process around how does this thing work - how do I turn this into reliable information rather than a whole bunch of data?" (C221).

Organization 2 could now be found on the border between the awareness and adoption stages. This not-for-profit organization could be understood as having a traditional organizational culture that relied on judgment and experience. However, due to executive M22 and head of department M21, organization 2 had reached full awareness and was currently in the process of changing its culture. Both managers had backgrounds in the finance industry, and therefore had been exposed to the use and application of data in their previous roles. This experience helped executive M22 to assess the strengths and weaknesses of organization 2, and helped drive the initiative of becoming more data-driven:

> We’re not great at making good, well-informed decisions. We haven’t got great access to our data, and I don’t think we’ve got a great understanding of some of our data as well. And with the establishment of our business intelligence capability we’re actually trying to get on top of that data. (M22)

As the example of organization 2 shows, the stage of adoption reflects an organization’s clear intent to become more data-driven. It serves as the first step in actualizing this intent. Other organizations determined to be in this stage are 4, 5, and 8. These organizations might have already hired BI talent, intensified their data collection efforts, or employed additional IT systems. However, their culture remains in transition, and individuals are still (at least partially) exhibiting resistance. Reflecting this state of transformation, Chapter 4 shows that managers of these organizations mostly made high-judgment and balanced decisions. While they were striving for more data-driven decisions, limited access to and experience with data often resulted in experience-driven decisions.

The findings of Chapter 5 also reflect the transition of this adoption stage; the decision makers could be sorted into three of the four different manager type categories. The majority were considered to be Type C, or insecure, managers. A few managers who were particularly influenced by their roles as managers or data champions, could be classified as Type A, i.e. analytics-bent. Lastly, the CEO of organization 5 was considered an all-rounder, i.e. decision maker Type B. No Type D managers were identified in this stage, likely because organizations in this stage would have access to data and encouraged managers to include it in their decision making.

Organizations in this stage display insufficient skills or technology to analyze the data collected. Data might still also need to be distributed among different silos, due to a lack of centralization. The key objectives of the organizations in this adoption stage are to increase their analytics capabilities and employ change management techniques to promote a more data-driven culture. This cultural shift is approached via building trust in data, tackling resistance, and sharing first successes and use cases.

Head of department M84 explained that organization 8 was in the process of creating tools that would allow them to use the additional data they had gained access to, but that were currently not used. While the full potential of data insights could not yet be harnessed, the extent of data use for decision making was still limited: “We have some information that we’re basing decisions on, but it’s still a fairly experience-based decision-making process that we’re going through” (M84). Access to data, which was categorized as an industry-level influence, is therefore considered a significant factor for analytics maturity. This emphasizes the relationship between the concepts with other influences from the managerial decision-making environment.

Similarly, the other levels of the ecological framework were found to play an essential role in affecting an organization’s analytics maturity. Executive M52 explained how departmental factors, including access to analysts and organizational culture, are key components of data-driven decision making. When asked about requirements for decision-making success, M51 described a team that was skilled, able to challenge data and human judgment results, and that espoused an organizational culture that enabled knowledge exchange:

> You need a team of people who are smart, experienced, and able to challenge. So, where there’s a culture where challenging someone’s

> view is acceptable rather than just saying, ‘Oh, the boss said that, so that’s all good’. So, if you have a collegial environment, where people are willing to help each other and share views, then the chances are you might get a synthesis of a good answer. (M51)

Sharing positive results and success stories helps to build this supportive organizational culture, enabling employees to see the potential and effect of data (M51, M85). Maturity eventually comes with gained experiences and familiarity with the datasets, which in turn leads to an even further improved understanding of and trust in the data. Manager M83 confirmed this by sharing his own experience on becoming more familiar with analytics and being able to judge the correctness of results: “What I’ve realized is that, if you operate between certain datasets and metrics every month, you just look at something, and then…You know there is something not right.”

The main obstacle for organizations in the awareness and adoption stages was resistance from employees (n=8). This resistance mainly stemmed from the complexity of the systems and lack of data access (M12, M41, M52, M82, M84, M91, M93). Other factors inhibiting data-driven decisions were the cost of data acquisition and of employing the required talent, and the managers’ lack of analytics skills. Furthermore, different managers have different analytics skills and preferences, a fact organizations must remain cognizant of.

Organizations that have reached the maturity stage are characterized as having their analytics teams and the required tools for data analysis in place. Their organizational culture is supportive of data-driven decision making, yet open to the challenging of data results. A wide and readily available range of data sources are frequently accessed and harvested. Organizations in this stage may additionally have champions for BI, analytics, and data. Their primary objective is to further explore sophisticated data analysis techniques and new data sources, through experimentation, for example, which is further discussed below. These organizations have a positive perception of data and consider it a key asset that improves their understanding of business problems. They also see the potential of data to explain phenomena and justify decisions (n=6).

Organizations 1 and 9 are considered mature. As noted in Chapter 4, high-data decisions were almost exclusively made by these two organizations. Their analytics maturity allowed for successful data-driven decisions. They were also found to make a considerate number of the balanced decisions. Correspondingly, as identified in Chapter 5, the managers of these organizations were mostly identified as both Type B decision makers, i.e. all-rounders, and Type A managers, i.e. analytics-bent. Both organizations are in the financial services industry, and participants have long-term experience with using data for their decision making. Organization 1 heavily integrated data analytics into their operational, tactical, and strategic decision-making processes. Data was used for scheduled reporting purposes, ad hoc discoveries, the piloting of new business segments, and was an embedded driver of the business model. Analytics was described as part of day-to-day work by general manager M12. When daily reports sent by their analysts showed anomalies, “tactically you jump on that straight away. That’s just part of our business process” (C123).

Organization 9 equally embedded analytics in all their key business processes (M93). However, even mature companies still have room to grow, which organization 9 notably recognized. Another characteristic of organizations in this stage is their awareness of their own limitations. Manager M92 identified these limitations in the company’s use of big data: “I understand big data, [but] I don’t use big data yet to make decisions. But we are trying to create the environment where we do." They approach overcoming these limitations with a pragmatic attitude and experimentation.

In these experiments, business owners typically set up small scale control and test groups to trial new business models or ideas. The concept is considered simple but effective, as it provides quick results, objective justification for decisions, and does not depend on historic data or complex analytics (M91, M92). One particular benefit of experimentation is the direct comparison of several different options. General manager M91 especially valued this aspect of experimentation, as it contributed to wise decision making; instead of only seeing in hindsight whether or not a decision was wise, managers are given the chance to see the outcome of their alternatives on a small scale before rolling the decision out on a larger scale:

> The problem [with not experimenting]–and this why experiments are so good–is that you don't know whether you might have gotten a better outcome, had you done something slightly differently. And that's where experiments can contribute to wisdom if you like, a wiser outcome. (M91)

Due to their simplicity, experiments were also found to cause less resistance in users and could even be seen as a gateway to the acceptance of more data use, as M91 highlighted:

> [Analytics] scares a few people, I think that's fair to say. But through that introduction of the process of experiments, we're going to have an ever greater reliance on analytics and analytical supports to enable the experiments to happen in the first place. (M91)

All participants agreed that analytics maturity contributes to the quality and sophistication of data-driven decision making. Reaching this maturity was considered a slow process (M93). Further, organizations identified two primary drivers for moving from the stages of awareness and adoption to maturity. One of the drivers is the promotion of analytics by executives of the organization (M83, M94). As head of department M94 emphasized, leadership is required in order to provide the necessary support, motivation, and necessary authority for switching to data-driven decisions: "It's got to be led by the absolute top of the organization. If it doesn't happen at the very, very top, it won't happen at all" (M94). The other key driver is the sharing of positive results, and the quick gathering of small wins to demonstrate the value and potential of adopting a new decision-making approach (M14, M71).

A general sentiment shared by several participants was to slowly adopt the data-driven organizational culture and thoroughly assess the reasons, requirements, and status quo (M21, M51, M83, M94). Head of department M94, a member of the most mature organization among the participants, provided his experience and insight for less mature organizations, which additionally summarizes the key insights found in this section:

> My advice to people would be: start with the question, not with the data. Where do you believe value could be in your business? And then, what's the fastest, cheapest way for you to demonstrate a test of where that value could be? Do you need to develop an analytical model, or can you simply create a set of simple hypotheses to test? If you don't even know where to start, you probably want to do some analysis, and some interpretation of insights…I think being clear on what things mean is a good start. So where exactly is your problem? Is it in reporting–well that's easy to solve. Is it analysis? Well, that's a business side function, so you need to get the right people focused on

> where they think value could be. If it's insights, do you have no idea of what's going on? Do you have any intuition that tells you things you could test? If it's analytics, it means you start off with hypothesis– fair enough, get some operational research PhD people in to discover if you believe you've exhausted all the insights that will come from just asking your people what's going on. (M94)

As this section showed, the concept of analytics maturity is closely tied to industry-level influences, i.e. data access; organization-level influences in the form of organizational culture; and department-level influences, particularly in the form of available analysts. Analytics maturity should therefore be considered the most critical component of the environmental framework affecting management decision making.

6.3. Discussion

This chapter's findings contribute to extant literature on decision making with (big) data analytics in two significant ways. One key contribution is the creation of a managerial decision-making environment in the age of big data. This holistic framework brings together each of the key decision-making influences, outlining their relation to each other. This chapter's second key contribution is the identification of the most significant environmental influences on managerial decision making. These influences, four in total, were found to be analyst support, organizational culture, access to data, and analytics maturity. Both of these key findings are discussed in the following sections in the context of extant literature.

6.3.1. Ecological Systems Framework

After focusing on decision-making processes in Chapter 4 and discussing different types of decision makers in Chapter 5, this discussion section evolves around the context of those decision makers. There have been several studies identifying the various obstacles organizations and managers encounter when using data analytics (e.g. Alharthi et al., 2017; H.-M. Chen et al., 2017; Davenport et al., 2013; LaValle et al., 2011; McAfee & Brynjolfsson, 2012; Watson & Marjanovic, 2013). Many of these obstacles are a result of external influences on the managerial decision maker. These external influences, which form the context of this study, were therefore explored further to identify exactly which factors in the decision makers' environment influence their decision-making processes. To accomplish this, the ecological systems framework created by Bronfenbrenner (1977, 1979) was used as a lens to systematically assess the effects of the external environment on managerial decision-making behavior.

