RESEARCH

Martin Kowalczyk

The Support of Decision Processes with Business Intelligence and Analytics

Insights on the Roles of Ambidexterity, Information Processing and Advice

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With a preface by Prof. Dr. Peter Buxmann

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Foreword

The support of managerial decision making with Business Intelligence and Analytics (BI&A) has gained high priority in many businesses and the importance of this topic is recognized among practitioners and scholars alike. Prior related research in decision support and information systems mainly investigated the technological perspective of introducing and using such decision support systems. Thereby the decision process perspective of supporting managerial decisions with BI&A remained largely unexplored. Furthermore, extant research mainly focused on individual decision makers or groups of equal peers without considering the need for specialization and collaboration between decision makers and analytics experts (i.e. data scientists or analysts). Better understanding of the actual decision process perspective is highly relevant for the success of utilizing BI&A to effectively support decision making.

The research that Martin Kowalczyk conducted as part of his dissertation approaches the existing research needs by considering the organizational and individual perspectives of BI&A-supported decision processes. The organizational perspective focuses on investigating the processual aspects of decision making, including process phases, roles that are involved and how these interact. The individual perspective refers to decision making at the level of the individual, including cognitive efforts and behaviors involved in decision making. The purpose of this dissertation was to empirically investigate both perspectives and thereby to address the challenges of how to design and establish BI&A-supported decision processes that achieve improved decision quality.

This dissertation begins with presenting the results from a structured literature review, which contributes an integrative perspective on the current state-of-the-art in research. Building on this foundation, the dissertation first focuses on the organizational perspective and presents results from two studies that examine what constitutes successful BI&A-supported decision processes. Grounded in the organizational information processing theory, the first study investigates how different types of information processing mechanisms are composed within various decision processes. The results contribute to a better understanding of how information processing mechanisms should be incorporated in BI&A-supported decision processes. A second study on the organizational perspective identifies procedural characteristics (i.e. agility and rigor) that are relevant for the design of BI&A-supported decision processes. The focus of the dissertation then turns to the individual perspective, which is addressed by two further studies that investigate how analytics experts should frame and conduct BI&A support for decision makers in order to be effective in improving the quality of decision making. The first study on this perspective explores a comprehensive set of conflicting task requirements and identifies ambidextrous tactics that can address these conflicts. Grounded in these empirical findings, this dissertation contributes a theory of ambidexterity in decision support. The final study of this dissertation investigates the relevance of advice that analytics experts provide to decision makers. The presented results show how analytics experts' BI&A support affects decision makers' information processing behavior, their utilization of analytic advice and the resulting decision quality. Thereby this research contributes to a better understanding of how to shape the BI&A support that analytics experts provide to decision makers.

In his work, Martin Kowalczyk presents previously unexplored perspectives on the BI&A support of managerial decision processes. This research contributes to a better understanding of what constitutes successful BI&A-supported decision processes and how to establish effective BI&A support in decision scenarios that involve collaboration between specialized roles (i.e., analytics experts and decision makers). Thereby this work extends the theoretical foundations of decision support and information systems research and it offers various starting points for future investigations of BI&A support in decision processes. Therefore, I wish for broad diffusion of these research results in science and business practice.

Prof. Dr. Peter Buxmann

Acknowledgements

Becoming a researcher at TU Darmstadt with the goal of exploring decision processes and particularly their support with business intelligence and analytics has been a great opportunity. During my time as researcher, at the Chair of Information Systems | Software Business & Information Management, I had the freedom and support to let my curiosity guide my research endeavors, which will remain an unforgettable experience. This allowed me to deeply investigate and elucidate the importance of ambidexterity, information processing and advice for the support of decision making with business intelligence and analytics. Looking back at this time I owe gratitude to many people without whom this would not have been possible.

First of all I would like to thank my thesis advisor Prof. Dr. Peter Buxmann for his trustful supervision, dedication of time and the excellent research environment. In addition, I would like to thank Jörg Besier for his guidance and for being an enthusiastic sparring partner concerning the practical relevance of my research. Further, I would like to thank Prof. Dr. Oliver Hinz for accepting the co-correction of this dissertation. The work presented in this thesis was supported by the House of IT e.V. with a research grant, for which I am very grateful.

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I am grateful to my parents and would like to thank them for their encouragement of true learning, their advice and their support in pursuing my goals throughout all the years.

Finally, I would like to express my deepest gratitude to my wife Nicole for her unconditional love and all her great support throughout this endeavor. During this time our wonderful daughter Amilia became part of our life and both of you are my source of inspiration and strength. This thesis is dedicated to you.

Martin Kowalczyk

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List of Acronyms

ACM	Association for Computing Machinery
AIS	Association for Information Systems
AISeL	AIS electronic Library
BA	Business Analytics
BI	Business Intelligence
BI&A	Business Intelligence and Analytics
CPM	Corporate Performance Management
CRM	Customer Relationship Management
DBMS	Database Management System
DM	Decision Maker
DSS	Decision Support System
DW	Data Warehouse
ECIS	European Conference on Information Systems
EIS	Executive Information System
ERP	Enterprise Resource Planning
ETL	Extract-Transform-Load
HSM	Heuristic–Systematic Model
IEEE	Institute of Electrical and Electronics Engineers
ICIS	International Conference on Information Systems
IS	Information System
JAS	Judge–Advisor System
MIS	Management Information System
MSS	Management Support System
OLAP	Online Analytical Processing
PDSS	Personal Decision Support System
PLS	Partial Least Squares
RG	Research Goal
RQ	Research Question
SEM	Structural Equation Modeling

1 Introduction

The general idea of improving managerial decision making through support with high quality information or facts is shared by the decision support specialty of information systems research (Arnott and Pervan, 2005, 2008, 2014), management research (e.g., Pfeffer and Sutton, 2006; Simon, 1960), and practitioners alike (e.g., Davenport et al., 2010; LaValle et al., 2011). The reason for this huge interest lies in research findings and practitioner reports that suggest that data-driven decision making results in better decisions and, as a consequence, in better organizational performance (Brynjolfsson et al., 2011; Davenport et al., 2010; LaValle et al., 2011).

Recent advances in the information infrastructure for Business Intelligence and Analytics (BI&A) have provided the technological foundation for collecting and analyzing unprecedented volumes and types of data. BI&A provides technological capabilities for data collection, integration, and analysis with the purpose of improving the quality of the information that is available to support decision making (Chaudhuri et al., 2011; Chen et al., 2012; Watson, 2010). Based on these technological advances, support of managerial decision making with BI&A has gained high priority in many businesses and has given new prominence to data-driven decision making, which is increasingly considered a competitive advantage (Davenport et al., 2010; McAfee and Brynjolfsson, 2012; Wixom and Watson, 2010).

While the supply of high-quality information through BI&A creates the potential for improving managerial decision making, this information must be used effectively in decision processes in order to live up to this potential (Pfeffer and Sutton, 2006; Sharma et al., 2014). Unfortunately, it seems that much of the potential remains untapped, as the BI&A systems that are introduced are subject to high failure rates and particularly suffer from not being utilized by decision makers (Arnott, 2010; Shah and Capellá, 2012). Hence, leveraging the benefits of BI&A depends not only on establishing a high-quality information infrastructure, but also on the organizational context and characteristics of the decision processes for which BI&A is deployed (Davenport, 2010; Popovič et al., 2012, 2014; Ross et al., 2013).

In this regard, while the technological evolution of BI&A has tremendously improved technological capabilities for supplying high-quality information and analytic business insights for the purpose of decision support, it has also induced the need for more specialized data-processing and analytic skills. These skills are required for effectively utilizing and analyzing data that is available to organizations through their internal and external data sources. This need for specialization has rendered the role of analytics experts (i.e., data scientists or analysts) increasingly important for decision support. These specialists have the required analytics expertise for utilizing BI&A to deliver analytic decision support to decision makers

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(Davenport et al., 2010; Davenport and Patil, 2012). Analytics experts support managerial decision making with respect to business decisions (e.g., competitive strategies, mergers and acquisitions, and managing product and service portfolios) by structuring decision problems, searching for relevant data, developing alternative solutions based on data patterns and analytic insights, and finally providing analytic advice to decision makers (Davenport and Patil, 2012).

Considering analytics experts' role as mediators between information and decision makers' use of that information, the success of BI&A support depends not only on the introduction of BI&A technology, but also on the presence of analytics experts and their collaboration with decision makers in the context of organizational decision processes. Thus, the constitution of a decision process – in terms of the phases, steps, mechanisms, and roles that are involved – is bound to have major implications for the effectiveness of BI&A support. Literature reviews on the use and effects of BI&A have identified a major need for research about decision processes and actual decision making in the context of BI&A (Arnott and Pervan, 2014; Kowalczyk et al., 2013; Shollo and Kautz, 2010). Similarly, a recent call for research indicates the need for further investigations from the decision process perspective, including behavioral and organizational aspects, in order to achieve a better understanding of how organizations can improve the quality of decision outcomes and thus create value from the utilization of BI&A (Sharma et al., 2014).

This thesis addresses these calls for research by investigating BI&A support in the context of organizational decision processes. The research presented herein elucidates several issues related to organizational and individual perspectives on BI&A-supported decision making by utilizing a mix of qualitative and quantitative research approaches. The following sections describe the research problem in more detail, provide an overview of the research background, define explicit research goals and questions, and outline the structure of this thesis.

1.1 Scientific Relevance and Problem Characterization

Although data-based decision support systems (DSSs) and BI&A in particular involve the support of decision making, research in this area has been found to have a rather limited grounding in relevant theories of decision making from reference disciplines (Arnott and Pervan, 2005, 2008, 2014). In particular, the traditional research perspective has been mainly oriented toward technology, with a focus on how data is transformed into high-quality information that can be supplied to decision makers as input for their decision making (Lycett, 2013; Shollo and Kautz, 2010). This perspective has been criticized for not considering the organizational and social contexts of decision support, which involve interactions between the people who are involved in decision processes. These interactions should have a major impact on the outcomes of BI&A-supported decision processes (Galliers and Newell, 2003; Shollo and Galliers, 2015).

Moreover, prior research on decision support has mainly assumed that decisions are made by either individual decision makers or groups of equal peers who use a decision support technology (Arnott and Pervan, 2005, 2008, 2014). In contrast, BI&A support of decision making increasingly depends on collaboration between analytics experts and decision makers, including the analytics experts' provision of analytic advice (Davenport and Patil, 2012; Viaene, 2013). Analytics experts and decision makers typically have complementary expertise in BI&A and the business domain, which can lead to gaps in understanding and information asymmetries. These gaps have been found to result in different kinds of challenges during the delivery of decision support and to impair use of the supplied information for decision making (Hogarth and Soyer, 2014; Viaene, 2013; Viaene and Van den Bunder, 2011).

In this regard, our understanding of how BI&A affects decision making in organizational settings is limited. Recent calls for research stress the importance of investigating the effects of BI&A support in the context of decision processes (Kowalczyk et al., 2013; Sharma et al., 2014) and of examining its influence on the processing of information in decision making (Arnott and Pervan, 2014). Achieving an understanding of these issues is regarded as a precondition for conceiving how to improve decision making and the quality of decision outcomes. Following these calls, the research presented in this thesis focuses on the BI&A support of decision processes and decision making in organizational contexts.

The overall goal of this thesis is to advance our understanding of how to design and establish successful BI&A-supported decision processes that result in improved decision making and higher quality decision outcomes. To this end, the thesis investigates what constitutes successful BI&A-supported decision processes and how to establish effective BI&A support that involves collaboration between analytics experts and decision makers. To obtain insights concerning both of these aspects of BI&A-supported decision processes, the research conducted for this thesis considered relevant explanations from reference disciplines. Thus, this work is grounded on fundamental findings from management research on decision processes and theoretical foundations from the cognitive sciences on decision making. Finally, in more general terms, by contributing to a better understanding of how to improve the overall quality of decision outcomes in BI&A-supported decision processes, this thesis thereby conduces to how the value proposition of BI&A can be successfully realized.

1.2 Research Context and Fundamentals

This section provides an overview of the basic terms and concepts that are relevant for this thesis's research context and central for understanding the research results. The following subsections provide a more detailed introduction to BI&A and distinguish between decision processes, decision making, and related conceptions of organizational and individual information processing.

1.2.1 Business Intelligence and Analytics

From the perspective of information systems (IS) research, BI&A represents the latest evolution of technologies that have been developed to support managerial decision making (see Figure 1.1, based on (Arnott and Pervan, 2014; Humm and Wietek, 2005; Shollo and Galliers, 2015)). This evolution began in the early 1960s, with the introduction of the first data processing systems. The idea of using the newly available data for supporting managerial decision making led to the development of the first Management Information Systems (MISs). In the following decades these systems evolved through several stages, from Personal Decision Support Systems (PDSSs) to Executive Information Systems (EISs) and Data Warehouses (DWs) towards the current state-of-the-art technologies in BI&A. Each stage in this evolution increased data-processing capabilities, thus improving the available data basis or analytic capabilities and thereby providing more advanced capacities for data analysis (Arnott and Pervan, 2005, 2008, 2014; Humm and Wietek, 2005).

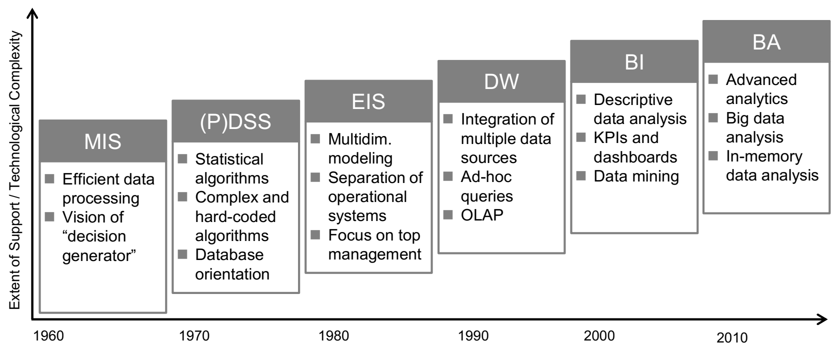

Figure 1.1: Evolution of Decision Support Technologies

Business Intelligence (BI) and Business Analytics (BA) represent the two most recent stages in the presented technological evolution. Wixom and Watson (2010) noted that the current literature did not have a universally accepted definition of BI&A. What most definitions had in common was a focus on the technological perspective, with reference to the systems or technologies that are used for gathering, storing, and analyzing data. In line with these definitions, Wixom and Watson (2010) defined BI as

> *[...] a broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions.* (p. 14)

Furthermore, Wixom and Watson (2010) contended that in recent years the term 'Analytics' was being used to describe applications that provide decision support, referring to the conception of Davenport (2006), who considered both of these concepts (i.e., Analytics and Business Intelligence) and noted that Business Intelligence

> *[...] encompasses a wide array of processes and software used to collect, analyze, and disseminate data, all in the interests of better decision making.* (p. 106)

Davenport further remarked that the Analytics concept was strongly related to the concept of Business Intelligence and noted that

> *[...] analytics competition is partly a response to the emergence of integrated packages of these tools.* (p. 106)

Subsequently, in their widely read book, Davenport and Harris (2007) established the term 'Business Analytics', defining it as

> *[...] the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions.* (p. 7)

Arnott and Pervan (2014) argue that this definition of BA is very similar to the definition of BI and that most practitioners do not see a significant difference between BA and BI, despite the wide use of both terms by software vendors and consultants. Chen et al. (2012) proposed a remedy to this issue and suggested, in line with Davenport's definition and the evolution of the systems, that the term BA mainly represents the key analytical component in BI. In consequence, they proposed Business Intelligence and Analytics (BI&A) as a unified concept that

> *[…] relies heavily on various data collection, extraction, and analysis technologies.* (p. 1166)

This thesis adopts Chen et al.'s (2012) unified conception of BI&A. Figure 1.2 presents an overview of a typical BI&A architecture that includes more details on the technologies for (1) data collection and integration, (2) data storage, and (3) analysis.

The effective use of data for decision support depends on the ability to efficiently collect and integrate data of high quality from different kinds of internal and external data sources. Extract-Transform-Load (ETL) refers to this procedure (see Figure 1.2) and the technical components that BI&A provides for the purpose of automating the extraction, transformation and loading of relevant data into a central data storage (Chaudhuri et al., 2011). Extract refers to establishing the technical connection to different kinds of internal and external data sources and thus making them accessible for further processing. Transform deals with the preprocessing (i.e., data integration and data cleansing) for converting data into standardized form (Inmon, 2002). Finally, load addresses the connection of the ETL component to a centralized data-base for the purpose of storing the transformed data (Chaudhuri et al., 2011).

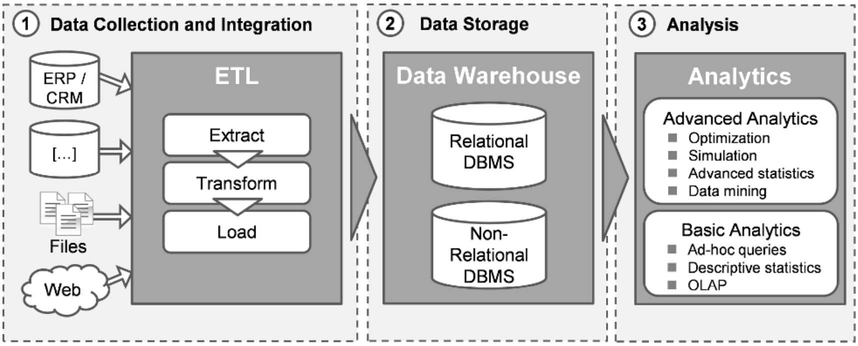

Figure 1.2: BI&A Architecture

Data storage refers to a centralized data-base, which is typically called the data warehouse in BI&A architectures (see Figure 1.2, based on (Chaudhuri et al. 2011)). A very established and traditional definition of the data warehouse defines it as a "subject-oriented, integrated, non-volatile, and time-variant collection of data in support of management's decisions" (Inmon, 2002). Recent innovations concerning the storage of data, such as in-memory databases and massively parallel data architectures, have created broadly available capacities for the handling of large volumes of heterogeneous data in (near) real-time (so-called 'big data') (Chaudhuri et al., 2011; Watson, 2010; Plattner and Zeier, 2012). Because data is the underlying resource for deriving potentially valuable insights from data analysis, it provides the impetus for the utilization of BI&A in organizations. In this regard, recently big data and big data analytics have been associated with BI&A (Arnott and Pervan, 2014).

BI&A systems provide a wide range of analytics functionalities (see Figure 1.2), which can be differentiated according to rather basic and more advanced analytics capabilities (Chaudhuri et al., 2011; Davenport and Harris, 2007; Watson, 2010). Those analytics functionalities that are considered to be rather basic include online analytical processing (OLAP), ad-hoc queries and simple descriptive statistics. These basic capabilities provide the foundation for exploring data in a descriptive manner, achieving a basic understanding of the data, and based on this also for deriving initial improvement suggestions or decisions (Davenport and Harris, 2007). Functionalities that are typically characterized as advanced analytics comprise data mining (e.g., neural nets, classification and regression trees, support vector machines), advanced statistical analysis (e.g., regression modeling, time-series analysis, factor analysis, forecasting, sensitivity analysis), and simulation or optimization approaches (e.g., solver approaches, heuristics, Monte Carlo simulation, agent-based modeling) (Chen et al., 2012; Davenport and Harris, 2007; Watson, 2010). The focus of advanced analytics lies on utilizing data for prediction and optimization and thereby providing support for decision making (Davenport and Harris, 2007).

1.2.2 Decision Processes and Organizational Information Processing

Researching BI&A as a means for delivering decision support requires a more precise definition of the decision making perspective, which can be organizational or individual. In addition, there is a need for a clear understanding of how information processing is conceptualized in reference to the organizational or individual perspective. This section focuses on the organizational perspective and the next section will address the individual perspective.

In line with management research, this thesis uses the term 'decision process' to describe the organizational perspective on decision making. The organizational perspective views decision making as a process that consists of several phases and involves multiple roles that interact throughout these phases. Decisions are then the final outcomes of these processes (e.g., Mintzberg et al., 1976; Nutt, 1993; Rajagopalan et al., 1993). This perspective is mainly grounded in the work of Simon (1960) and his conceptualization of the phase theorem of decision making that considers three phases: intelligence, design, and choice. The phase theorem has been widely adopted in management research (e.g., Mintzberg et al., 1976; Nutt, 2008; Rajagopalan et al., 1993) and IS research (e.g., Gorry and Scott Morton, 1971; Shim et al., 2002) and different variations and derivatives of the initial phase theorem have been developed. For example, Mintzberg et al. (1976) distinguish between three phases for identification, development and selection. The identification of the decision problem involves recognition of the issue and might include additional diagnosis or validation of the decision problem. The development phase deals with the design or search for alternative solutions. The selection phase involves the actual decision making and leads to a choice regarding one preferred solution. Whenever this thesis uses the decision process perspective, it follows the conception of Mintzberg et al. (1976). Additionally, management research on decision processes has investigated a number of different decision process characteristics that were found to affect the quality of decision outcomes. These include fundamental characteristics, like uncertainty and nonroutineness that describe the decision type, as well as decision process properties like the extent of political behavior or procedural rationality (Hutzschenreuter and Kleindienst, 2006; Papadakis et al., 2010; Rajagopalan et al., 1993). Investigating these characteristics in the context of BI&A-supported decision processes provides an opportunity for better integration of IS research with management research.

Organizational information processing theory encompasses a conceptualization of how information is processed, considering the organizational perspective. It assumes that organizations build their information processing capacity by combining different information processing mechanisms that are based on organizational and technological resources. The purpose of information processing is to reduce decision-specific uncertainty and ambiguity (Daft and Lengel, 1986; Galbraith, 1974; Tushman and Nadler, 1978). Organizational information processing theory considers mechanisms that reduce ambiguity to be different from mechanisms that reduce uncertainty. Information processing mechanisms that reduce ambiguity involve face-to-face contact between individuals (e.g., through direct personal contact), in order to provide adequate richness of information for the purpose of clarifying questions regarding the decision context. In contrast, information processing mechanisms that address uncertainty are supposed to optimize the amount of information that is made available (e.g., in dashboards or reports) to the decision makers (Daft and Lengel, 1986; Zack, 2007). Organizational information processing theory proposes that different combinations of information processing mechanisms are needed for decision contexts that exhibit different levels of uncertainty and ambiguity (Tushman and Nadler, 1978; Zack, 2007). Distinguishing between different types of information processing mechanisms and their composition provides an opportunity for improving our comprehension of the organizational information processing that occurs in the context of BI&A-supported decision processes.

1.2.3 Decision Making and Individual Information Processing

In contrast to the organizational decision process perspective, cognitive sciences refer to decision making at the level of the individual. The goal of the individual perspective is to explain the cognitive processes and behaviors involved in human decision making (Evans, 2008).

In line with cognitive sciences, this thesis uses the term ‘decision making’ to refer to the individual level. Theories from cognitive sciences are particularly valuable for achieving a detailed understanding of how BI&A support might affect decision makers (Arnott and Pervan, 2014). Dual-process theories represent a well-established family of theories that address information processing and decision making at the individual level. Although this family of theories encompasses many different variations of dual-process theories, they all distinguish between two basic modes of information processing and decision making – one is fast, effortless, associative, and selective, whereas the other is slow, effortful, deductive, and comprehensive (Evans, 2008; Kahneman and Frederick, 2002). These theories have been thoroughly evaluated in experimental research (Arnott and Pervan, 2014) and have been successfully transferred to different research domains, including IS research (e.g., Davis and Tuttle, 2013; Kahlor et al., 2003; Trumbo, 2002; Watts et al., 2009).

In this thesis decision making is investigated by relying on a well-established dual-process theory from social psychology: the Heuristic–Systematic Model (HSM) (Chaiken, 1980; Chaiken et al., 1989). The HSM distinguishes between a systematic and a heuristic mode of information processing on which individuals rely when attending to information in decision situations. Systematic processing is analytic and makes extensive use of information by scrutinizing it for its relevance to the decision task and by integrating all available information for decision making (Chaiken et al., 1989). In contrast, heuristic processing is a rather limited information processing mode. The use of information is less analytic, typically relies on an incomplete subset of available information and decision making is characterized by the application of simple inferential rules. Inferential rules can be understood as simple structures of a decision maker's prior knowledge or experience (Chaiken et al., 1989). Relying on the heuristic mode of information processing has been found to lead to different kinds of biases and systematic errors in decision making (Kahneman and Frederick, 2002). Distinguishing between both modes of information processing and the associated behaviors of decision makers in using information that is delivered through BI&A support provides an opportunity to achieve deeper insights on the effects of data-driven decision support on decision making.