Introduced in section 6.1., Bronfenbrenner's ecological framework postulates the influence of an individual's surroundings on their development (1977, 1979). The hierarchical levels of influence outlined by this framework were applied to the findings of this research to find an explanation for the collected data, which ultimately led to the creation of Figure 17. The resulting model is a managerial decision-making environment. As the center of the model, the managerial decision maker is influenced by the microsystem, i.e. their department and colleagues. The next level of influences is the mesosystem, representing organizational culture in this study. The outermost identified level of influence found during data analysis was the exosystem, in this case in the form of industry-level influences, or more specifically the industry's access to data.

Bronfenbrenner's (1977) exosystem was also in fact the final layer identified in the context of this research, as the macrosystem–encompassing economic, legal, social, and political systems–did not show any immediate impacts on managerial decision making in this study. Another factor, however, was found to significantly effect managers in their decision making: the analytics maturity of their respective organizations. This factor was interpreted, named, and consolidated to form an important additional influence that interacted with all the other levels of environmental influences, having a direct impact on decision makers.

A practical application of the ecological framework on managerial decision making was found in Harrison's (1995) work on management decision making. His environmental system places the decision maker at its core, with the group–i.e. groups of decision makers–and the organization as the next hierarchical levels. Further external influences then stem from the economic system, social system, political system, and technology.

In the context of this thesis, the social and political systems did not apply directly, as mentioned in the section 6.2.1. These factors come in the form of legal, privacy, and ethical concerns, but they were not explicitly expressed as significant influences by the participants on their decision making. Instead, they are more likely to influence the stages of data collection, which is an organizational concern that was not found to have a direct impact on the actual individual decisions that managers made. If those factors did arise, they were identified as part of the industry or organizational level, similar to industry standards or organizational governance, not as society-level influences.

The economic system as outlined by Harrison was ultimately considered too broad for this study, as it contains findings on employees, customers, competitors and other industries (Harrison, 1995). In this study, these elements were considered separately at the industry and team levels. For this study, technology was also not considered as an external potential influence, but as an inherent influence, as this specific framework evolves around data-driven decision making. The framework created in section 6.2.1.

therefore extends Harrison's (1995) model and applies it specifically to the context of data-driven decision making.

Bronfenbrenner's (1979) ecological framework allowed for the systematic identification of all significant environmental factors influencing managerial decision making, as well as their interactions. This provided the outline for a holistic framework incorporating insights from the previous Chapters 4 and 5. The result is a depiction of managerial decision making in the age of big data as a multi-factorial issue. This original framework is thus seen as a key contribution, as existing frameworks in extant literature proved insufficient to explain the findings of this research, as is further discussed in the following sections.

Generally, extant frameworks in the discipline of information systems serve the purpose of facilitating understanding for complex systems by identifying the different system components and their relationships (Phillips-Wren et al., 2015, p. 23). This understanding is considered paramount for the implementation of information systems to support decision making. While a number of these frameworks were identified in the literature, this research is not exclusively focused on technological aspects of data-driven decision making. Indeed, this more in-depth approach to answering the research questions demanded an interdisciplinary framework that accounted for the diversity among managerial decision makers, different decision types, and the various additional external factors that influenced the decision maker's environment. Selected examples of information systems frameworks that show at least partial applicability to the findings of this study are discussed below.

The earliest applicable model in this context is Huber's (1990) theory of the effects of advanced information technologies on organizational design, intelligence, and decision making. At the time of publication, advanced technology was understood as communication and decision support technologies, e.g. DSS and KMS. Huber postulates that introducing these technologies will lead to their use, which will in turn increase information accessibility. Increased information accessibility is expected as a result to improve the effectiveness of decision making and the organizational design.

While these general mechanisms could be identified in the findings of this thesis, the effects outlined in Huber's theory were not as straight-forward, and not sufficient to reflect the full meaning of the collected data. Firstly, the use of the advanced technology was, in most cases, met with significant resistance. Secondly, mastering these technologies required a significant amount of experience, and therefore only led to an increase of accessible information after a prolonged period of time–if ever.

Changes in organizational design were also considered by the participants of this study to have a positive effect on managerial decision making. Particularly on a team level, the organizational changes that led to increased access to analysts were seen as a key motivation for employing data analytics in decision making. However, Huber's (1990) theory lacks the range of contextual factors accounted for in this study's examination of the decision-making environment. The framework created in section 6.2.1. accounts for a more modern and holistic context, and therefore enhances Huber's model.

A related model with limited applicability was created by Cao, Duan, and Li (2015). This empirical study focuses on a similar, if limited, context, exploring the relations among business analytics, a data-driven environment and decision-making effectiveness. Their findings suggest that a data-driven environment functions as a mediator of the business analytics effects on the decision makers' information processing capabilities. This in turn was found to have a positive effect on decision-making effectiveness. A data-driven environment is understood in this case to as organizational practices that facilitate the use of business analytics activities.

The findings of this study are supported by Cao and colleagues (2015) who found a slight industry influence on business analytics' enhancement of decision-making efficiency. They furthermore conclude that organizational size had no significant effect, supporting the results of this study but contradicting Shepherd and Rudd (2014). In essence, while Cao et al.'s (2015) findings ultimately support the effects of the decision-making environment found in this thesis, the complexity and level of context in their study is limited.

One model that was found to address the conversion of big data into knowledge is the performance triangle, as discussed in Bumblauskas et al. (2017). The model highlights the importance of peoples' relationships, purpose and collaboration in their journey to reach organizational success. Key components of this model are culture, leadership, and systems. Organizational culture and leadership were also identified as key influences on the organization level in section 6.2.3. of this study, as was analytics maturity, discussed in section 6.2.5. The importance of the above factors was clearly emphasized by the managers in this study. However, the model outlined in Bumblauskas et al. (2017) is limited to only these factors, which did not sufficiently represent the experiences of this study's participants.

A more comprehensive model is presented by Shepherd and Rudd (2014), who assess the influences of context on the strategic decision-making process in their conceptual literature review. Four different categories of influences are identified, all of which showed a direct effect on the strategic decision-making process, and consequently a moderating effect on decision outcomes. The first of these categories is the high-level management team, which is characterized by demographic factors, personality, and so forth. This matches the findings of Chapter 5, which outline the influence of different managerial characteristics on the decision-making process. This study extends the model of Shepherd and Rudd by going more into depth and recognizing distinct types of decision makers.

The second factor introduced in their conceptual review are strategic decision-specific characteristics such as motive, time pressure, and uncertainty (Shepherd & Rudd, 2014). This study addressed these decision-specific influences on the decision-making process in Chapter 4, and further contributed by determining three distinct decision types that can be observed in the age of big data. The third factor in Shepherd and Rudd's study is called the external environment. This factor accounts for external elements of dynamism, instability, and so forth. This factor essentially matches the industry-level factors which were assessed as part of the environmental framework of this thesis chapter. Shepherd and Rudd's last factor considers firm characteristics, such as structure, size, performance, etc. In this study, these factors were also assessed, but were also categorized as part of the environmental framework. While the different organizational sizes, etc. were covered in the description of the sample in section 3.3.1., their effect on the participants' decision-making processes were not deemed significant.

Three influence categories of the Shepherd and Rudd (2014) model, namely the high-level management team, external environment and firm characteristics, showed direct effects on the decision outcomes, while decision-specific factors were only found to have a moderating effect. Contrasting results can be seen in the framework depicted in section 6.2.1.: Each environmental factor shows an effect on the managerial decision-making process, but the most immediate effects were identified as the decision type, i.e. the embedded unit of analysis, analytics maturity, and team-level influences in the form of access to data analysts. While Shepherd and Rudd's model included a number of factors that were deemed relevant and significant for the context of this study, their overall structure and the relationships between factors did not suffice to explain the findings of this thesis.

Tom Davenport and colleagues have also provided a framework that covers key elements of a successful analytics program. First introduced in 2010, the DELTA model, as it was named, covers the components of data, enterprise, leadership, targets, and analysts (Davenport, Harris, & Morison, 2010). The first component refers to the structure and quality of, as well as access to, the data that is required for the successful use of data analytics. An enterprise approach to data analytics refers to the implementation of a single and consistent organization-wide analytics strategy, including a unified mission and the absence of data silos. Leadership support is seen as crucial for the success of an analytics program and is a prerequisite to data-driven organizational culture acceptance. Targets in this context refer to the setting of strategic targets by managers to better focus their analytics efforts, as not all parts of an organization's business can be equally analytic. Analysts refers here to the talent with sufficient analytics skills needed to fill positions of professional analysts, but also to advocates and champions of analytics use.

The aspect of data management has been addressed in several sections of this thesis, but the findings of this literature particularly resonate with the analytics maturity component of this decision-making environment. The enterprise factor is also addressed in several of the environmental components, but particularly matches the identified importance of organization-wide access to data analysts. The leadership aspect is addressed as a crucial driver of organizational culture and analytics maturity. Targets have not been addressed as crucial factors within this study, seemed most relevant for the promotion of the use and acceptance of analytics. The importance of analysts has also been highlighted in this thesis, particularly as a team-level influence.

While all of the DELTA model's factors proved to be relevant in the context of this thesis, the model itself does not in the end succeed in reflecting the complexity, dynamics, and relations among the factors in the environmental framework created as part of this study. Most of the DELTA factors could be interpreted as important components of the analytics maturity concept, but on the whole the study fails to match the holistic nature of the managerial decision-making framework in section 6.2.1.