1.3 Research Goals and Questions

The overarching purpose of this thesis is to advance our understanding of how to design and establish successful BI&A-supported decision processes that deliver high quality decision outcomes. This requires understanding what constitutes successful BI&A-supported decision processes and how to establish effective BI&A support that involves collaboration between the specialized roles of analytics experts and decision makers.

Considering fundamental findings from management research and cognitive sciences as well as recent calls for research, contributions towards this overarching purpose can be made from two main perspectives: an organizational perspective and an individual perspective. The organizational perspective considers how BI&A-supported decision processes and their characteristics evolve throughout their different phases (Sharma et al., 2014). The individual perspective focuses on the influences of BI&A support on the actual decision making and, as part of it, also on the information processing behaviors of individuals (Arnott and Pervan, 2014).

In order to address the gaps in the current state of research on BI&A, which were identified in section 1.1, the research in this thesis pursued three research goals and eight derived research questions. The first two research goals focus on the organizational decision process perspective, while the third goal relates to the individual decision making perspective. This section provides an overview of these research goals and research questions. The following chapters will then present more detailed discussions of the relevant literature and existing research gaps that led to the formulation of the thesis's research agenda. Additionally, the following chapters will discuss the research methods that were used for answering the research questions and thereby achieving the thesis's research goals.

The first goal of this thesis was to provide an integrative perspective on the state of the art in research by examining how data-based DSSs, and BI&A in particular, affect the main phases and outcome characteristics of decision processes. To better understand the state of the art and to establish and validate the general research direction for this thesis, the following research question was investigated:

Research Question 1: According to prior research findings, how do decision support technologies, and BI&A in particular, affect the phases and characteristics of decision processes?

Addressing the first goal validated the general research direction and established a foundation for further examining BI&A-supported decision processes. In line with these initial findings, the second goal of this thesis was to contribute to a better understanding of what constitutes successful BI&A-supported decision processes that result in high-quality decision outcomes. This includes understanding the use of information processing mechanisms and how these are composed as well as the effects of various types of procedural characteristics throughout the phases of BI&A-supported decision processes. To address this second research goal, the following three questions were examined:

Research Question 2: How are the different types of information processing mechanisms composed in the context of BI&A-supported decision processes?

Research Question 3: How do political behavior and procedural rationality in BI&A-supported decision processes affect the quality of decision process outcomes?

Research Question 4: How do procedural characteristics of the collaboration between analytics experts and decision makers affect BI&A-supported decision processes and the quality of their outcomes?

The research findings related to the second goal suggested that analytics experts' collaboration with decision makers during BI&A-supported decision processes is crucial for how decision makers use the analytic results and, in consequence, also for the quality of the decision outcomes. In this regard, the third research goal was to achieve a better understanding of how to shape analytics experts' BI&A support for decision makers in order to be effective in improving the quality of decision making and decision outcomes. To address this research goal, four research questions were investigated. The first two of these questions focus on challenges that analytics experts face in providing effective BI&A support for decision makers:

Research Question 5: What challenges do analytics experts face in providing effective BI&A support for decision makers?

Research Question 6: How do analytics experts cope with such potential challenges in order to provide effective BI&A support?

In the research on these two questions, the advice that analytics experts give to decision makers emerged as a crucial aspect of BI&A support. To further analyze the important role of advice and the extent to which advice giving, as part of analytics experts' BI&A support, actually influences decision makers' information processing behavior and decision making, the following two research questions were investigated:

Research Question 7: How does the analytic advice provided by analytics experts as part of their BI&A support affect decision makers' information processing behavior?

Research Question 8: How does analytics experts' advice giving as part of their BI&A support affect decision makers' utilization of the analytic advice and the quality of decision outcomes?

1.4 Thesis Structure and Outline

This thesis is structured according to the previously presented research goals and questions and comprises a total of seven chapters. The structure of the thesis is shown in Figure 1.3, which additionally provides an explicit mapping of research goals and questions to the thesis's chapters. Following this introduction in the first chapter, the subsequent chapters 2 to 6 present the research that was conducted as part of this thesis and published in scientific articles. Finally, chapter 7 concludes this thesis by summarizing and discussing its theoretical and practical contributions.

Overall, the thesis comprises five scientific articles that constitute its main chapters. In the following, a brief summary of the contents of these main chapters shows how they address the identified research goals and provide answers to the derived research questions.

Chapter 2 (Study A) attends to the first research goal. It presents the results from a structured literature review that addresses the first research question, by investigating extant findings on the effects of decision support technologies on the phases and characteristics of decision processes. This research finds that prior studies have mainly investigated individual phases of decision processes in experimental research settings. Further characteristics of decision processes and phases have been considered rather isolated. This means that only a low fraction of the identified studies addresses decision process phases, as well as process characteristics and outcomes. As decision process phases are interrelated, research in this direction could be enhanced by considering entire decision processes, including their characteristics and outcomes. Such an integrative perspective would be of great value for explaining differences in observations of isolated characteristics. Further this study finds that more BI&A-specific research on decision processes is needed. To this end it additionally proposes considering the interaction between BI&A experts and decision makers, as the constitution of decision processes and involved roles could affect the characteristics of decision process phases and their outcomes. In sum, this structured literature review identifies current research needs and points to promising research directions.

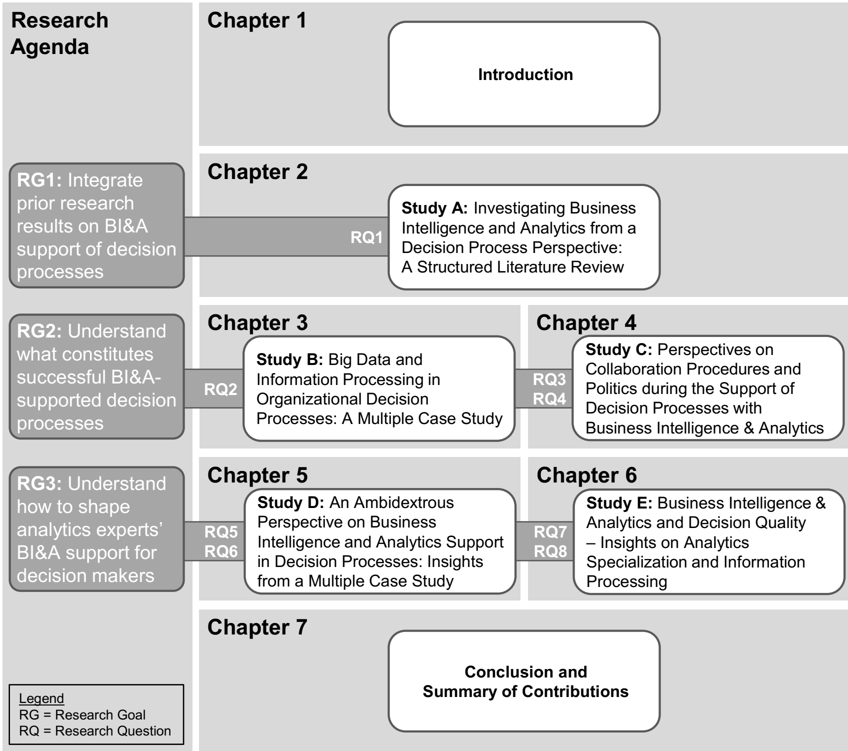

Figure 1.3: Structure of the Thesis

Chapter 3 (Study B) contributes to the second research goal by focusing on the second research question, which is investigated by means of a multiple case study. Based on the theory of organizational information processing, this chapter develops a conceptual framework that considers the composition of data-centric and organizational information processing mechanisms in the context of BI&A. This conceptual framework is used for investigating the compositions of the different types of data-centric and organizational information processing mechanisms in decision processes that differ with respect to their nonroutineness and uncertainty. Additionally, the reliance on different types of data according to the characteristics of volume, variety and velocity is examined. The results from this research suggest that data-centric and organizational information processing mechanisms exhibit a complementary relationship due to a need for effective integration of analytic capabilities with domain-specific knowledge, in the context of BI&A-supported decision processes. Further, the study finds that the composition of mechanisms, the use of data and the dynamics of mechanism composition vary according to different levels of nonroutineness and uncertainty within the investigated decision processes. Thereby, the findings from this study contribute to a better understanding of how to incorporate the different mechanisms within BI&A-supported decision processes.

Chapter 4 (Study C) addresses the second research goal and answers the third and fourth research questions. The presented research focuses on non-routine decision processes and a multiple case study examines the effects of political behavior and procedural rationality on the use of (high quality) information and the quality of decision outcomes. Further, this study explores characteristics of collaboration procedures (i.e., rigor and agility) between analytics experts and decision makers in BI&A-supported decision processes. Despite being a relevant topic in practice, collaboration procedures between analytics experts and decision makers have been marginally considered in prior research. This research particularly examines the interplay between the supply of high quality information and the characteristics of collaboration procedures, as well as how they shape the extent of political behavior and procedural rationality in BI&A-supported decision processes. Further, in the context of this study, the effects on overall decision quality are considered. Thus, the findings from this study reveal that rigor and agility are relevant procedural characteristics for the design of BI&A-supported decision processes that achieve high-quality decision outcomes.

Chapter 5 (Study D) focuses on analytics experts' collaboration with decision makers in the context of delivering BI&A support and thus contributes to the third research goal. The analysis of data from a multiple case study on non-routine decisions provides deep insights into the challenges that analytics experts have to cope with during the delivery of BI&A support to decision makers. This allows answering the fifth and sixth research questions. This research identifies a comprehensive set of conflicting task requirements that induce previously unexplored tensions, which can impair analytics experts' ability to provide effective BI&A support. In this regard, this study also explores analytics experts' tactics for coping with those tensions and thus facilitating ambidexterity in successfully managing the conflicting task requirements. Analyzing and comparing decision situations with varying levels of ambidexterity provides initial evidence on the effects of ambidexterity on decision making and the quality of decision outcomes. Based on the empirical findings a theory of ambidexterity in decision support is developed, which proposes how ambidexterity can be facilitated and how it positively affects decision quality.

Chapter 6 (Study E) quantitatively examines the impact of analytics experts' advice giving as part of their BI&A support for decision makers and thus provides a complementary perspective on the third research goal. The survey-based study addresses the last two questions of this thesis's research agenda. For this purpose the study develops theoretical propositions based on theoretical explanations from cognitive sciences (i.e., Heuristic-Systematic Model and Judge-Advisor Systems) and the research findings that were previously presented in this thesis. This allows proposing explanatory mechanisms concerning the potential influences of analytics experts' advice giving on decision makers' information processing behavior and utilization of analytic advice. Further, the conceptual model that is developed explicitly links BI&A support with decision makers' information processing behavior, their utilization of analytic advice, and the resulting decision quality. Partial least squares analysis is conducted regarding the theorized relations and confirms most of the study's research hypothesis. In sum, these findings contribute to a better understanding of how to shape analytics experts' BI&A support for decision makers.

2 Study A: A Structured Literature Review on Business Intelligence and Analytics from a Decision Process Perspective[1]

2.1 Introduction

In recent years the idea of business intelligence and analytics (BI&A) has gained an increasing amount of interest among researchers and practitioners due to a number of published success cases. These success cases report tremendous improvements in organizational performance, based on improved decision making and new business insights (Chen et al., 2012; Davenport, 2006). BI&A systems provide support for collecting and transforming data and put particular emphasis on data analysis with the purpose of improving decision making (Chen et al., 2012; Davenport, 2006; Shanks et al., 2010). BI&A systems can be attributed to the research area of decision support systems (DSS), which deals with information systems and their potential to support decision making (Arnott and Pervan, 2008). In this respect, what is understood today as BI&A has been shaped by DSS research and developments in systems like personal decision support systems, executive information systems and data warehouses (Arnott and Pervan, 2008; Chen et al., 2012; Shanks et al., 2010; Watson, 2010).