Davenport's DELTA model was extended in a more recent publication by the two factors of technology and analytics techniques, creating the DELTA Plus Model framework (Davenport & Harris, 2017). Technology here refers to the selection of the right tools, enabling more and more employees to meet their data needs independently from analysts. Analytics techniques refer to the ever-growing number of available data analysis methods and an organization's requirement to identify the most suitable methods for their purposes. Both added factors are mentioned in section 6.2.5., as important components in determining an organization's analytics maturity. An application of the six-factor Delta Plus Model is found in a Danish study by Mueller and Jensen (2017) . This study did not account for the factors of analytics techniques but confirmed that the creation of value with big data depended on all six researched factors.

Still other frameworks in the information systems literature proved insufficient to explain the findings of this thesis or had limited applicability due to differences in the scope or setting of the study (e.g. Anya, Moore, Kieliszewski, Maglio, & Anderson, 2015; Cao et al., 2015; Curry, 2016; Elgendy & Elragal, 2016). Curry (2016) , for example, provides a contextual framework that identifies key actors required for a well-functioning data ecosystem. However, this system approaches the topic from a macro-level, mentioning both end-users and vendors in the same breath when identifying factors that are relevant for a well-functioning big data ecosystem in Europe.

While the previously mentioned information systems frameworks offered valuable insights into several of the components identified in the findings, none of them had the potential to provide a sufficient structure for a comparable equivalent to the results of this thesis. The ecological framework thus provided a more suitable basis and lens for exploring the collected data and creating a suitable environmental framework for managerial decision making with data analytics. In the following sections, the components of this environmental framework are further discussed and compared to extant literature.

6.3.2. Team-Level Influences

An immediately apparent influence on the decision makers was the team surrounding them. The findings showed that managers considered access to analysts the primary influence at the team level. This aspect was discussed in the previous section, and the extant literature confirms it as an important component of successful analytics use (Davenport et al., 2010; Müller & Jensen, 2017). According to Wirth and Wirth (2017) , one of the key challenges for organizations is the definition of use cases when it comes to analytics use. They outline the importance of first clarifying the requirements and the actual purpose of the data before wasting time and financial resources on unnecessary data collection and analysis. Bumblauskas et al. (2017, p.16) confirm this, and identify the managers' 'lack of vision' to ask questions that can be answered with data as a key problem of big data analytics.

In these situations, analysts take on the role of challenging managers to further define their questions and determine their requirements. As outlined in the findings, participants saw analysts as a valuable contribution to the decision-making process when taking on this role. Access to analysts was therefore considered a key determinant of successful decision making. Several organizations had centralized analytics units (e.g. organization 1, 8, and 9), which benefitted managers by providing them with organization-wide data, state-of-the-art analytics capabilities, and sufficient human resources to support their data needs. LaValle et al. (2011) confirm this finding by stating that centralized analytics units offer several benefits. As a center of excellence, these units can provide advanced insights, manage the available resources efficiently, and provide governance around data analytics use. They add that these centralized units should be an addition to existing local resources and should not detract from the often valuable close relations that local analysts might have to their own departments.

A key advantage of this close contact with local analysts, is that managers can gain an advanced understanding of the data that informs their decisions, and in turn lead analytics techniques that transform that data into meaningful insights. Janssen, van der Voort, and Wahyudi (2016) confirm the participants' sentiments. They state that managers' ability to interpret the outcomes of analytics and their understanding of the relationships of problem variables significantly improve their decision quality. They add that interactions with analysts are therefore equally expected to positively affect decision quality, as they contribute to the managers' exposure to and understanding of data analytics.

The concept of computer self-efficacy (CSE) introduced in section 5.3.1.3. would support these assumptions. As postulated by Bandura's (1978) self-efficacy theory, peoples' belief in their abilities, and in this case, the interaction with analytics, is highly influenced by other peoples' behavior. To develop confidence in their data analytics abilities and become comfortable in the realm of data-driven decision making, managers greatly benefit from interactions and exposure to analysts.

A key obstacle to establishing centralized analytics units and providing access to local analysts is the aspect of talent management (Alharthi et al., 2017; H.-M. Chen et al., 2017). Organizations face a shortage of skilled individuals that have sufficient experience with data analytics and an understanding for its business applications. Overcoming these obstacles is part of the data journey the organizations undertake on their way to transforming their traditional culture into data-driven decision making.

6.3.3. Organizational Culture

Organizational culture was understood as a major contributor to the success of data-driven decision making by all participants in this study, as well as by the extant literature (Watson, 2016). Managers in organizations with highly data-driven cultures credited their environment for the extent of data they used in their decision making. Participants described the benefits of this culture as being able to defend decisions with objective information and as avoiding flying blind, since the data provided valuable insights. The use of analytical and technical reports as justification in the decision-making process was also seen as a benefit of data-driven cultures, according to the extant literature (McAfee & Brynjolfsson, 2012; Nicolas, 2004).

Organizations 1 and 9, which already embraced data-driven decision making before the age of big data, were found to be furthest along in their data journeys. Having been in a data-driven environment for a significant amount of time provided these organizations with a competitive advantage regarding the exploitation of big data analytics, as well as their progress in terms of analytics maturity. As is stated in the extant literature, these large, data-driven and competitive corporations particularly benefit from increasing analytical capabilities (Davenport, 2006; Huber, 1990; McAfee & Brynjolfsson, 2012). A strong foundation in analytics understanding, skills, infrastructure, and an openness to data use are the advantages that these large organizations have over smaller and/or judgment-driven organizations. The findings of this study serve to this strong relationship between the organizational culture and success in employing data analytics.

The benefit that organizations with a data-driven culture have becomes particularly apparent when looking at the effort and duration of changing organizational culture. But as Ross, Beath, and Quaadgras (2013) outline in their work, this transition to a more data-driven culture should be understood to work best as a gradual shift. A top-down approach, which usually works for most change management efforts, is not recommended in the instance of readying organizations for big data decision making. Ross et al. (2013) advise instead that organizations begin this cultural shift by introducing data-driven approaches into ‘important repetitive work that includes some discretion and some application of rules’ (p.98). Service work is seen as an ideal starting point for this gradual introduction (Motamarri et al., 2017; Ross et al., 2013).

These repetitive tasks should be enriched through clear business rules, metrics should be defined, and decision makers should be provided with sufficient data (Ross et al., 2013). Once these tasks are more data-driven, the expectation is that this culture will slowly spread to most other roles. The authors furthermore point out that in these early stages, problems with business rules, data quality and metrics can also be easily identified. This was confirmed by the findings of this study, as participants often emphasized their struggles in the beginning stages of their data journey and their resulting need to experiment in smaller test environments to more quickly find those problems. These challenges often revolved around data quality issues (M21, M51, M83).

Besides this high-level strategy, the literature outlines several ways to drive overarching cultural change, which are reflected in the findings, and also serve to demonstrate the interrelation between the organizational culture and other influences of the managerial decision-making environment. Watson (2016) suggests several approaches for facilitating the shift towards a data-driven culture.

The first factor Watson (2016) outlines is the use of dashboards. This refers to addressing the varying needs of different managerial decision maker types, as discussed in Chapter 5. Certain managers benefit from a visualization of their data input (Makonin, McVeigh, Stuerzlinger, Tran, & Popowich, 2016; Moore, 2017). Providing managers with dashboards that contain KPIs (Key Performance Indicators) relevant to their and their teams' performance holds them accountable while simultaneously demonstrating the significance of using metrics (Watson, 2016). Participants expressed strong interest in visualized data (M82, M93), and some had initial successes in using KPIs displayed on a dashboard when they framed reaching them as a competition among their employees (C831).

Furthermore, Watson (2016) agrees with Ross et al. (2013) by suggesting that operational decision making should be encouraged, as it allows for the showcasing of the value of analytics for decision making in a scaled and governed environment. This approach is also related to the recommendation of focusing on early wins to overcome skepticism and promote acceptance (H.-M. Chen et al., 2017; Watson, 2016). The participants of this study confirmed the importance of this approach and highlighted their success in sharing positive results (M51, M85) and quick wins as use cases with their employees (M14, M71).

To further encourage each employee to use analytics, decision makers should be more frequently questioned regarding the data sources and analytics techniques used to arrive at their decisions (Watson, 2016). As discussed in section, 6.3.2., analysts can actually take on the role of supporting managers to learn more about the data and analytics to further develop their understanding. Employing incentives for the use of data analytics can work as an external motivator for employees. However, as with most major change management initiatives, not all employees will accept the organizational change. Watson (2016) therefore concedes that some employees will ultimately have to be replaced to create an organization-wide data-driven decision-making culture.

A general difference in organizational culture could be observed when zooming out to the broader context: the industry of each organization. Smaller organizations particularly displayed a more traditional judgment-driven culture. These organizations of small to medium size, i.e. 3, 5, and 6, had not yet needed to justify their decisions in detail. Hanlon (2011) reports on this effect and describes how organizations in small private sectors and family businesses are mostly intuition-driven. In contrast, organizations that had a lot of public exposure were faced with the expectation of justifying their decisions and of therefore employing a rational decision-making process. Consequently, industry context is perceived as a further influence on the managerial decision-making environment and is discussed in the following section.

6.3.4. Industry

The findings of this research suggest a significant, if indirect, influence of industry on managerial decision making. Generally, the findings suggested that participants in a data-rich industry significantly benefited from their organizations' access to data and analytics. As discussed in the previous section, long-term exposure to data can support the slow and steady journey towards a data-driven culture. However, even industries that have historically had access to large amounts of data, such as the financial sector, have faced external limitations when attempting to use that data.

Extant literature confirms this by highlighting that the industry often determines the level of regulations, legal constraints, and level of confidentiality required, which in turn affects the use of data (Hensman & Sadler-Smith, 2011; Richey Jr et al., 2016). The significance of industry influences also seems to outweigh the relevance of organizational size in the context of adopting a data-driven culture. A study by Cao et al. (2015) on the effects of business analytics on decision-making effectiveness examined the influence of these organizational factors. The authors determined that the company size of large and medium organizations in fact had a statistically insignificant impact on the companies' path from business analytics to data-driven decision making. However, they found differences between the manufacturing and professional services industry, indicating a moderating industry-specific effect. Despite this finding, the study fails to delve deeper into the specific differences between the industries.