In order to achieve performance benefits from BI&A systems, organizations need to focus on their decision processes (Davenport, 2010; Shanks et al., 2010). Decision processes represent the routines by which decisions are made in organizations (Mintzberg et al., 1976; Nutt, 2008). The success of utilizing BI&A technologies highly depends on their integration with organizational decision processes (Brohman et al., 2000; Davenport, 2010; Kanungo, 2009; Shanks et al., 2010). Achieving such integration requires an understanding of how these technologies affect decision processes. Therefore, missing understanding of these effects can constrain successful utilization (Watson et al., 2002).

In this context, recent literature reviews however find that decision processes have not received enough attention: Shollo and Kautz (2010) analyze conceptions of business intelligence (BI) and conclude that only very few studies address decision processes. Moreover, they find that although BI is described as a data-driven process for decision support, it often remains unclear how BI is used in decision processes and what effects it has on decision processes. Arnott and Pervan (2008) provide a review of the DSS discipline and find that, although DSS research has the mission of improving managerial decision making, less than half of the investigated publications are explicitly related to managerial decision making research.

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[1] This is the accepted author's version of the following article: Kowalczyk, M., Buxmann, P. and Besier, J. (2013), "Investigating Business Intelligence and Analytics from a Decision Process Perspective: A Structured Literature Review", European Conference on Information Systems 2013. The definitive publisher-authenticated version is available online at: http://aisel.aisnet.org/ecis2013_cr/126.

M. Kowalczyk, *The Support of Decision Processes with Business Intelligence and Analytics*, DOI 10.1007/978-3-658-19230-3_2

They state that this creates a risk for the relevance of DSS research. Furthermore, they find that the amount of interrelation to managerial decision making research even decreases for technologies like data warehouses and business intelligence. Hence, recent literature reviews suggest more focus on decision processes and better integration of insights from managerial decision making research (Arnott and Pervan, 2008; Shollo and Kautz, 2010).

In light of these results, it becomes less surprising that although the general ideas of DSS research are consistent with management research on decision processes, the actual visibility of DSS research seems to be quite low in related management research (Papadakis et al., 2010). Papadakis et al. (2010) identify a major research gap with respect to the effects of information systems use on managerial decision making processes and explicitly call for more research in this area.

Taking into account the discussed perspectives it seems that there is a need for more integrative research with respect to the effects of technologies like business intelligence and analytics on decision processes. Therefore the goal of this research is to investigate and give an overview on the effects of those systems on decision processes. Research on decision processes is interdisciplinary and in order to support future work at this interface this paper makes three main contributions. First, we develop a research framework, based on existing results from managerial decision process research and decision support systems research. Then, using this research framework, we present results from a structured literature review and thereby integrate existing insights on the effects of decision support technologies on the distinct phases and attributes of decision processes. Finally, we propose future research directions in the area of managerial decision processes, as well as business intelligence and analytics.

This paper is organized as follows: The second section discusses the DSS background of this research. Additionally it develops a decision process research framework, which will be used for analyzing the results of our literature review. The third section describes our procedure for performing the literature review and documents the literature search process and its results. The fourth section presents the results from the literature study and the fifth section discusses those results. The sixth section identifies future research opportunities and the last section concludes this paper.

2.2 Decision Support and Decision Processes

This section starts with a conceptualization of the DSS research area. Next we discuss decision processes and we integrate existing concepts into a research framework that will be used for structuring and analysis of our literature review, as recommended by Webster and Watson (2002). The conceptualization and scoping performed in this section are also the basis for specifying search terms and inclusion/ exclusion criteria for the literature search process (see vom Brocke et al., 2009).

2.2.1 DSS Background and Technological Conceptualization

Although BI&A are the most current technologies for supporting managerial decision making, research and systems in this area have evolved over several years. One of the earlier reviews on the effects of use of decision support systems was done by Benbasat and Nault (1990). In their analysis they come to the conclusion that empirical investigations on the overall performance effects of DSS are inconclusive, as some studies report positive effects and others do not. They find several reasons for this, which are variances in the investigated variables, a lack of distinction between decision aiding techniques and a lack of process focus. Benbasat and Nault (1990) provide a functional classification of DSS, but they do not link it to distinct decision processes phases or characteristics.

The recent review by Arnott and Pervan (2008) provides a high-level overview on the DSS field. They classify the DSS field into: Personal DSS, group support system, negotiation support systems, intelligent DSS, knowledge management-based DSS, data warehousing and enterprise reporting and analysis systems (incl. business intelligence, executive information and performance management systems). In their study they find, among others that within the DSS field, the newer technological sub-fields of data warehouses and BI are least grounded in decision making research. This creates a risk of decoupling technologies from their actual purpose in decision processes (Shanks et al. 2010). These results are supported by findings of Shollo and Kautz (2010) in the context of BI systems and they conclude that decision processes have not been considered sufficiently.

BI&A includes collection, analysis and dissemination of information with the purpose of supporting decision making (Davenport 2010; Watson 2010). Thus, the focus of BI&A can be related to process models for modeling and predicting real-world processes, choice models for supporting decision making, analysis and reasoning methods, as well as information control techniques. We subsequently focus our research on these technological aspects. We do not include representational aids, judgment and group supporting techniques, as former are broadly covered in human-computer interaction research and latter mainly address different facets of communication and group collaboration. After this technological conceptualization, we develop a research framework for decision processes.

2.2.2 Decision Process Background and Research Framework

In order to systematically investigate the effects that decision support technologies have on decision processes it is necessary to operationalize those effects. For this purpose we define decision processes by using a phase-based conception defined by Mintzberg et al. (1976) and we discuss common quality attributes of decision processes from management research.

Mintzberg et al. (1976) developed a decision processes conception, which includes phases for (1) identification, (2) development, and (3) selection. They investigated the decision process phases and found that distinct steps within those phases are performed iteratively, rather than sequentially during decision making. Additionally, they found that competing steps exist within each phase. This conception of the decision process has been further refined and extended in decision process research (e.g. Nutt 2008), as well as partially adopted in the DSS field.

For investigations of the quality of decision processes two main dimensions of attributes have been suggested in management research: Decision process characteristics and decision process outcomes (Papadakis et al., 2010; Rajagopalan et al., 1993). Process outcomes describe the results from a decision process or its sub-phases. In contrast, decision process characteristics encompass procedural attributes that are related to the execution of the process (Papadakis et al. 2010; Rajagopalan et al. 1993). In order to obtain a comprehensive view on a decision process it is important to consider attributes related to process characteristics and process outcomes (Forgionne, 1999; Phillips-Wren et al., 2004). Research by Forgionne (1999) comes to the conclusion that this is seldom the case in DSS research. This may lead to a fragmentation of insights with respect to the effects on decision processes.

Therefore, our research framework combines a selection of process outcomes, as well as process characteristics that are considered as relevant in managerial decision process research. The framework considers the decision process phases (1) identification, (2) development and (3) selection, and we focus on the following attributes for each of the three phases:

- Information quality: One of the major benefits of BI&A systems is the provision of accurate, high quality information which is easily accessible (Davenport 2010; Watson et al. 2002). Therefore usage of such systems should make available information of better quality.
- Comprehensiveness and procedural rationality: In managerial decision process research procedural rationality describes the level of reliance upon analysis of information in decision making and comprehensiveness characterizes the extent to which analysis is exhaustive within the decision process (Dean and Sharfman, 1996; Papadakis et al., 2010).
- Speed: Time savings are another major benefit that is proposed to be realized by BI&A systems (Davenport 2010; Watson et al. 2002). Such systems should not only provide faster access to information but also help to speed-up the decision process.

- Phase outcomes: The final decision is not the only result, within a decision process. Each phase produces results, which can be analyzed with respect to their quality and quantity. For the identification phase this is a set of problems and opportunities that are identified and specified. The development phase deals with defining a set of solution alternatives. Finally the selection phase deals with analysis and choice of alternatives. The analyzed alternatives and whether a choice was made are outputs from this phase (Nutt 2008; Phillips-Wren et al. 2004).

Additionally we focus on decision results and total decision speed:

- Decision result: The decision result is the outcome of the overall process. The quality of this outcome can be evaluated using performance and accuracy measures or on the basis of expert evaluations (Papadakis et al. 2010; Phillips-Wren et al. 2004).
- Total decision speed: The total decision speed characterizes duration of the overall decision process, which is expected to be reduced (Davenport 2010; Watson et al. 2002).

2.3 Review Method

For structuring the literature review we used the guidelines provided by vom Brocke et al. (2009) and Webster and Watson (2002). This section describes our review procedure in detail, with the purpose of making our review procedure as transparent as possible in order to achieve high validity and reliability. In this context, validity means the degree of accuracy in identifying and handling sources, which includes selection of scientific databases and search terms. Reliability refers to the replicability of the search process and can be achieved by thoroughly documenting the procedure and making selection criteria explicit (vom Brocke et al. 2009). In the following, we first define the review scope, search terms and explicit inclusion/ exclusion criteria. Then, we describe the search process and sources used in this literature review, as well as our approach for data extraction and analysis.

2.3.1 Review Scope

Following the recommendations by vom Brocke et al. (2009) we used the taxonomy proposed by Cooper (1988) in order to characterize the scope of our literature review. The focus of our research is mainly on research outcomes and partially on the research methods of the analyzed publications. Our goal is to integrate existing results on the effects of decision support technologies on decision processes. We organize our results conceptually according to the distinct phases of a decision process. Through summarizing and synthesizing findings we aim at a neutral perspective for representing the findings. We tried to achieve exhaustive coverage of the literature with respect to our research goal by performing searches in eight scientific databases, but simultaneously we were limited to the sources available in the chosen databases. Our intended audience is researchers specialized in BI&A systems or DSS in general, as well as management researchers in the field of decision processes. The results might also be interesting for practitioners who want to gain insight into the effectiveness of such technologies.

2.3.2 Search Terms

At the beginning of a literature review it is recommended to start with a conception of the topic and a definition of key terms in order to derive meaningful search terms (vom Brocke et al. 2009). As discussed in the previous section, we investigated existing reviews on decision making, decision processes and supporting technologies. During this initial investigation we identified two main topics: Decision processes, including their characteristics and outcomes, and decision support technologies, including their effects on decision processes. We discussed those topics with experts and practitioners in order to extract the relevant terms and their relationships. Using those terms, we experimentally searched through a set of databases with different combinations of search queries in order to verify their usefulness and to improve the search queries iteratively. Thus we enhanced the queries by adding synonyms, abbreviations and wildcard symbols, which account for different spellings. We created the final search query, which addresses the two main topics by combining search terms through logical operators. The search query presented below was used for the EBSCOhost database. Queries for other databases differed slightly due to the technical specifics of each database.

Terms related to decision support technologies:

(("business" AND (analytic* OR "intelligence")) OR (("decision support" OR "executive information" OR "management information" OR "management support" OR "corporate performance management") AND system*) OR ("data warehouse" OR "data warehousing") OR ("BI" OR "BA" OR "DSS" OR "EIS" OR "MIS" OR "MSS" OR "CPM" OR "DW"))

Terms related to decision processes and their characteristics:

(decision* AND ((process* OR routine* OR pattern* OR "making" OR procedure* OR practice* OR activit*) OR (effic* OR effectiv* OR satisfaction* OR performance* OR "commitment" OR "consensus" OR participation* OR "involvement" OR conflict* OR "confidence" OR "speed" OR time* OR qualit* OR comprehen* OR "extensiveness" OR rationalit* OR "interaction" OR adaptiv* OR flexibil*)))

2.3.3 Inclusion and Exclusion Criteria

In order to guide our evaluation procedures during the literature search process, we derived a set of explicit inclusion and exclusion criteria in accordance with our research goal. Those criteria provide additional transparency, not only on the search procedure but also on follow-up literature evaluation procedures (i.e. title, abstract and full text evaluation). Publications were eligible for inclusion if they provided empirical results related to our research goal and we included suitable qualitative and quantitative research studies. With respect to time frame, we anchored our study using the review of Benbasat and Nault (1990) as it provides an overview on DSS research from its early beginnings. Thus, we focused on research performed after 1990 and furthermore publications had to be peer-reviewed, written in English and available in full text. Due to the diversity of DSS research topics we also defined a number of explicit exclusion criteria. Publications were excluded if they dealt solely with aspects related to design, interface, architecture or implementation of DSS. Additionally, publications that focused on the effects of user characteristics like satisfaction, learning and group collaboration techniques were not in our scope. Many DSS publications concentrate exclusively on decision results (Forgionne 1999) and as we focused our research on decision processes, we excluded such studies. Finally, we excluded publications that dealt with implementation, validation or verification of specific optimization techniques or algorithms from a purely technical perspective.