A significant example of this contradiction between access to data and regulations for data use is the financial sector, which was part of the sample of this study and is further discussed in this section. While today banks are among the industries spending the most on big data and analytics solutions (Goepfert & Shirer, 2018), the banking industry did not have the most impressive start compared to other industries, such as retail, insurance, or internet companies such as Google (Keenan, 2015). Part of the reason for this late entry into big data decision making are the regulations that the banking industry must adhere to, despite having access to large amounts of data. Due to the financial crisis in 2008, new legislation impacted the adoption of big data in the industry, as “trading operations…are re-written to comply with the more prescriptive requirements of the new rules” (Kemp, 2014, p. 484). Participants in the financial services industry confirmed this influence of legislation by stating that they felt an impact of both social and regulatory responsibility (M12, M93).

These responsibilities and the high demand for decision justifications also leads to a rather minimized use of human judgment in the financial services industry. When comparing strategic decision making in the computer industry versus banks and utilities, intuition was found to be more prevalent and had a more positive association with the financial performance of the computer industry (Khatri & Ng, 2000). Meanwhile, banks and utilities reported a negative association with the use of intuition regarding their financial performance. Generally, companies in the finance industry rely to a significant extent on data and objective validation of their decisions (Hensman & Sadler-Smith, 2011).

While there is room for intuition, the prevalent organizational culture is more data-driven (Hensman & Sadler-Smith, 2011; Trönnberg & Hemlin, 2014): “Policies and procedures may impede fast, intuitive decision making in complex, judgmental (that is non-programmable) scenarios because of the accountability and auditing requirements imposed by the industry’s and government regulatory frameworks” (Hensman & Sadler-Smith, 2011, p.57). Shepherd and Rudd (2014) confirm that external control forces organizations to adapt their decision making, as they rely on reporting and formalization of processes.

The transportation industry also faced difficulties in capitalizing on data analytics, even though companies in this industry have a data-rich past resulting from early adoption of computerization and standardization (Kemp, 2014). One of the key problems is information silos within and among organizations that complicate the analysis of data, and therefore the gathering of insights from vast amounts of that data (H.-M. Chen et al., 2017; Kemp, 2014). This was confirmed by the participants as they outlined their difficulties in accessing and integrating the various data sources and gaining permissions from different business units to access certain datasets (e.g. M86). On the other hand, participants were also optimistic about more recent data sources, such as the increasing availability of geographical and sensor data, which provides further insights for planning and maintenance (Alharthi et al., 2017).

6.3.5. Analytics Maturity

The above described influences follow the hierarchical levels outlined in the managerial decision-making environment in Figure 17: the individual decision makers are influenced first by factors in their departments, then by their organization, and lastly by their industry. However, an additional factor was also identified, which could not solely be attributed to just one of the hierarchical levels, as it touches on several of the already outlined factors. This key influence on the managerial decision-making environment was identified as analytics maturity. The concept interacts with several of the hierarchical levels discussed above and is therefore depicted as a parallel force to each of them within the environmental framework.

In the context of this study, the concept encompasses a combination of organizational culture and analytics capabilities. Extensive analytics capabilities and a data-driven culture are therefore seen as the key determinants qualifying an organization as having reached analytics maturity. Analytics maturity also accounts for factors enabling this data-driven culture and these sophisticated analytics capabilities. Qualifying organizations need to be ready for data-driven decisions from a technological point of view (Jagadish, 2014). They also need to consider HR and change management perspectives (Shah et al., 2017), and trigger a cultural shift (Watson, 2016).

Analytics maturity is understood as a state that is achieved by organizations at the end of their data journey after completing the stages of (analytics) awareness and (analytics) adoption. The awareness stage describes an organization's recognition and assessment of the potential benefits data analytics could offer their business. Issues with current technology, data quality or a lack of required skills were identified as hurdles at this stage. The adoption stage signifies the organization's transition from traditional to data-driven culture, and thus the tackling of various related management and technological challenges. Organizations reach maturity once a data-driven culture is adopted; that is, once analytics practices are both embedded in decision making and accepted by the workforce.

These stages were defined by thematically analyzing the data and consulting existing maturity frameworks in the extant literature. During the interviews, managers spoke about their analytics capabilities, organizational culture, acceptance and use of data analytics, and other related aspects. Considering the topic of the study, most participants used qualifiers to describe where they saw themselves in comparison to other companies in terms of data use. Participants referred to their organizations respectively as 'mature', 'far along' in their data journey, in 'early stages,' etc. These qualifiers supported the creation of an analytics maturity spectrum, which is depicted in findings section 6.2.5. in Figure 18.

Extant literature presents a range of analytics maturity frameworks, that depict similar concepts, albeit with differing factors or relations (Lahrmann et al., 2011; LaValle et al., 2011). Business Intelligence (BI) maturity models before 2010 were discussed by Lahrmann et al. (2010) in order to highlight commonalities, differences, and their reliability. Only ten such models had been identified, mostly originating from practice. The authors therefore offered a criticism that extant maturity models did not have a theoretical foundation sufficient to explain the connection between maturity, impact and organizational success (Lahrmann et al., 2011). This shortcoming is addressed in this thesis by considering the concept of maturity as a component of the ecological systems framework of managerial decision making.

More recent articles specifically include aspects of big data maturity (Comuzzi & Patel, 2016; Davenport & Harris, 2017; M. Gupta & George, 2016; LaValle et al., 2011; Motamarri et al., 2017). A selection of these frameworks is discussed below to provide insights into commonalities with and differences to the findings of this research.

An empirical study by Gupta and George (2016) addresses seven resources that are required to build big data analytics capability. These seven resources are data, technology, basic resources such as investments and time, managerial and technical big data skills, as well as data-driven culture and intensity of organizational learning. These factors can be compared to Davenport and Harris' (2017) DELTA model below but are also recognized in the managerial decision-making environment of this study. Particularly for this component of analytics maturity, data and technology, in combination with analytics skills, are accounted for via the extent of analytics capability. Organizational culture is seen as a separate factor from analytics capabilities but is required as a foundational component of analytics maturity. Capabilities refer to the organization's potential to employ data analytics, whereas organizational culture refers to the acceptance and actual use of data-driven decisions.

In 2010, Davenport, Harris, and Morton developed the DELTA model, outlining five components required for the success of a data analytics program. Davenport and Harris then extended this model by two further components in 2017 to account for the extensive requirements of big data. Their model reflects the factors covered in the managerial decision-making environment. The five original components of the DELTA model were accessible and high-quality *data*, *enterprise*-orientation of data and analytics management instead of decentralized silos, *leadership* supportive of analytics, analytics aligned with strategic *targets*, and skilled *analysts*. In 2017, the DELTA Plus model was developed by adding the components of fast-developing *technology*, as well as and different models and tools for *analytics techniques*. All factors outlined by the model are accounted for in the managerial decision-making environment of this study. The importance of analysts, leadership, organization-wide buy-in, and strategic alignment have been identified in the different levels of the framework. Technology, analytics techniques, and data quality are considered factors that are particularly relevant in this stage of analytics maturity, as they define an organization's analytics capabilities.

While these factors are considered prerequisites of successful data programs, Davenport and Harris (2017) additionally outline five stages of analytics maturity. These stages are: analytically impaired, localized analytics, analytical aspirations, analytical companies, and analytical competitors. In contrast, LaValle et al. (2011) identify just three stages: aspirational, experienced, and transformed. To fully assess these frameworks in light of this study's findings, Table 31 below compares all three frameworks of maturity stages.

Table 31. *Analytics Maturity Stages*

<table>
<tr><th>Source</th><th colspan="5">Maturity Stages</th></tr>
<tr><td>Davenport & Harris (2017)</td><td>Stage 1: Analytically Impaired</td><td>Stage 2: Localized Analytics</td><td>Stage 3: Analytical Aspirations</td><td>Stage 4: Analytical Companies</td><td>Stage 5: Analytical Competitors</td></tr>
<tr><td>Findings 6.2.5.</td><td colspan="2">Stage 1: Awareness</td><td>Stage 2: Adoption</td><td colspan="2">Stage 3: Maturity</td></tr>
<tr><td>LaValle et al. (2011)</td><td colspan="3">Stage 1: Aspirational</td><td>Stage 2: Experienced</td><td>Stage 3: Transformed</td></tr>
</table>

The stages of all three maturity frameworks map similar conditions but apply different levels of granularity. In the findings of this research, the awareness stage is the first stage on an organization’s journey toward data-driven decision making. This stage encompasses the first two stages of Davenport and Harris’ (2017) framework, who distinguish between virtually no analytics capabilities, and localized analytics efforts that are only employed in silos. This study does not distinguish between these two stages, as they were considered to pose very similar challenges to organizations. LaValle et al.’s (2011) first aspirational stage encompasses the awareness stage of this research. However, it also goes beyond that and covers parts of Davenport and Harris’ (2017) analytical aspirations stage.

The analytical aspirations stage (Davenport & Harris, 2017) was widely congruent with the adoption stage of this research, referring to the organization’s transition from a traditional to a data-driven culture. More centralized data management efforts are employed, leaders start recognizing the value of analytics, and analysts become more involved in all business units. LaValle et al.’s (2011) second (experienced) stage could be seen as part of this adoption stage, as well as the maturity stage.

In the third stage of this study’s framework, organizations reach analytics maturity and are therefore able to make data-driven and analytics-informed decisions. The organizational culture is accepting and supportive of data-driven decisions, and related practices are embedded in all key organizational processes. This maturity stage encompasses stages four and five of Davenport and Harris’s (2017) framework, which distinguishes between organizations that have reached this level of maturity and organizations that compete on analytics capabilities. These analytical competitors have world-class analysts at their disposal who continuously search for new data sources and ways to analyze data. LaValle et al.’s (2011) third (transformed) stage matches these criteria. Looking at the findings of this research, the last stage of analytics maturity seemed sufficient to cover both of those stages, given that the framework in section 6.2.5. is understood as and displayed in form of a spectrum.

Neither the frameworks from Davenport and Harris (2017) nor LaValle et al.’s (2011) account for organizational culture to the extent of the framework outlined in section 6.2.5. In the findings of this research, culture was identified to be a critical determinant of data use and acceptance and is therefore considered an integral part of the concept of analytics maturity.

While the models outlined above clearly vary from the managerial decision-making framework introduced in the findings, most components can be found and accounted for. The framework developed in this study was specifically created for the findings reported by the participants. The concept of analytics maturity therefore focused primarily on the aspects of organizational culture and analytics capabilities, as these were the key determinants as identified by the managers themselves. Even though the specifics of the models in extant literature might differ from one another, as well as the findings of this research, the key assertions were found to match. Equally, similar challenges to reaching analytics maturity were identified in both this study and in the extant literature.

Technological challenges are one of the first challenges organizations encounter on their data journey. In particular, insufficient data quality and systems incapable of processing the organizations' data were mentioned as key problems by the participants (M21, M51, M83). As discussed in the literature review, establishing an infrastructure capable of supporting big data and advanced analytics incurs substantial costs for organizations (Alharthi et al., 2017). Therefore, management is advised to select the right framework and tools for big data storage and analysis carefully, and to thoroughly consider their organization's needs (McAfee & Brynjolfsson, 2012; Watson & Marjanovic, 2013). Experimentation with various tools is recommended in a rapidly changing product landscape in order to find the best fit with the organization's use cases (Wirth & Wirth, 2017). Given the different managerial decision makers, as identified in Chapter 5, organizations need to cater to the varying needs of their managers.

Reaching analytics maturity at the end of an organization's data journey depends on a variety of contributing factors. Leadership support is particularly crucial (Davenport & Harris, 2017; Davenport et al., 2010; Ross et al., 2013; Watson, 2016). Both leadership support and managerial oversight might be required when it comes to enforcing the use of a single source of truth, and therefore a consistent, integrated, and well-maintained foundation for data-driven decision making (Ross et al., 2013). In addition to leadership support, coworkers and fellow employees are also found to have a significant effect: "Based on findings of critical success factors literature, overall organizational support in the form of sponsorship and championship are preconditions to establish successful BI [business intelligence] capabilities" (Lahrmann et al., 2011, p. 5).

This was especially highlighted in company 9, which had champions for business intelligence, data, and experiments. Particularly its instances of experimentation helped characterize organization 9 as a very mature organization in terms of analytics; indeed, constant experimentation is part of Watson's (2016) suggested framework towards a data-driven culture. He postulates that analytics-driven organizations heavily rely on regular experimentation to inform their business decisions. Driven by organization 9's champion for experimentation, the company had begun using experiments as a decision-making tool, and the practice found quick acceptance. As the participants described, business owners quickly adopted the practice of setting up these experiments to trial new business models or ideas.

These experiments were seen as a simple, yet effective method for obtaining quick results. They were therefore considered a reliable way of introducing facts-based decision making. Through experimentation, managers were able to see the benefits of objective justification and data-based information for decisions without engaging in complex analytics or searching for historic data (M91, M92). In contrast to descriptive historical data, experiments offered the benefit of comparing actual decision options in a scaled environment, enabling realistic predictions. Additionally, due to their benefits and ease of use, experiments were met with less resistance and encouraged managers to adopt more data-driven decision-making processes.

This acceptance of data use in decision making is the most important indicator of analytics maturity, according to how this concept is woven through the context of this study. In contrast to mere awareness and the interim stage of adoption, analytics maturity refers to the actual use of data analytics to improve decision-making quality and success. Analytics maturity is therefore found to be a highly significant component of the managerial decision-making environment, with important relations and connections that span all other influences in the framework.

6.4. Summary of Findings and Discussion: Chapter 6

Even though environmental factors influencing decision making were not incorporated into the research from the outset, participants reported frequently and unprompted on factors influencing their decision-making process that exceeded decision types, decision context, and personal preferences. To explore these environmental factors, the ecological systems framework, originally developed by Bronfenbrenner (1977, 1979), was employed as a lens for constructing an outline of the managerial decision-making environment. This lens, consisting of influences at the individual, the microsystem, mesosystem, and exosystem levels, corresponded well with the managerial, team-level, organization-level, and industry-level influences identified in this study. The application of these levels is further summarized below. The macrolevel of Bronfenbrenner's framework was identified as general big data concerns, such as legal and privacy aspects; however, those aspects were not identified as key components of the managerial decision-making environment and were therefore exempt.

At the team level, the main influencing factor was identified as 'access to analysts'. The analysts typically took on the role of the challenging counterpart in the decision-making process, providing managers with learning opportunities to improve their skills, and ensuring that the manager they were supporting had access to high-quality data.

The availability of analysts was, in turn, influenced by whether the organizational culture valued and prioritized data-driven decision making. Therefore, at the organizational-level, the key influencing factor was found to be organizational culture, and whether analytics was used and accepted. In fact, culture was found to be even more crucial than technological challenges and analytics techniques in the decision-making process.

At the industry-level, whether or not an organization operated in a data-rich industry influenced to a certain degree the organization's tendency to successfully adopt a data-driven culture. These influences at the industry-level could be placed into three categories. First, organizations experience restrictions due to industry standards or regulations that impact what data they can use and how to use it. Second, organizations are dependent on the availability of and access to data from within their industry. Third, organizations within data-rich industries are increasingly expected by customers and competitors to use data-derived insights in the age of big data.

In addition to the influencing factors corresponding to the different levels of the ecological system framework, a final influencing factor was identified that extends across all these levels: analytics maturity. Analytics maturity refers to the combination of an organization's analytics capabilities, the extent to which these capabilities are exploited for decision making, and their embeddedness in the organizational culture. It contributes significantly to the quality of data-driven decision making and was found to be the most important environmental factor affecting managerial decision making, prompting the need to explore its influences in more depth.

Analytics maturity was found to consist of three stages. The first stage, awareness, describes an organization's recognition and assessment of the potential data analytics could have for their business. The second stage, adoption, signifies the organization's transition from traditional to a data-driven culture by tackling various management and technological challenges. The third stage, maturity, is achieved once a data-driven culture had been adopted, analytics practices have been embedded in the decision-making process, and the use and benefits of analytics are widely accepted by the workforce.

While several different frameworks were identified in the extant literature, none of them covered the same ground as this thesis regarding the environmental, individual, and decision criteria that influence the decision-making process. The result is a holistic original managerial decision-making framework that accounts for all of these interdisciplinary factors.

CHAPTER 7: CONCLUSION

Managerial decision making in the age of big data has been found to be highly reliant on both human judgment and data analytics, each in varying capacities and roles. The decision-making process was influenced significantly by the decision context, as well as managerial perception and understanding of human judgment and data analytics. These factors in turn were influenced by the managers' characteristics, such as their previous relevant experience, training, and aptitude, but also by their environment. Organizational maturity in regard to analytics, the managers' co-workers and leaders, as well as their industry, were therefore also found to be of importance to the managers' decision-making behaviour. The implications and contributions of these findings will now be discussed in more detail to emphasize the importance of this study. Furthermore, study limitations as well as recommendations for future research will also be addressed. The chapter and thesis conclude with a reflective journey providing insights on the research journey and sharing final thoughts.

7.1. Overview of Findings

The aim of this study was to thoroughly and holistically explore managerial decision making in the age of big data. Many organizations have perceived the increasing amounts of available data and methods of data analysis as a value-adding opportunity. However, once organizations begin employing data-driven decision making, they encounter numerous challenges that are often difficult to overcome. Big data is therefore seen by some as a valuable addition to traditional decision making, and by others as a hindrance, too complex, or not applicable. To learn more about how individual managers perceive big data, and how they incorporate it into their decisions, this research posed the following two research questions:

1) How do managers perceive the role of advanced analytics and big data in the decision-making process?
2) How do managers perceive the alignment of advanced analytics and big data with more traditional decision-making approaches such as human judgment?

To cover the different facets of data-driven decision making and to identify key influences on the managerial decision-making process, this study employed a qualitative, multi-level research design. The first level of analysis addressed decisions as the embedded unit of analysis, further identifying significant decision types that influenced managerial decision making in Chapter 4. For the purpose of this study, 25 participants shared several critical incidents that then became the main data source for this phase of the analysis. Their case study interviews were additional sources of valuable information, often complementing or contradicting the gained insights from the critical incidents. Looking at both perspectives enabled deep insights into the changing decision-making processes of managers, as well as the relevant influences on these processes.

In Chapter 5, the second and main level of analysis focused on the managerial decision maker. The chapter builds on the decision-making process insights gained in Chapter 4. The managers' understanding of big data and analytics was assessed first to determine the participants' familiarity with the topic. Then the significance of managerial characteristics for their decision-making processes was explored, differentiating between the four different types of managers, highlighting their varying preferences, experiences, and so forth.

Lastly, the final findings and discussion Chapter 6 was added as it became evident from the analysis of the results that there were additional influencing factors. It explored the last level of analysis, i.e. the case context. This led to the identification of several external factors that showed a significant impact on individual managers and their decision making. These factors were arranged into a managerial decision-making environment according to the directness of their impact and relation to other factors. This framework was created using the ecological systems framework as a lens. Significant external factors were identified on the team-, organization-, and industry-level. Furthermore, the component of analytics maturity was determined as a key influence in this environment that spanned across several influence levels.

7.2. Theoretical Implications

The extant literature has provided numerous insights on big data technologies, its impact on different industries, corporate performance, and analytics techniques. However, the application of these insights on an individual level has fallen short. A similar statement can be made about the extant literature in the field of decision making. Various studies have managed to convey understanding of different forms of decision making.