2.3.4 Data Sources and Search Process

For finding relevant data sources we queried scientific databases, which contained journals and publications from relevant conferences (Webster and Watson 2002). We decided to query the scientific databases by title and without further restricting the searches to specific journals or conference proceedings in order to be exhaustive and address the interdisciplinary nature of the topic. We performed searches in the following databases: EBSCSOhost (Business Source Premier and Econlit), Science Direct, Thomson Reuters Web of Knowledge (Web of Science), Wiley Online Library, ACM Digital Library, IEEE Xplore Digital Library and AIS Electronic Library. This selection of databases allowed us to search more than 3000 journals from the information systems, management and computer science, including the top 25 MIS journals listed by the AIS. Additionally, we searched through the most important information systems conferences like ECIS and ICIS.

Figure 2.1 gives an overview of our literature search process and the number of publications at the end of each process phase. Using the keyword-based search we obtained a total of 1136 publications. These publications were entered into a Zotero database for better handling and documentation of the process phases. For each phase of the search process we created a separate Zotero database. Having the initial set of publications we read through titles and abstracts of those publications and excluded those that did not match our defined inclusion and exclusion criteria. In uncertain cases we kept the publications for subsequent full text analysis. This resulted in a set of 121 publications for which we intensively investigated the full text and again applied our inclusion and exclusion criteria as part of the evaluation. Additionally, we excluded similar publications by the same author groups and in such cases we kept results from the highest quality source or if those were similar we kept the newest one.

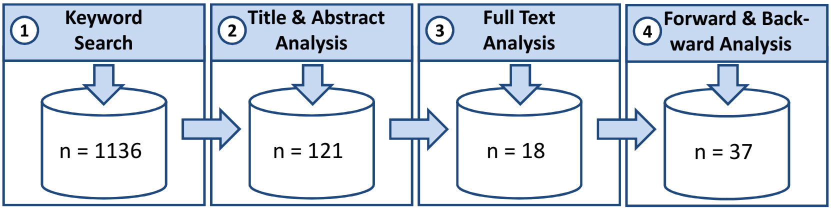

Figure 2.1: Search Process

Following this procedure we obtained a set of 18 publications, which were in scope of our research goal. As recommended by Webster and Watson (2002), we additionally conducted a forward and backward search on the set of relevant publications. We searched backward by analyzing the references of the publications. We searched forward by utilizing respective functions of Thomson Reuters Web of Knowledge and Google Scholar for identifying citing publications. During forward and backward search we adhered to the same procedure as before by identifying potentially relevant candidates through their title and abstract and further investigating them with a full text analysis. At the end we obtained a final set of 37 publications from which we extracted data for the analysis.

2.3.5 Data Extraction and Analysis Procedures

From the final set of 37 publications, data was extracted using a predefined extraction form. Besides basic bibliographic information (date, author and source), we encoded information on the research design (research method and research context), system type, the decision under investigation and related tasks that were described. Furthermore we noted a short summary of the most important results and for documenting the effects on the decision processes, we extracted independent variables (if available), decision process characteristics and outcomes, as well as reported effects on those elements.

For analyzing the extracted information, we applied the research framework. In our analysis we distinguish contributions that explicitly examine distinct decision process phases, from contributions that examine decision processes implicitly. In this context we used the information about the investigated decision types and performed tasks for identifying such implicit process contents, including distinct process phases. With respect to the actual effects on decision process phases, we analyzed the variables that were investigated within the publications and assigned the evidence on their effects to the respective categories of the research framework.

2.4 Results of the Structured Literature Review

This section presents the results from the literature review. The complete list of publications that have been used for this analysis is provided in the appendix. In the set of 37 publications the majority has been published in journals (33 publications) and some on conferences (4 publications). Research related to the effects of decision support technologies on decision processes has been performed mainly in the information systems (28) but also in management literature (7) and other domains (2). Most prevalent research methods are experiments (21), followed by surveys (11) and case studies (5).

2.4.1 Studies on the General Support of Decision Processes

Within the set of publications we identified five survey studies that were performed in industrial contexts and deal with perceived support of decision support technologies (see Table 2.1). In those studies, the subjects were directly asked about their perceived level of support for the distinct process phases. Most of those studies (2-5) report positive effects with respect to the perceived support of the investigated technologies. In the oldest study (1) from this sample support was only found for the selection phase. This is consistent with the development of the DSS field, as initial developments in DSS focused on techniques for the selection phase.

Table 2.1: Overview of Survey Studies on Support of Decision Process Phases

Nr.	Year	Research Method	Context	System Type	(1) Identification	(2) Development	(3) Selection
1	1990	Survey	Industrial (n = 87)	DSS	o	o	+
2	1998	Survey	Industrial (n= 55, 63)	IS	+ (most support)	+	+ (most support)
3	2002	Survey	Industrial (n=51)	EIS	+	+	+
4	2004	Survey	Industrial (n=117)	IS	+ (most support)	+	+ (most support)
5	2008	Survey	Industrial (n=42)	BI	+ (most support)	+	+ (most support)

Notes: “+” indicates support and “o” indicates that no effect was found.

2.4.2 Studies on the Specific Effects on Decision Processes

This sub-section presents studies that focused on distinct phases of decision processes, as well as the associated process characteristics and outcomes. We divided the overall set into three sub-sets according to the number of phases (one, two or three) that have been investigated in the studies. Tables 2.2, 2.3 and 2.4 present the analysis results and they provide information about research method and context, the investigated technology, and explicit or implicit conceptualization of process phases. Furthermore, they provide results on the effects with respect to the specific process attributes. For each of the three phases (1) Identification, (2) Development and (3) Selection, the associated attributes (IQ) Information Quality, (C) Comprehensiveness and Procedural Rationality, (S) Speed and (O) Phase Outcome are covered explicitly. In the last two columns the effects on (D-Res) Decision Results and (DP-Speed) Total Decision Speed are provided. The interpretation of the effects is as follows: "+" and "-" indicate the direction of the effect with respect to an attribute. "++" and "- -" additionally indicate that the effect was found to be statistically significant. "o" shows that the attribute was investigated but no resulting effect was found. Additionally, in order to provide transparency on assignments of effects to process phases that were only covered implicitly, we use brackets "( )".

Table 2.2 presents the results of ten single-phase studies. Two studies (6, 7) explicitly address the identification phase using case studies in an industrial context. Studies 8-15 focus on the selection phase using experiments in an academic research setting. System type is mainly classified as general DSS. Single-phase studies concentrate on attributes 3-C and D-Res. Six studies (8, 9, 11, 12, 13, 14) find positive effects with respect to 3-C and six studies (9-11, 13-15) find mainly positive effects on D-Res.

Table 2.2: Overview of Single-Phase Studies and Investigated Effects

						(1) Identification				(2) Development				(3) Selection					
Nr.	Year	Research Method	System Type	#-implicit / explicit	Phases	1-IQ	1-C	1-S	1-O	2-IQ	2-C	2-S	2-O	3-IQ	3-C	3-S	3-O	D-Res	DP-Speed
6	1994	Case Study (Industrial)	DSS	1-explicit	Identification	++		++	o										
7	2003	Case Study (Industrial)	DSS	1-explicit	Identification		+	-											
8	1994	Experiment (Academic)	DSS	1-explicit	Selection										+				
9	1996	Experiment (Academic)	DSS	1-explicit	Selection										++			++	
10	1997	Experiment (Academic)	ES	1-explicit	Selection													++	
11	1998	Experiment (Academic)	DSS	1-explicit	Selection										++			++	
12	2000	Experiment (Academic)	DSS	1-explicit	Selection										+				
13	2001	Experiment (Academic)	DSS	1-explicit	Selection										++			++	
14	2004	Experiment (Academic)	DSS	1-explicit	Selection										++			++	o
15	2007	Experiment (Academic)	DSS	1-explicit	Selection										o			+	

Notes: "+" and "-" indicate the direction of the effect, "++" and "- -"additionally indicate significance of the effect.

The results from eleven two-phase studies are presented in Table 2.3. Experiment research is also the prevailing research method. We find a focus on the development and selection phases. General DSS remain the most common system type. D-Res is covered ten times (17-26) and mainly positive results are reported. The coverage of the other four phase-specific attributes is higher than in single-phase studies. IQ is addressed in one study (23) and we find positive implications. For C we find positive implications in three studies (22, 23, 25). For S, O, and DP-Speed we find mixed results.

Table 2.3: Overview of Two-Phase Studies and Investigated Effects

						(1) Identification				(2) Development				(3) Selection					
Nr.	Year	Research Method	System Type	#-implicit / explicit	Phases	1-IQ	1-C	1-S	1-O	2-IQ	2-C	2-S	2-O	3-IQ	3-C	3-S	3-O	D-Res	DP-Speed
16	1995	Case Study (Industrial)	EIS	2-explicit	Identification Selection			+								+			+
17	1993	Experiment (Academic)	DSS	2-implicit	(Development) (Selection)													+	
18	1994	Experiment (Industrial)	DSS	2-implicit	(Development) (Selection)											- -	- -	-	
19	1994	Experiment (Academic)	DSS	2-implicit	(Development) (Selection)								(++)				(++)	+	-
20	1995	Experiment (Academic)	DSS	2-implicit	(Development) (Selection)													++	
21	1996	Experiment (Academic)	DSS	2-implicit	(Development) (Selection)								(++)				(++)	++	
22	1998	Experiment (Academic)	DSS	2-implicit	(Development) (Selection)						(++)	(++)			(++)	(++)		+	++
23	2001	Experiment (Industrial)	DSS	2-implicit	(Development) (Selection)					(+)	(+)			(+)	(+)			+	-
24	2001	Experiment (Academic)	DSS	2-implicit	(Development) (Selection)													++	++
25	2004	Experiment (Academic)	DSS	2-implicit	(Development) (Selection)						(+)	(+)			(+)	(+)	o	++	
26	2006	Experiment (Academic)	DW	2-implicit	(Development) (Selection)													++	o

Notes: "+" and "-" indicate the direction of the effect, "++" and "- -"additionally indicate significance of the effect. "( )" indicate assignment of effects to implicitly covered decision process phases.

Table 2.4 presents eleven studies that encompass all three decision process phases. We find a variety of research methods, with survey-based research being the largest group. In contrast to the other sub-sets, general DSS is not the prevailing system type and business intelligence and executive information systems are represented more often. The coverage of process attributes is broader and we do not observe a concentration on one attribute. Instead IQ is addressed by eight studies and C, as well as S are addressed by six studies. Attributes O, D-Res and DP-Speed are only addressed by five or less studies. With respect to IQ we find rather positive implications throughout the three phases and particularly for BI and EIS systems (33, 36, 37). Evidence on the effects on C is mainly positive throughout the phases (28-30, 33, 36, 37). Interestingly we find that studies related to the overall process are less focused on actual phase outcomes and even fewer consider decision results. For studies that address both, process characteristics and outcomes (29, 30, 32, 34) we find rather positive effects. We find mixed results for decision speed.

Table 2.4: Overview of Three-Phase Studies and Investigated Effects

						(1) Identification				(2) Development				(3) Selection					
Nr.	Year	Research Method	System Type	#-implicit / explicit	Phases	1-IQ	1-C	1-S	1-O	2-IQ	2-C	2-S	2-O	3-IQ	3-C	3-S	3-O	D-Res	DP-Speed
27	1992	Experiment (Industrial)	DSS	3-explicit	Identification Development Selection			- -				- -				o			- -
28	1993	Survey (Industrial)	EIS	3-explicit	Identification Development Selection		++	++			++	(++)			++	++			
29	1995	Case Study (Industrial)	IS / DSS (different per case)	3-explicit	Identification Development Selection	+	+	+	+	+	+	+	+	+	o	+	+		
30	1996	Experiment (Mixed)	MSS (=EIS+ ES+ DSS)	3-explicit	Identification Development Selection	(o)	++		o	(o)	o		++	(o)	++		++	++	- -
31	2000	Case Study (Industrial)	BI	3-explicit	Identification Development Selection													+	-
32	2000	Experiment (Academic)	DSS	3-explicit	Identification Development Selection	(o)			o	(o)			+	(o)			+	+	+
33	1995	Survey (Industrial)	EIS	3-implicit	(Identification) (Development) (Selection)	(++)	(++)	(++)		(++)	(++)	(++)		(++)	(++)	(++)			
34	1996	Survey (Industrial)	IS	3-implicit	(Identification) (Development) (Selection)	(++)		(o)		(++)		(o)	(++)	(++)		(o)	(++)	++	
35	1998	Survey (Industrial)	IS	3-implicit	(Identification) (Development) (Selection)	(- -)				(- -)			(- -)	(- -)			(- -)	- -	
36	1999	Survey (Industrial)	EIS	3-implicit	(Identification) (Development) (Selection)	(++)	(++)	(++)		(++)	(++)	(++)		(++)	(++)	(++)			
37	2012	Survey (Industrial)	BI	3-implicit	(Identification) (Development) (Selection)	(++)	(++)			(++)	(++)			(++)	(++)				

Notes: "+" and "-" indicate the direction of the effect, "++" and "- -"additionally indicate significance of the effect. "( )" indicate assignment of effects to implicitly covered decision process phases.