The theoretical foundation of this thesis is an example of this: For one, the dual process theory has provided key insights into the difference between the use of intuition and reasoning in decision making (Bazerman & Moore, 2013; Kahneman, 2003). The theory postulates the existence of two different systems, one of which is characterized as automatic, unconscious thought (Stanovich & West, 2000), the other as a deliberate use of analytic intelligence (Dane & Pratt, 2007). Further academic work, such as the Unconscious Thought Theory (Dijksterhuis & Nordgren, 2006) as well as seminal work on decision-making processes (Bazerman & Moore, 2013; Eisenhardt & Zbaracki, 1992; Harrison, 1995; Mintzberg et al., 1976; Simon, 1960) also contributed to the understanding of decision-making processes. While the literature provided a rich foundation, it did not account for the changing circumstances of decision making in the age of big data.

This exploratory, in-depth study built on this theoretical foundation and contributed to the listed works in four major ways. The first of these theoretical implications was achieved by assessing the validity of seminal decision-making process work (Bazerman & Moore, 2013; Eisenhardt & Zbaracki, 1992; Mintzberg et al., 1976; Simon, 1960) in the age of big data. These seminal decision-making models and theories were applied to this study's research data collected in the context of data-driven decision making. The findings confirmed that decision-making processes still consisted of three main steps: identification, development, and selection. However, several observations led to an improved understanding of these steps in a data-driven environment, concluding that their length and thoroughness were affected.

In the identification step, four distinct triggers were identified in the context of data-driven decision making, and analytics was found to be an important one of these four initiators of the decision-making process. Analytics furthermore contributed to the decision-making process by providing additional insights in the development step, which allowed for a more thorough development and evaluation of alternatives. The most significant benefit of adding data analytics to the decision-making process was identified in the selection step, as data allowed managers to objectively justify their choices to other stakeholders.

The second theoretical implication stems from the use of the dual process theory (Bazerman & Moore, 2013; Dane & Pratt, 2007). The two-system view allowed for the identification of distinct roles that analytics and human judgment have in the decision-making process, in which stages, and to what extent. This highlighted how data's growing potential is leading to an increased importance and variety of the roles analytics fulfils within the decision-making process. These insights led to the extension of the classic decision-making processes (Bazerman & Moore, 2013; Eisenhardt & Zbaracki, 1992; Mintzberg et al., 1976; Simon, 1960) in order to account for the different roles of data analytics and human judgment, furthering current understanding for the use of both. The findings also showed that the influence of Systems 1 and 2 differed depending on the decision type the managers encountered, which led to the next contribution.

The third theoretical implication lies in the addition to extant decision categories (Ackoff, 1990; Snowden & Boone, 2007), which were deemed insufficient in explaining the findings of this study. Therefore, this thesis contributed by putting forward new decision types that more accurately reflect decision-making processes in the age of big data. These emerging decision types were defined as high-judgment, high-data, and balanced decisions, according to their extent of data and judgment use. Furthermore, it was examined which decision situations would benefit of which decision type, providing insights on when data and judgment are most appropriate to use.

The fourth theoretical contribution goes beyond individual decision-making processes and delivers insights regarding the decision maker's environment. To this end, Bronfenbrenner's ecological systems framework (1977, 1979) was used as a lens to view the collected data from a holistic perspective and identify key influences on managerial decision making in the age of big data. While Harrison (1995) has created a version of this framework for decision making, this study builds on it by applying the framework to the specific context of data-driven decisions.

The creation of a managerial decision-making environment in the age of big data provides valuable insights, as it highlights key internal and external influences: the individual managers themselves; their team-level influences such as the access to business analysts for support with data-driven decisions; organizational-level aspects such as the prevalent organizational decision making culture, traditional or data-driven; and industry-level influences such as the access and exposure to data. The framework also incorporates the concept of analytics maturity, providing this concept with a theoretical foundation, which had been criticized previously as missing (Lahrmann et al., 2011). This holistic look at managerial decision making offers an extensive foundation for future research.

7.3. Methodological Contributions

The methodology underlying this research contributes by offering a combination of CIT and case study research, which, to the researcher's knowledge, has never before been employed in such depth. The combination of both methodologies facilitated a data collection and analysis approach that allowed for the collection of rich, in-depth data that connected real-life experiences with general perceptions. The approach provided a contrast between managers' actual decisions and their views on general decision-making processes. This gave participants the opportunity to reflect on their own decision-making behavior.

The methodology applied in this research was, to the best of the researcher's knowledge, the first of its kind by combining CIT and case study research together. Both methodologies have previously been used individually in studies on decision making (e.g. Coetzer et al., 2012; Popovič et al., 2018; Trönnberg & Hemlin, 2014); however, using critical incidents as an embedded unit of analysis within the case studies allowed for the collection of particularly rich data. For the field of decision-making literature, this combination shows great promise as a significant methodological contribution, as it enabled both the analysis of data in the context of real-life experiences and general perceptions from the same participants. The approach consequently provided a contrast between managers' actual decisions and their views on general decision-making processes. This gave participants the opportunity to reflect on their own decision-making behavior, which led to positive feedback from the managers taking part in the study.

The combination of both methods particularly benefitted the CIT part of the study. Participants were often hesitant at the beginning of the interview, were unsure about the topic, or did not have example decisions ready. However, when answering questions from the case study portion, they became more at ease and often remembered decisions from their past. At these points, the CIT questions could be asked to add further incidents to the sample. Furthermore, employing CIT provided an interview framework that led to the collection of thorough and comparable data. The collected incidents could as a result both be analyzed within the context of their cases and could also be cross-case analyzed in the content analysis.

The combined methodology allowed for a variety of analyses, as can be seen in the multi-level analysis of this study and enabled a holistic exploration of the topic. The specific questions and preparation material required for the application of this methodology, as discussed in the methodology section 3.3.2., can therefore also be recommended for future research on decision making.

7.4. Practical Contributions

Given the topical nature of the research focus, the findings of this study made several practical contributions. An immediate contribution participants identified was the opportunity for reflection that the interview instrument provided them with. By preparing for the CIT section and responding to the case study questions, managers reflected upon their past decisions.

Reflective thinking is considered an important component of judgment and decision making (Wray, 2017). However, managers do not always engage in reflective thinking, are often unaware of the reasons for their choices, and might only show minimal concern for those reasons (Harrison, p.10). Their participation in the study itself can therefore already be considered a practical contribution, as it can be replicated as a beneficial practice for managers. This was confirmed by several participants, who referred to the interview as a helpful exercise, like executive M61, who highlighted: “It’s been quite good actually to think these things out. I really haven’t sat down and stopped and thought about these things.”

The interview experience also provided the participants with more clarity around their own decision making and the role of data analytics in it. Manager M41, for example, emphasized how he was not aware of how much data he had been using until he prepared for the interview. He mentioned that the interview made him realize just how reliant he was on data analytics for his decision-making processes. Managers were furthermore provided with a report of the initial findings after the interview, which was appreciated and created more awareness (M91).

Looking beyond the pool of participants, the study also contains practical contributions for individual managers and organizations: for one, the upcoming textbook ‘Management Decision-Making, Big Data and Analytics’ by Gressel, Pauleen, and Taskin (2020) guiding managers on their journey to becoming apt decision makers in the age of big data.

One of these contributions is the definition of different decision-making processes, according to decision types and the extent of data and judgment use. These processes can assist managers in finding ways to balance data and judgment use and adjust the extent of this use, depending on decision-specific factors. The explanation of the various roles of data and judgment furthermore clarify their distinct purpose, benefits and relations in the decision-making process. Understanding these distinct roles enables managers to make more informed use of them and consider their benefits and drawbacks.

Organizations planning to embrace a more data-driven culture can also draw valuable insights from the findings of this research. The distinct managerial decision maker types discussed in Chapter 5 can particularly support the approach of increasing the acceptance of data use among employees. The findings revealed the participants' understanding of analytics and big data to be often limited. Despite the limitations of this understanding, however, it was found to highly impact the managers' trust and actual use of data in their decision-making processes. As such, it was one of the key factors that served as a distinguishing criterion when establishing different types of managerial decision makers. These four different types, 'analytics-bent' (A), 'all-rounder' (B), 'insecure' (C), and 'old-fashioned' (D) were defined by the managers' characteristics, preferences, experiences, training, and understanding of analytics.

Every decision maker type was found to have different requirements for data-driven decision making. While some managers merely required access to good quality data, others relied on analysts, training, and peer support. By being given the tools to distinguish between four different types of managers, organizations can customize their change management approach to their employees. Each manager type displayed different preferences and varying requirements. Organizations who meet these varying needs with more customized solutions can expect the resistance of employees to decrease.

Furthermore, organizations can gain valuable insights on external factors that influence their employees' decision-making behavior. The managerial decision-making environment developed in Chapter 6 summarized these external influences, their interactions, and the immediacy of their impact on the individual decision maker. This knowledge can assist organizations in creating a beneficial environment for data-driven decision making. The concept of analytics maturity can particularly inform the planning of an organization's data journey. The information captured in the different stages outlined in the chapter can convey insights into the organization's current stage, but also prepare it for upcoming obstacles.

7.5. Limitations and Suggestions for Future Research

This study aimed at providing a holistic view of managerial decision making in the age of big data by applying a rigorous research methodology that was best suited to answer the research questions. However, certain limitations should be pointed out. One such limitation is the use of qualitative research methods and the resulting limited generalization of the findings (Walsham, 1995). The insights outlined in this study are embedded in their context. This means that the results gained from the 25 participants from a total of nine organizations cannot realistically be transferred beyond these companies without reservations. The findings should therefore be considered as propositions or hypotheses to be tested in different contexts in future research projects.

More specific limitations pertaining to the use of case study research are the aspects of triangulation and sample diversification. Case study research relies on triangulation to ensure consistency and credibility (Yin, 2014). As described in Chapter 3, this study employed data source, methods, and theory triangulation. However, the use of data source triangulation is considered to be limited. This was mainly due to the nature of the research and the confidentiality of managerial decisions. Access to the documents or systems of the participating organizations was not an option in most cases and would have furthermore required a very high technical understanding on the part of the researcher.