Table 2.5 provides an overview of the attribute coverage in studies 6-37. Attribute coverage describes for each attribute the fraction of studies that address this attribute. Attribute coverage is generally around one third or less and thus relatively low. Only two attributes achieve higher coverage. 3-C is covered by half of the studies and D-Res is covered by two thirds of the studies. Additionally, Table 2.5 presents the number of positive, negative and neutral effects that have been reported in those studies. It provides the relative fraction of positive effects in comparison to negative and neutral effects. The fraction of positive effects is larger than two thirds in most cases, which gives an indication of the positive effects on decision processes, but those effects don't seem to be self-evident.

Table 2.5: Attribute Coverage, Number/Fraction of Reported Effects

	1-IQ	1-C	1-S	1-O	2-IQ	2-C	2-S	2-O	3-IQ	3-C	3-S	3-O	D-Res	DP-Speed
Attribute Coverage	0.28	0.22	0.28	0.13	0.28	0.28	0.25	0.22	0.28	0.5	0.31	0.28	0.66	0.34
# Positive	6	7	6	1	6	8	6	6	6	14	7	6	19	4
# Negative	1	0	2	0	1	0	1	1	1	0	1	2	2	5
# Neutral	2	0	1	3	2	1	1	0	2	2	2	1	0	2
Fraction of Positive Effects	0.67	1.00	0.67	0.25	0.67	0.89	0.75	0.86	0.67	0.88	0.70	0.67	0.90	0.36

2.5 Discussion of Results

Within the results from the literature review we identified a set of studies (studies 1-5) that provides evidence for the general perception that decision support technologies have a positive effect on decision processes. As these studies have a high-level view on the decision process, it is difficult to derive specific insights for distinct decision processes phases or specific characteristics and outcomes.

As part of this research we also identified a larger set of studies (6-37) that provides more detailed information on effects that are specific for decision process. Those results show that the overly positive perception from the high-level point of view is less clear when we take a more detailed look at decision processes and their characteristics and outcomes. Thus a lower level of abstraction is needed in order to understand the actual effects of decision supporting technologies on decision processes.

Within this set of studies we distinguished single-, two- and three-phase studies. We find that single-phases studies have a strong focus on the selection phase. In these studies comprehensiveness and decision results are investigated in experimental settings. This research mainly deals with choice support in academic, highly structured problem environments (i.e., alternatives and decision variables are predefined). Its purpose is to reduce biases during choice-making. In the two-phase studies this research approach is extended to the development phase. In most cases studies were also performed in experimental settings, which focused on more realistic decision problems. In those experiments subjects typically had to develop solution alternatives by themselves, before they performed the analysis and choice. In order to gain more conclusive insights, research needs to be extended to the whole decision process, including its characteristics and outcomes. In this context, three-phase studies offer insights on the effects on process characteristics and outcomes throughout the decision process. We observed that those studies are typically less decision result oriented but tend to focus more on process characteristics. This allows for investigating the direct effects of decision support technologies on decision processes and not only the resulting or indirect effects on outcomes.

Another issue, besides phase coverage, is the coverage of distinct decision process characteristics and outcomes. We find in most cases a low coverage, which is an indication for isolated investigations of process attributes. In order to obtain conclusive results with respect to decision processes it is important to consider attributes related to process characteristics and process outcomes (Forgionne 1999; Phillips-Wren et al. 2004). This is needed in order to explain observed differences in positive and negative effects (see Table 2.5) of decision supporting technologies. In this context we find that those attributes that have been investigated the most (D-Res and C) have also the highest fraction of reported positive effects. Due to a high fraction of isolated investigations of these attributes it remains an open question if those effects will be stable in more realistic decision environments.

2.6 Research Opportunities

The results from the literature analysis help to characterize the current state of research related to BI&A systems, decision support technologies in general and their effects on decision processes. This provides the basis for identifying further research opportunities.

(1) BI&A coverage: For BI&A technologies we observe the need for more empirical research in relation to decision processes. Although knowledge about their implications is important for decision makers (Watson 2010), the fraction of those technologies is low within the analyzed set. Thus it would be beneficial to investigate the effects of those technologies on the phases of decision processes and their characteristics and outcomes. For example, research on current in-memory BI&A technologies would be highly valuable, as they do not only promise to impact the speed of decision processes but also have the potential to change their constitution and structure. Knowledge about these implications is important for decision makers in the context of the adoption and utilization of those technologies.

(2) Decision process coverage: In our analysis we find low values for attribute coverage. Only less than one third of the studies address decision process phases, as well as process characteristics and outcomes. Only six studies did this in an explicit manner. Therefore we see a need for more research that addresses decision processes from an integrative perspective. This means that process characteristics need to be studied together with process outcomes (Forgionne 1999). This research is relevant as it is a prerequisite for explaining the observed differences in the effects of technologies. In particular, it remains unclear if decision process attributes have properties of complements or substitutes in the context of technological decision support. Furthermore we find a high research focus on the selection phase. The preceding identification and development phases should be considered with the same priority as they provide the input for the selection phase. If an organization fails in those phases, the overall decision result will be in danger (Nutt 2008). Research in this direction is particularly relevant for the successful utilization of BI&A systems as those are supposed to support all decision process phases.

(3) Decision process constitution: Based on the implications of BI&A technologies we find indications that more research is needed on the constitution of decision processes and the roles involved. Research from DSS and management domains has found that structure and formalization of decision processes can impact their effectiveness and efficiency (Kanungo 2009; Nutt 2008) and also the usage of technology to support decisions. Decision processes supported by business intelligence were found to be highly iterative and dependent on the interaction between BI specialists and decision makers (Brohman et al 2000). Thus, the role

of BI&A specialists and their interaction with decision makers gains increasing importance (Davenport 2006) and can become a success factor for the execution of decision processes. Consequently more research in this area would be of great value in order to help organizations in designing suitable decision processes that integrate BI&A technology effectively.

2.7 Conclusion

The purpose of this paper was to systematically investigate evidence on the effects of decision support technologies, particularly business intelligence and analytics systems, on distinct phases of decision processes. For this purpose we developed a research framework, we analyzed and presented results from a comprehensive and structured literature review and we identified future research opportunities.

Hence, we "analyzed the past to prepare for the future" (Webster and Watson 2002). Although we followed acknowledged procedures for performing a structured literature review (Webster and Watson 2002; vom Brocke et al. 2009), our results are not without limitations. Our search and analysis focused on a fixed number of scientific databases and thus we cannot for sure exclude having missed some articles. With regards to the selection procedures we defined explicit criteria and followed a rigorous procedure, but nevertheless the choice may remain subjective to a certain extent. Similarly, the categorization by using the suggested research framework is derived from existing research, but is mainly characterized by the perspective of the authors on this topic.

Drawing a conclusion from this research, we can state that for BI&A more research from the decision process perspective is needed. Therefore we hope that this literature review will support further research at the interface between BI&A systems and managerial decision processes.

3 Study B: Big Data and Information Processing in Organizational Decision Processes[2]

3.1 Introduction

In recent years, data-centric approaches such as big data and related approaches from business intelligence and analytics (BI&A) have attracted major attention in both the academic and the business communities (Buhl et al., 2013; Chen et al., 2012; LaValle et al., 2011). The interest is driven by expectations of tremendous improvements in organizational performance based on new business insights and improved decision making. In this context, big data and BI&A can be regarded as two sides of the same coin. Whereas big data addresses the supply of data as a resource that can be utilized by organizations (Buhl et al., 2013, p. 67, p. 67), BI&A provides the methodologies and technologies for data analysis that can improve business understanding and decisions (Chen et al., 2012, p. 1166; Davenport and Harris, 2007, p. 8).

Incorporating data-centric approaches into organizational decision processes is challenging, and it is not self-evident that the expected benefits will be realized. While recent reviews of research on big data (Pospiech and Felden, 2012, p. 6) and BI&A (Arnott and Pervan, 2008, p. 661; Shollo and Kautz, 2010, p. 8) find a broad coverage of the technological aspects, they also identify a lack of research on the utilization of data in decision processes. To realize the expected benefits of data-centric approaches in this connection, a good understanding of the complementary organizational mechanisms is required (Zack, 2007, p. 1665), as well as an understanding of the context of the decision processes in which these approaches are to be applied (Davenport, 2010, p. 2; Goodhue et al., 1992, p. 299; Işık et al., 2013). Hence, although technologies for handling vast data volumes with huge variety and high velocity are becoming broadly available throughout industries, the question of whether this results in better decision making cannot be answered from a purely technical perspective (Buhl et al., 2013, p. 68).

In this regard, organizational information processing theory (Daft and Lengel, 1986; Galbraith, 1974; Tushman and Nadler, 1978) suggests that effective utilization of data requires an appropriate, context-specific composition of information processing mechanisms. In this paper we address the question of which mechanism compositions can be considered appropriate for decision processes in the context of BI&A and big data. By using a multiple case study

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M. Kowalczyk, *The Support of Decision Processes with Business Intelligence and Analytics*, DOI 10.1007/978-3-658-19230-3_3

approach, we investigate four different types of BI&A-supported decision processes from organizations located across different industries. This paper makes the following contributions.

(1) We show how facets of big data and different compositions of information processing mechanisms are utilized in different types of BI&A-supported decision processes. (2) We contribute to information processing theory by providing new insights about organizational information processing mechanisms and their complementary relationships to data-centric mechanisms. (3) We demonstrate how information processing theory can be applied to assess the dynamics of mechanism composition across different types of decisions.

In the next section of this paper, we discuss the theoretical background and develop a conception of data-centric and organizational information processing mechanisms. Then we illustrate our case study approach by describing details of the study design and the data analysis procedure. Following that, we present results from the case study. The article closes with a discussion of the research findings and limitations, as well as directions for future research.

3.2 Theoretical Background

3.2.1 Big Data and BI&A

Big data refers to the vast growth of data that organizations are currently experiencing. A definition of big data that is relatively established is based on the 3-V model (Klein et al., 2013, pp. 319-320). The 3-V model considers three dimensions of challenges in data growth: data volume, velocity, and variety. *Volume* refers to the growing amount of data. Volumes that are typically considered big are in the range of several terabytes and more (Klein et al., 2013, p. 320). *Velocity* describes the speed of new data creation, as well as how quickly data can be accessed for further processing and analysis. Real-time access speed is often mentioned in connection with velocity (Buhl et al., 2013, p. 65; Klein et al., 2013, p. 320), but the utility of this dimension is considered to be strongly dependent on the actual usage scenario (BRAC, 2013, p. 30; Polites, 2006, p. 1390). *Variety* describes the range of different data sources and types, which can be more or less structured (Buhl et al., 2013, p. 65; Klein et al., 2013, p. 320).

BI&A is strongly interrelated with big data, as it provides the methodological and technological capabilities for data analysis (Chen et al., 2012, p. 1166). BI&A has its origins in database management and data warehousing, and comprises a number of data collection, extraction, and analysis technologies (Watson, 2010, p. 5; Watson and Wixom, 2007, p. 96). BI&A systems aim at improving data processing procedures and thereby increasing the quality of information (Chamoni and Gluchowski, 2004, p. 119; Dinter, 2012, p. 1; Popovič et al., 2012, p. 737). Recent innovations at the backend of BI&A systems, such as in-memory databases and massively parallel data architectures, allow the handling of big data during analysis (Chaudhuri et al., 2011, p.93; Plattner and Zeier, 2011; Watson, 2010, pp. 6-7). Analytics capabilities associated with BI&A include basic techniques for accessing and analyzing data, e.g., ad-hoc queries and descriptive statistics. Additionally, more elaborate techniques for working with data in a structured way are available, including online analytical processing (OLAP) and interactive dashboards or reports. BI&A also provides capabilities for predictive modeling and data mining (Chaudhuri et al., 2011, p. 97; Watson, 2010, p. 5; Watson and Wixom, 2007, p. 97). To realize the benefits of data-centric approaches, organizations require a good understanding of how they should be utilized in different decision process contexts (Davenport, 2010, p. 2; Işık et al., 2013). Our research provides insights into the utilization of big data facets and analytics with respect to four different types of decision processes.