One aspect of the sample composition was considered a further limitation, i.e. the imbalance of male and female participants. Female participants were underrepresented, which was attributed to the seniority level required of participating employees. As outlined in Chapter 3, efforts to include more female participants did not achieve the desired results. However, there were no clear differences found between the answers of participating male and female managers. For example, while manager M72 referred to her experience as a mother as a significant influence on her decision making, this did not signify a gender difference, as male participants also referred to their experiences as parents as important influences on their decision making (M12, M31, M41). As stated by Harrison (1995), there is no significant evidence that male and female leaders behave differently in their managerial roles. It may also be worth noting that this study is not the first in the field of information systems with a low ratio of female participants (Thomas & Bostrom, 2010).

Another limitation regarding the methodology employed was the number and nature of the collected critical incidents. When creating the research design, the sample of incidents was envisioned as balanced, reporting equally on negative- as well as positive-outcome decisions. Obtaining a balanced sample of incidents was expected to enable the identification of positive as well as negative influences on the decision-making process.

At the conclusion of data collection, only three of the shared incidents had negative outcomes. However, this did not prevent the identification of negative influences on the decision-making process: several of the positive-outcome decisions reported significant obstacles, setbacks, and complications encountered during the decision-making process. The limited number of negative outcome incidents therefore did not prevent the research objective of identifying negative influences on managerial decision making.

The overall number of collected critical incidents is considered another limitation, as it was below the target of three to five incidents per participant. Even though participants were sent forms in preparation for recollection of the incidents, many of them were nonetheless unprepared. The participants that were prepared rarely adhered to the instruction asking for a description of three to five incidents. This was in part attributed to a general limitation of CIT, as it relies on the participants' ability to recollect past events (Coetzer et al., 2012). On average, participants contributed only 1.6 incidents. This low number led to the increase in the initially planned sample size of 12-15 managers. As saturation had not been reached, the number of scheduled interviews was increased to 25. The eventual number of usable incidents was 43, which matches the quotient of 40-50 incidents of other studies reaching theoretical saturation (Gogan et al., 2014).

There are several reasons that could be attributed to the suboptimal turnout of critical incidents. For one, several participants were uncomfortable with the topic, as they were not very familiar with the subject of analytics, did not understand the terminology, or simply felt inferior to competitors due to the impression of ubiquitous big data use covered in the media. However, this leads back to the benefits of combining CIT with case study interview questions: as described above, participants at times felt more comfortable during the course of the interviews, and thus began sharing incidents as it carried on.

Another reason for the low number of incidents, that could also be related to the participants' insecurity around the topic of big data was uncertainty; participants seemed unsure of which decisions to pick, or which decisions might be most relevant. Several of the managers were also unprepared, or unwilling to share sensitive information, which impeded the amount of detail that was provided in describing their decision-making process (e.g. M91). This hesitance to share information might have also contributed to the low number of shared decisions with negative outcomes, even though this was encouraged.

Not only due to these limitations but also to generally expand on the insights gained in this study, further research into data-driven decision making–particularly decision making informed by big data and advanced analytics–is advised. As this study contributed to the general understanding of decision-making processes in the age of big data by identifying distinct roles of analytics and human judgment use, these findings could be further explored in depth and breadth. For one, this study could be replicated in different geographical settings to explore cultural effects and differences in countries that are (less) further progressed in regard to big data. For increased generalizability, a quantitative study could be conducted as an extension of this thesis, as demonstrated by Taskin, Pauleen, Intezari, and Scahill (2019). An international sample with respondents from all over the world would particularly benefit this purpose.

To expand on the insights gained in Chapters 5 and 6, further in-depth qualitative studies could explore in more detail the nuances of different managerial decision maker types and the effects of their environment. This study distinguished between four managerial types focusing on their different approaches to decision making. Further characteristics could be explored and focused on. Behavioral studies using storytelling might be a suitable approach for this. Focusing on the management decision-making environment, longitudinal studies set in companies at the beginning of their data journey would be an interesting methodology. These approaches could provide further insights into aspects of organizational culture shifts, change management, and technology adoption. Specifically, action-based research exploring customized training for different managerial decision-making types could provide valuable insights for organizations.

7.6. Reflective Journey and Final Thoughts

Big data has been promising advantages to innovative companies that are willing and able to exploit its capabilities (Gantz & Reinsel, 2012). Businesses and managers are therefore eager to capitalize on big data and build a competitive advantage. This can be seen in the form of their yearly spending, as the revenue generated by big data and business analytics (BDA) is expected to reach $189.1 billion in 2019 (Goepfert & Shirer, 2019). One of the ways for organizations to realize the value of big data is by incorporating it in the decision-making processes of managers.

Decision making is the most critical component of a manager's profession (Simon, 1960). More so, managers' decision-making skills determine their effectiveness (Harrison, 1995). Big data has the potential to significantly improve this decision making (Bumblauskas, Nold, Bumblauskas, & Igou, 2017; Davenport, Barth, & Bean, 2013; McAfee & Brynjolfsson, 2012). However, not all managers are successful in incorporating big data into their decision-making process, as it requires a certain way of thinking (S. Shah et al., 2012).

This study aimed at identifying what a successful decision-making process is, how it balances (big) data analytics and judgment, and how managers and organizations can get to that level of effective decision making to capitalize on the value of big data. Setting out on this research journey, initial plans evolved into the thesis that is presented here today. While the reviewed practitioner and academic literature left the impression of big data being an omnipresent phenomenon, early stages of sampling and data collection showed a much lower awareness of big data among organizations. One of the first adjustments to this research was therefore in scope.

The initial outline of this research focused solely on big data and advanced analytics use in managerial decision making. However, this focus had to be extended to the use of more traditional BI&A tools in order to represent an accurate picture of the various organizations at the point of data collection. While all organizations in the sample were on a journey to data-driven decision making with the eventual goal of using big data, most of these organizations were still in the awareness stage of analytics maturity. These organizations were not immersed in big data, but mostly still relied on simpler BI functionalities and descriptive analytics. In order to provide an accurate depiction of current decision making in these organizations, this exploratory study therefore adapted its context.

Another adjustment to the scope of this research can be attributed to its exploratory nature. Initially, the research focused on decision-making processes and the managerial perceptions thereof, as is illustrated in the research questions. This initial setup, however, was extended due to early findings in the data collection. The heterogeneity of managers came to be seen as a significant determinant of the decision-making processes they followed. Multi-level analysis therefore became an essential tool to transform the data collected into holistic insights. It became clear, that the understanding of managerial decision making went beyond process steps and decision types. In order to fully comprehend why managers acted in certain ways, they themselves had to be examined more closely.

When differentiating between the distinct managerial types, external factors in the form of the managers' environment were found to significantly contribute to their decision making. During the interviews, the participants often brought up factors in their external environment that had a significant influence on their actions. Once more, this led to an extension of the scope of findings. The ecological systems framework was therefore selected during the course of data collection and beginning stages of data analysis in order to fully explain the diverse levels of influences on managerial decision making.

Another adjustment in response to challenges encountered during data collection could be seen in the increase of the sample size. Reflecting upon the research design of this thesis, the data collection methods delivered the expected rich quality of insights, but not the anticipated quantity. Early in the data collection, it became clear that managers were not as willing to prepare and share the average 3-5 incidents that are common in the use of the Critical Incident Technique. For several of the companies, especially small- and medium-sized ones, it was also impossible to get access to more than two participants. The initial research design had different targets, expecting 12-15 participants, in 3-4 companies, each sharing 3-5 incidents. These targets therefore had to be adjusted to include more participants from a greater number of organizations. Overall, this led to the inclusion of more diverse contexts and environments. Despite the required adjustments, the data collected was therefore very rich and particularly the use of multi-level analysis enabled meaningful insights and significant contributions.

Through the analysis of managers, their decisions, and their environment, a holistic framework was created that accounts for all the identified factors in a single framework. While the initial setup of the study would have led to a research outcome solely focused on the decision-making process itself, this more comprehensive framework can now be used as a baseline for managers and organizations to create a roadmap, evaluate where they stand, and what potential next steps are to improve their decision making even further. As decision making is a complex process, this framework is by no means complete, however, it is a step closer to understanding managerial decision making in this modern age, where technology is prevalent.

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APPENDICES

Appendix A. Information Sheet

Advanced Analytics and Decision Making:

An Exploration of the Roles of Advanced Analytics and Human Judgement

INFORMATION SHEET

Project Description and Invitation

This project aims at exploring the role of advanced analytics and human judgement in management decision making, and is part of the PhD Management program of the researcher Simone Gressel. The main questions driving this research project are: How do managers perceive the role of advanced analytics in the decision making process? How does advanced analytics align with more traditional decision making approaches such as intuition, experience, judgment, and wisdom? Through your participation you could contribute to a deeper understanding of practical aspects of the decision making process as well as the identification of critical factors that lead to successful and prudent decisions. Based on these findings strategies for improved decision making will be developed, and a deeper understanding for the role of big data is hoped for. Participating organizations will receive an executive summary of the results in the context of current best practices.

Participant Identification and Recruitment

Managers and key decision makers, such as yourself, that are confronted with decisions that are at least partially based on advanced analytics results (such as from big data or predictive analytics), will be recruited for this research to gain a unique practical perspective of the research project. Participants will be selected from several organizations and will have different experience levels with decision making and analytics. Approximately 20-25 managers will be interviewed in total (3-5 managers per organisation) to provide diverse perspectives and backgrounds.

Project Procedures and Data Management

Your participation in this research would be in form of a two part interview, reporting on 3-5 critical decisions you had to make in the past with the help of advanced analytics, and that led to significantly positive or negative outcomes. Furthermore, you would be asked to reflect on your general perceptions on decision making with advanced analytics in the second part of the interview.

The interview is expected to be at most 60 minutes long. The interview will be sound recorded and transcribed and you will be able to review the transcript. Your details will be kept confidential and findings will be reported in a way that will insure your anonymity. All details that could potentially identify individuals or the organisations in which they work will be removed from any research publications.

Participant's Rights

You are under no obligation to accept this invitation. If you decide to participate, you have the right to:

- decline to answer any particular question;
- withdraw from the study (up until one week following the interview);
- ask any questions about the study at any time during participation;
- provide information on the understanding that your name will not be used unless you give permission to the researcher;
- be given access to a summary of the project findings when it is concluded;
- ask for the recorder to be turned off at any time during the interview.

Project Contacts:

Simone Gressel (project researcher)
PhD Candidate
School of Management, Massey University
Email: S.Gressel@massey.ac.nz

Dr. David Pauleen (project supervisor)
Associate Professor
School of Management, Massey University
Email: D.Pauleen@massey.ac.nz

This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named above are responsible for the ethical conduct of this research.

If you have any concerns about the conduct of this research that you wish to raise with someone other than the researcher(s), please contact Professor John O'Neill, Director (Research Ethics), telephone 06 350 5249, e-mail humanethics@massey.ac.nz

Appendix B. Participants Demographics Data

Participant #	Organization	Gender	Age	Experience DM (years)	Experience Analytics (years)	Experience Big Data (years)	Experience in Role	Position	Department	Organization Size	Industry	Academic Qualification	Formal Training in Management	Formal Training in Analytics
M01 Pilot	1	Male	30	4	2	<1	2	Analyst	Analytics	Large	Financial Services	Master of Information Management	Prince 2, AGM Change Management	None
M10	1	Male	47	25 +	25+	10	15	C-Level	CEO	Large	Financial Services	Bachelor of Management	Management Courses	Through Degree
M11	1	Male	42	17	4	4	4	Manager	Marketing	Large	Financial Services	Bachelor of Commerce	1-day Courses, Internal Leadership Courses	None
M12	1	Male	39	9	5	1	1	General Manager	Operations	Large	Financial Services	Bachelor of Business	Bachelor Major Management	Certificate in Business Computing
M13	1	Male	46	25	15	<3	10	General Manager	Operations	Large	Financial Services	Management Diploma	Management Courses	None
M14	1	Male	40	13.5	5.5	4	4	Analyst	Analytics	Large	Financial Services	Master of Business	Management Courses	Software and Predictive Modeling Courses
M21	2	Male	43	25+	15	0	2	Head of Department	Finance	Large	Non-Profit	NCA Level	Change/Agile Management, Leadership	None
M22	2	Male	56	30	15	0	2.5	C-Level	Finance	Large	Non-Profit	Bachelor of Commerce	Management Courses	None
M31	3	Male	37	5	2	<2	2	C-Level	CEO	Small	Agency	Undergraduate Degree and Postgraduate Diploma	None	None

Participant #	Organization	Gender	Age	Experience DM (years)	Experience Analytics (years)	Experience Big Data (years)	Experience in Role	Position	Department	Organization Size	Industry	Academic Qualification	Formal Training in Management	Formal Training in Analytics
M41	4	Male	34	16	5.5	0	4.5	Manager	Finance	Large	Financial Services	Bachelor of Business	Courses and Seminars	None
M51	5	Male	n/a	n/a	n/a	n/a	15	C-Level	CEO	Medium	Computer/ Software	PhD of Finance	n/a	Through Degree
M52	5	Male	23	2	0	0	2	Analyst	Analytics	Medium	Computer/ Software	Bachelor of Engineering Science	None	Through Degree
M61	6	Male	48	n/a	n/a	n/a	n/a	C-Level	CEO	Small	Non-Profit	Master of Arts	None	Marketing Workshops
M71	7	Male	59	n/a	n/a	n/a	1	C-Level	CEO	Medium	Non-Profit	Postsecondary School	Internal Trainings	None
M72	7	Female	n/a	16	n/a	n/a	1	Manager	Operations	Medium	Non-Profit	Bachelor of Social Work	Certificate in Management	Through Degree
M81	8	Male	51	30	10	0	2	Head of Department	Operations	Large	Transport	Master of Engineering	Management Courses, MBA	None
M82	8	Male	60	15	7	n/a	1.5	Head of Department	Operations	Large	Transport	Post College Qualifications	Management and Leadership Courses	None
M83	8	Male	48	9	9	<1	2	Manager	Operations	Large	Transport	Master of Engineering	Management and Leadership Courses	Internal System-specfic Introductory Courses
M84	8	Male	46	27	27	<1	3	Head of Department	Operations	Large	Transport	Trade Qualification	Management and Leadership Courses	Through Management Training

Participant #	Organization	Gender	Age	Experience DM (years)	Experience Analytics (years)	Experience Big Data (years)	Experience in Role	Position	Department	Organization Size	Industry	Academic Qualification	Formal Training in Management	Formal Training in Analytics
M85	8	Male	49	25	18	16	6	Head of Department	Operations	Large	Transport	Trade Qualification	Leadership Courses	None
M86	8	Female	32	5	5	<1	<1	Analyst	Analytics	Large	Transport	Master of Engineering Management	Management and Leadership Courses	None
M91	9	Male	56	30	30	30	7	General Manager	Operations	Large	Financial Services	Diploma	Internal Trainings	None
M92	9	Male	47	20	20	0	<1	Manager	Operations	Large	Financial Services	High School	Internal Trainings	None
M93	9	Male	54	30	7.5	<1	2	General Manager	Operations	Large	Financial Services	Business Diploma	Internal Trainings	None
M94	9	Male	42	n/a	n/a	n/a	2	Head of Department	Analytics	Large	Financial Services	Postgraduate Diploma in Information Systems	Internal Trainings	Through Degree

Appendix C. Preparation Document for Managers

Advanced Analytics and Decision Making:

An Exploration of the Roles of Advanced Analytics and Human Judgement

PREPARATION - MANAGERS

II. Critical Incidents

We are trying to learn in detail just what successful decision making with analytics as a manager includes. In order to get a better understanding for the decision making of managers, we need to know, just what managers do that makes them especially effective or ineffective.

I would like you to tell me about an incident, i.e., a specific decision you made that led to an either significantly positive or negative outcome. Describe in as much detail as possible what you did when you made this decision (Who, What, When, Where).

Think of the last time you made a decision with the support of data/analytics that led to a very positive or negative outcome. Each time you made a decision with the help of data/analytics that led to a significant outcome was an incident. These decisions might be of a day to day nature (operational decisions) or more critical (tactical) and strategic decisions.

Preparation and Memory-Aid for Managers Before and During the Interview	
What were the circumstances leading up to this decision?	
Did you follow a certain process when making the decision?	
Was the process related to a specific type of decision?	
Was the process affected by specific big data characteristics/problems with analytics?	
Were there any personal/organizational factors that influenced this process?	
What was the outcome of this incident?	

Appendix D. Coding Schedule for Content Analysis

CI Number	0.1.1
Simple	
Complex	
Complicated	x
Strategic	
Tactical	x
Operational	
Group	x
Individual	
Use of Data (1-7)	7
Use of Human Judgment (1-7)	3
General Aim	Risk Management
Role of Data	Enabler of Judgment / Challenger of Judgment
Role of Human Judgment	Initial Assessment / Identifier of Need for Analytics
Behavioural Bias	n/a
Type of Data Used	Internal, Several
Process: Identification	Anecdotal (Problem)
Process: Development	Statistical Data Analysis
Process: Selection	Analysis Results + Consultation with Departments
General Process Comments	
Outcome	positive
Lessons Learned	Established as new DM process enforcing data input
1 Word Summary	Fraud

Appendix E. DRC 16 Forms

DRC 16

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Simone Gressel
Name/title of Primary Supervisor:	Professor David Pauleen
Name of Research Output and full reference:	
Gressel, S., Pauleen, D., & Taskin, N. (2020). Management Decision Making in the Age of Big Data. Sage Publishing.	
In which Chapter is the Manuscript /Published work:	Chapters 1-7
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	50
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
This thesis is the foundation of the book contracted with Sage Publishing. The materials of the book are almost entirely based on the insights gained during this research.	
For manuscripts intended for publication please indicate target journal:	
Candidate's Signature:	Simone Gressel Digitally signed by Simone Gressel Date: 2019.09.26 14:51:44 +02'00'
Date:	26.09.2019
Primary Supervisor's Signature:	Pauleen, David Digitally signed by Pauleen, David Date: 2019.09.27 12:52:01 +12'00'
Date:	26/09/2019

(This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis)

GRS Version 4– January 2019

DRC 16

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Simone Gressel
Name/title of Primary Supervisor:	Professor David Pauleen
Name of Research Output and full reference:	
Intezari, A., & Gressel, S. (2017). Information and Reformation in KM Systems: Big Data and Strategic Decision-Making. Journal of knowledge management, 21(1), 71-91.	
In which Chapter is the Manuscript /Published work:	Chapters 1,2,4
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	30
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
The contribution to this conceptual paper was made by providing insights about big data and advanced analytics, as well as strategic decision making, based on extant literature.	
For manuscripts intended for publication please indicate target journal:	
Candidate's Signature:	Simone Gressel Digitally signed by Simone Gressel Date: 2019.09.26 14:57:28 +02'00'
Date:	26.09.2019
Primary Supervisor's Signature:	Pauleen, David Digitally signed by Pauleen, David Date: 2019.09.27 12:51:29 +12'00'
Date:	26/09/2019

(This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis)

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Simone Gressel
Name/title of Primary Supervisor:	Professor David Pauleen
Name of Research Output and full reference:	
Bradbury, T., Gressel, S., & Forsyth, D. (2017). Intuition and Decision Making within the Context of Athlete Selection: Perspectives from National Sport Coaches. New Zealand Journal of Human Resources Management, 17(2).	
In which Chapter is the Manuscript /Published work:	Chapter 2
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	30
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
The contribution to this paper was in the form of insights on intuition based on extant literature. Furthermore, the research results obtained by Bradbury and Forsyth were framed in the context of intuition, creating a model of athlete selection	
For manuscripts intended for publication please indicate target journal:	
Candidate's Signature:	Simone Gressel Digitally signed by Simone Gressel Date: 2019.09.26 15:02:15 +02'00'
Date:	26.09.2019
Primary Supervisor's Signature:	Pauleen, David Digitally signed by Pauleen, David Date: 2019.09.27 12:50:25 +12'00'
Date:	

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