3.2.2 Information Processing Theory and Decision Processes

Organizational information processing theory considers information as one of the most important organizational resources. It assumes that the design of organizations – their structures, mechanisms, and processes – revolves around information flows, and has the goal of reducing context-specific uncertainty and equivocality through information processing (Daft and Lengel, 1986, p. 555; Galbraith, 1974, p. 29; Tushman and Nadler, 1978, p. 614). Uncertainty is conceptualized as the absence of information (Goodhue et al., 1992, p. 298; Zack, 2007, p. 1665). Organizations that are confronted with high levels of uncertainty are assumed to acquire more information to reduce uncertainty (Zack, 2007, p. 1666). In contrast, equivocality concerns the existence of ambiguity or lack of understanding of the problem context (Daft and Lengel, 1986, p. 557). Equivocality can be resolved through integration of different views and requires interpretation and discussion (Daft and Lengel, 1986, p. 557; Zack, 2007, pp. 1666-1667). This distinction implies the need for different information processing mechanisms.

Existing research results on organizational decision processes (Elbanna and Child, 2007; Mintzberg et al., 1976; Nutt, 2008; Simon, 1960) consider both dimensions – uncertainty and equivocality – as relevant for adequately characterizing decision contexts. Decision makers often find themselves in uncertain and non-routine situations where ambiguity or equivocality prevail and the appropriate questions are not obvious. Decision processes can be described as consisting of three phases: (1) identification of the issue, (2) development of solution alternatives, and (3) analysis and selection of one alternative (Mintzberg et al., 1976; Simon, 1960).

Information processing theory suggests that information processing mechanism designs are effective if they are capable of handling the amount and type of information that is required in a given problem context. Thus, effectiveness implies achieving a context-specific fit between information requirements and information processing capacities (Daft and Lengel, 1986, p. 568; Fairbank et al., 2006, p. 295; Huber, 1990, p. 65; Tushman and Nadler, 1978, p. 622).

Information processing capacities are created through a combination of organizational and technological resources, and effective designs are associated with high performance levels (Tushman and Nadler, 1978, p. 619; Zack, 2007, p. 1667). Hence, different combinations of information processing mechanisms are needed for different decision process contexts.

Mechanisms that reduce equivocality or ambiguity are considered to be different from mechanisms that reduce uncertainty. In this context, the richness of information and the amount of information are distinguished. Information richness is defined as the ability of information to change understanding within a certain time interval (Daft and Lengel, 1986, p. 560; Zack, 2007, pp. 1666-1667). Mechanisms that facilitate richness of information typically involve face-to-face contact between individuals in the decision process. These mechanisms enable the clarification of context and related questions. In contrast, mechanisms that address uncertainty are supposed to optimize the amount of information that is available to the decision maker (Daft and Lengel, 1986, p. 559; Zack, 2007, pp. 1666-1667). In this regard, Daft and Lengel (1986, p. 561) define seven mechanisms (rules, information systems, special reports, planning, direct contact, integrator, and groups) and propose a continuum of mechanisms with varying capacities for reducing equivocality and uncertainty in decision making. We adapt and modify this conception by explicitly considering the capabilities of BI&A systems.

3.2.3 Data-centric and Organizational Information Processing Mechanisms

In this section we develop a conception of data-centric and organizational information processing mechanisms based on the continuum proposed by Daft and Lengel (1986, p. 561), taking into account the specific BI&A capabilities (see Figure 3.1). We distinguish four data-centric mechanisms that exhibit different capacities for reducing uncertainty and equivocality. *Data mining* comprises data analysis and discovery algorithms for identifying patterns or models (Fayyad et al., 1996, p. 30). Hence, data mining can contribute to reducing uncertainty and equivocality. Big data enhances the capacities for discovering patterns that are robust and that can create the foundation for predictive analytics (Dhar, 2013, pp. 71-72). We subsume under *ad-hoc queries and descriptive analytics* those mechanisms that allow for open descriptive data analysis with a question or hypothesis in mind. These include one-time studies with the purpose of gathering and analyzing data about a specific issue for a decision maker. *OLAP and dashboards* include the periodic delivery of information that answers predefined questions and provides structured means of data analysis, such as drilling, slicing, and dicing (Chaudhuri et al., 2011, p. 92; Davenport and Harris, 2007, p. 8). *Predictive analytics* refers to the utilization of defined models for accurate prediction of recurring or well-understood issues (Chaudhuri et al., 2011, p. 97). This means that equivocality has been reduced beforehand.

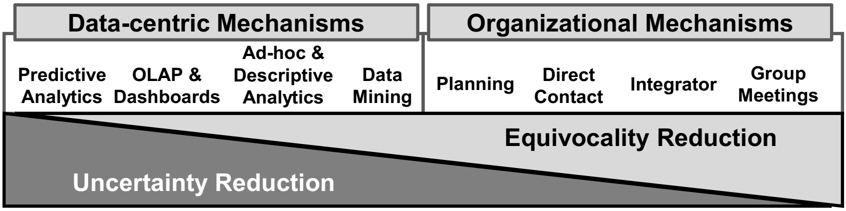


Figure 3.1: Overview of Information Processing Mechanisms

We adapt the following four organizational information processing mechanisms from Daft and Lengel (1986, pp. 560-562). *Planning* refers to a joint effort of decision stakeholders to reduce equivocality and uncertainty. Equivocality is initially high but can be reduced through personal information processing. Common goals and a course of action are then established and monitored. *Direct contact* represents simple forms of personal contact that allow stakeholders to discuss issues personally. The *integrator* is a lateral organizational position that deals with the integration and distribution of information with the purpose of establishing a common understanding and reducing equivocality. *Group meetings* are primarily concerned with reducing equivocality through collective judgment and building joint understanding. In the case studies, we investigate the BI&A specifics of those organizational mechanisms.

This conception of information processing mechanisms can be used to assess the extent of uncertainty and equivocality reduction in decision processes. According to the continuum presented in Figure 3.1, the mechanisms contribute different amounts to uncertainty and equivocality reduction. The overall extent of uncertainty and equivocality reduction can be represented as a linear combination of these mechanisms. We use this conception of phase-specific combinations of information processing mechanisms as the basis for understanding the mechanism composition and dynamics throughout the phases of decision processes.

3.3 Research Approach

3.3.1 Research Design

Investigating the composition of data-centric and organizational information processing mechanisms in BI&A-supported decision processes involves a complex research setting. We considered the case study approach to be particularly suitable for in-depth analysis of such a complex phenomenon (Benbasat et al., 1987, p. 369; Dubé and Paré, 2003, p. 598; Yin, 2003, p. 13). Additionally, to gain further insights into organizational mechanisms and the facets of big data that are utilized, an exploratory research approach was advisable.

To address the criticism of case studies for their lack of generalizability (Benbasat et al., 1987; Dubé and Paré, 2003; Lee, 1989), we chose a multiple case design, which allows more general results to be achieved based on a number of individual cases (Yin, 2003). Organizational decision processes that are supported by BI&A are our study's unit of analysis. A foundation comprising several cases aids the derivation of more elaborate insights and explanations for the observations made (Benbasat et al., 1987, p. 373; Miles and Huberman, 1994, p. 172), based on explicit consideration of the different decision contexts. This research follows a positivist research approach, which assumes that the researchers adopt a neutral and passive perspective and do not intervene in the phenomenon under study (Dubé and Paré, 2003).

In this study, we investigate twelve organizational decision processes, which were selected following theoretical and literal replication logic (Dubé and Paré, 2003, p. 609). For literal replication, we ensured that the organizational and technological contexts of the investigated decision processes were similar in each case. In particular, the case study organizations are all large enterprises, and the investigated decision processes were supported by BI&A systems. Furthermore, the decision processes had to be completed, as we were interested in investigating all three phases, including the information processing mechanisms that were utilized. To handle potential sector-specific influences, the set of enterprises covers different industry sectors, including finance, transport, telecommunications, media, and consumer products. For theoretical replication, we primarily aimed at investigating different types of organizational decisions according to the two dimensions of non-routine and uncertainty. This allowed us to contrast the results obtained according to four different decision types.

3.3.2 Data Collection

To maintain reliability throughout the course of our study, a case study protocol and database were set up before data collection began. The protocol defined the study's objectives and its data collection. To enhance the validity of our findings, we employed data triangulation and used multiple sources of evidence (Yin, 2003, pp. 97-101). We conducted in-depth expert interviews and collected additional company documentation where possible. Furthermore, we collected complementary data by using a follow-up questionnaire, in order to increase the reliability of our findings (Yin, 2003, p. 86).

For the expert interviews, we developed a semi-structured interview guide with open-ended questions. We decided to use the key-informant method for capturing knowledge about the decision processes (Bagozzi et al., 1991). We performed two pilot case interviews (technical and business-oriented analysts) in order to test and refine the guide. The final version of the interview guide consists of three parts. In the first part, we ask the interviewees about their educational background, professional experience, and current role in the organization. In the second part, we elicit general information about the technological context and the decision process in question. The third and major part of the interview concerns one specific organizational decision process that had been supported by the interviewed expert.

For our case studies, we relied on BI&A experts and analysts. Typically, these experts support all phases of a decision process and have deep insights into the data-centric and organizational mechanisms of information processing. Hence, focusing data collection on their perspectives helped us to maximize the visibility of the decision process phases and the mechanisms that were used. During the expert interviews we had to rely on retrospective reports, which are considered to be increasingly incomplete and prone to errors as the elapsed time between the investigated event and its verbalization increases (Ericsson and Simon, 1993, pp. 19-20). We tried to increase reliability by explicitly focusing on one specific organizational decision process, concerning which we encouraged the experts to speak openly about everything that came to their minds. We explored the three phases of the decision processes in detail, with a focus on the organizational mechanisms. Use of a laddering technique helped us gain deeper insights through successive questions (Reynolds and Olson, 2001).

The interviews were followed up with a questionnaire that was pre-tested by two research assistants and in the context of the pilot study. The purpose of the questionnaire was to collect complementary data for cross-validation and quantification of specific aspects of the decision processes. Specifically, the questionnaire focused on characterizing the decision types, the facets of big data, and the usage of data-centric mechanisms. All characteristics were measured using seven-point Likert scales, and we relied on existing scales where available (BRAC, 2013; Klein et al., 2013; Popovič et al., 2012).

The study was conducted over a three-month time period, beginning in July 2013. Most of the interviews were conducted in the form of face-to-face meetings and some also over the telephone. The average working experience of the interviewed experts in the area of BI&A was eleven years. On average, each appointment lasted two hours, of which the average interview time was approximately 70 minutes. The remainder of the time was used for presentations or demonstrations by the participants and also, in most cases, for filling out the questionnaire. The interviews were audio recorded in all cases. In summary, this research approach provided a rich combination of qualitative and quantitative data as the basis for the data analysis.

3.3.3 Overview of Cases

Table 3.1 presents an overview of the case firms and interviewees that participated in our study. It summarizes the investigated cases' organizational decisions and their technology types.

Table 3.1: Overview of Investigated Cases

CaseID	Industry	Decision Content	Technology Type	Expert Role	Experience
Case 1	Telco	Reaction to new competitor	Business Intelligence & Analytics	BA Unit Lead	>10 Years
Case 2	Media	Product portfolio pricing	Business Analytics	Analyst	18 Years
Case 3	Finance	Product portfolio segmentation	Business Intelligence & Analytics	Analyst	>15 Years
Case 4	Consumer	Product portfolio - product mix	Business Intelligence	BA Unit Lead	6 Years
Case 5	Tourism	Product development	Business Intelligence	BI Unit Lead	14 Years
Case 6	Transport	Fleet constitution	Business Intelligence & Analytics	Analyst	5 Years
Case 7	Finance	Introduction of new risk-models	Business Intelligence & Analytics	Analyst	>10 Years
Case 8	Pharma	M&A portfolio	Business Intelligence & Analytics	Analyst	14 Years
Case 9	Finance	Product pricing	Business Intelligence & Analytics	BA Unit Lead	>10 Years
Case 10	Consumer	Sales discount	Business Intelligence & Analytics	Analyst	>10 Years
Case 11	Engineering	Service planning & control	Business Intelligence & Analytics	BI Expert	13 Years
Case 12	Transport	Capacity planning & control	Business Intelligence & Analytics	BI Expert	8 Years

To better characterize the decision contexts, we distinguish decisions based on the characteristics of 'non-routine' and 'uncertainty', following Daft and Lengel's (1986, p. 563) conception. By interpreting these two characteristics as dimensions of the decision context, we obtain four quadrants containing decision types based on different combinations of the characteristics (see Figure 3.2). We were able to obtain at least two cases per quadrant.

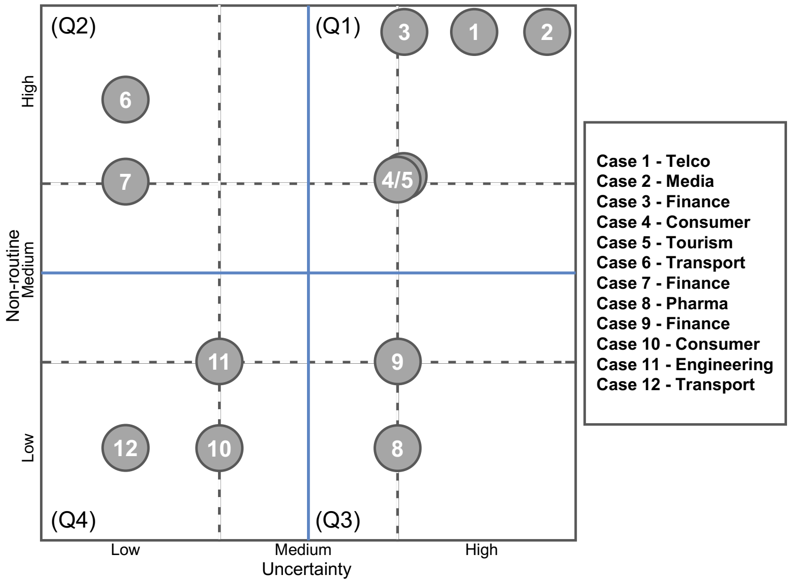


Figure 3.2: Categorization of Decision Types

Quadrant Q1 contains five cases that were characterized as being non-routine and uncertain. In all these cases, the participating interviewees described the decisions as one-time decisions. Case 1 is from a telecommunications firm. The decision process was triggered by the appearance of new competitors with new messaging services that began cannibalizing the firm's established text-messaging service. During the decision process, different scenarios about how to react were modeled. Those were analyzed with the aim of developing predictions concerning their impact on integrated service usage volumes and hardware sales. Case 2 comes from a media company that had to address declining sales volumes. The management decided that a new pricing strategy should be developed for the overall product portfolio. During the decision process, different pricing scenarios that considered regional pricing discrimination were developed. Predictions were created concerning the impacts on sales and subscription volumes. Case 3 is from the financial sector. The firm was losing ground against its competitors and had to address declining sales. Management issued the need to develop a new pricing strategy for the overall product portfolio and to additionally consider introducing a new product segmentation schema. During the decision process, different pricing scenarios were developed and the impact of the introduction of product segmentation was modeled. Based on these, predictions were made about the impact on sales volume. The firm in case 4 comes from the consumer goods industry. The decision process was initiated due to an unexpected dramatic decline in profit from one of their major brands. The product is often sold in a product mix with other products of this firm, and this situation was investigated during the decision process. Different solution alternatives concerning pricing and product mixes for the brand were developed and integrated into distinct scenarios. Based on those scenarios, implications for profit were forecasted and recommendations for restructuring the product mix and portfolio were derived. Case 5 comes from a firm in the tourism sector. The decision dealt with investing in a new and undeveloped destination. During the decision process, models were developed that supported decision making about where and how much to invest.

Quadrant Q2 contains cases that were characterized by relatively low levels of uncertainty but were nevertheless regarded as non-routine. Despite the cases' non-routine character, the interviewees indicated that the data required for making the decisions could be found inside the organization, which seemed to reduce their perceived level of uncertainty. Case 6 involves a firm from the transportation sector. The decision process was triggered by revenue issues for specific routes. During the decision process different solution alternatives were investigated, including changing frequencies, capacities, and particularly the constitution of the fleet. The effects of those changes on the revenues for the routes were modeled and simulated. The firm in case 7 comes from the financial sector. After an acquisition of another financial firm, the case organization had to address severe profit issues in one product segment. An initial validation showed that the issue arose from a lack of risk and pricing models. Hence, new models needed to be developed and new customer segments were evaluated as part of the decision process. The effects of the newly developed models on profits were furthermore simulated.

Quadrant Q3 contains two cases of decisions that, in contrast to Q1, were characterized as being more routine. The firm in case 8 comes from the pharmaceutical industry, and the decision process is situated in a yearly planning cycle that addresses the acquisition of new active ingredients. As part of the decision process different investment scenarios are developed, and the process is supported by an analytic solution consisting of a model that simulates and predicts the effects of those investment scenarios for long-term timeframes. Case 9 comes from the financial industry, and the investigated decision process is performed twice a year as part of the product pricing of insurance policies. During this decision process, the existing pricing structure is revised and alternatives for improvement are developed and evaluated. Then improvement suggestions are made, and their impacts on the financial results are predicted.

Finally, quadrant Q4 encompasses three decisions that were rated low for both non-routine and uncertainty. Case 10 is from the consumer goods industry, and the decision process, which concerns sales discounts, is iterated on a weekly basis. The decision process is supported by an analytics system that delivers discount suggestions for the overall portfolio. These suggestions are revised by a central unit, and if the overall volume falls within a defined range, discounts can be committed directly – otherwise, the process is escalated to higher-level management. Case 11 comes from the engineering industry and concerns the operational planning and control of service capacities. The decision process is supported by an analytics system that combines capacity, routing, and weather information in order to optimize the assignment of service and maintenance personnel. The firm in case 12 comes from the transportation sector and manages a major traffic hub. The supported decision process is an operational one that addresses passenger capacity and flow control. The process is supported by a BI&A system that delivers simulations every five minutes to a supervisor in charge of controlling passenger capacities to prevent passenger overflows.

3.3.4 Data Analysis

In the first step of data analysis the audio files were transcribed, producing an approximate average of twenty transcript pages per case. In the second step, the transcripts were coded using qualitative data analysis software. The coding used a list of codes that were defined a priori (Corbin and Strauss, 2008; Ericsson and Simon, 1993; Miles and Huberman, 1994). We were able to develop this list using literature on decision processes and the mechanisms comprised in information processing theory. Developing codes a priori is recommended and is seen as the basis for theoretical integration of raw data (Ericsson and Simon, 1993, p. 266; Strauss, 1987, p. 33). More specifically, we identified segments of the transcripts that related to the specific phases of the decision process, based on the contents of the task descriptions (Ericsson and Simon, 1993, p. 205). Then we utilized first-level coding to assign codes to all statements that reflected aspects of information processing mechanisms. During the coding process, additional necessary codes were added (Miles and Huberman, 1994). Next, qualitative data from the interviews and quantitative data from the questionnaires were brought together for cross-validation. This resulted in the removal of one case due to inconsistencies in its classification that could not be clarified. In order to facilitate analysis, various displays of the qualitative and quantitative data regarding different aspects of decision types, data facets, and information processing mechanisms were created, which supported the identification of patterns by using cross-case analysis. All intermediate results during the analysis were discussed among the authors in order to create a common understanding of the cases and patterns as well as a convergence in joint interpretations of the data.

3.4 Empirical Results

In this section, we present and provide evidence for the findings that emerged during the analysis of the multiple case study.

3.4.1 Big Data in Different Decision Contexts

Table 3.2 provides an overview of the underlying data basis for the different decision scenarios according to the three dimensions associated with big data (variety, volume, and velocity). In Table 3.2, the scale of ratings for the dimensions has been simplified to three levels (3-high, 2-medium, and 1-low) to allow for easier interpretation.

Table 3.2: Overview of Data Variety, Volume, and Velocity per Case

	CaseID	Industry	Variety	Volume	Velocity	SUM-3V
Q1	Case 1	Telco	(3) high	(2) medium	(1) low	(6) medium
	Case 2	Media	(2) medium	(1) low	(2) medium	(5) medium
	Case 3	Finance	(3) high	(3) high	(2) medium	(8) high
	Case 4	Consumer	(1) low	(2) medium	(2) medium	(5) medium
	Case 5	Tourism	(2) medium	(1) low	(1) low	(4) low
Q2	Case 6	Transport	(2) medium	(1) low	(2) medium	(5) medium
	Case 7	Finance	(3) high	(2) medium	(1) low	(6) medium
Q3	Case 8	Pharma	(3) high	(1) low	(3) high	(7) medium
	Case 9	Finance	(3) high	(2) medium	(1) low	(6) medium
Q4	Case 10	Consumer	(3) high	(3) high	(2) medium	(8) high
	Case 11	Engineering	(3) high	(3) high	(3) high	(9) high
	Case 12	Transport	(3) high	(3) high	(3) high	(9) high

Taking a closer look at Q1 (high non-routine and high uncertainty), the decision types show that these decision processes are highly variable in their utilized data basis. We find mainly low and medium ratings, and none of the investigated cases have high ratings in all three data facets. In this group, case 3 displays high ratings for variety and volume. A unique factor in case 3 was that the decision context allowed for enough time to explore the situation upfront and then to combine the decision process with a BI&A infrastructure project, which led to a complete redesign of the online-sales channel. This allowed for focused harnessing of online-sales data in the context of the decision process. For the cases that are characterized by either non-routine (Q2) or uncertainty (Q3), we also find high variability in the ratings of the three facets, whereas the majority of the ratings have moderate values.

Interestingly, in nearly all cases in the first three quadrants, the ratings for variety are higher than or equal to those for volume and velocity. This suggests that the focus for all these types of decisions seems to be on gaining broad coverage of the decision context by utilizing a multitude of different sources. A possible explanation could be that by considering a variety of sources, the decision process is driven with a priority toward addressing ambiguity and equivocality through an integration of different viewpoints. There is also theoretical support for this explanation, as ambiguity is assumed to induce further uncertainty if it is not addressed (Daft and Lengel, 1986, p. 558) and should therefore be reduced beforehand (Zack, 2007, p. 1667).

For the cases located in Q4 (low non-routine and low uncertainty), we find mainly high ratings for all three facets. This implies that all three facets of big data are utilized in these decision scenarios. This finding is quite consistent with reports on big data success cases from different industries that describe applications of big data in relatively well-defined decision contexts (BITKOM, 2012, pp. 51-92). When looking at the ratings sums for the three facets, a weak pattern can be identified. Besides case 3, we find that non-routine cases (Q1 & Q2) have ratings sums that are 6 or lower, while cases that are more routine (Q3 & Q4) exhibit ratings sums that are 6 and higher.

This overview of the utilized data basis shows that it is important to explicitly consider differences between decision types in order to better understand big data utilization in decision processes. In this regard, we found the non-routine of the decision to be relevant. To better understand the utilization of data in the context of BI&A-supported decision processes, we turn next to the actual data-centric and organizational information processing mechanisms

3.4.2 Data-centric and Organizational Information Processing Mechanisms

In this section we focus on the relationship between data-centric and organizational information processing mechanisms. One insight that we gained concerning the support of organizational decision processes with BI&A is that relying purely on technological analytics capabilities was considered to be insufficient. The following expert statement highlights that existing data can only address factors that have been relevant in the past and do not consider potential future factors that might become relevant for the decision:

"We can come up with great algorithms, but the world changes regularly […] therefore I think that analytic processes that are purely based on systems do not contain much value. […] Gaining insights won't be achievable by systems only. […] The problem is that we can only make statements based on retrospection, but this does not mean that the environmental factors that will be relevant tomorrow have been considered. This can go really bad." (Case 8)

This view is supported and extended by the following statement from the business analytics unit lead from case 1, who highlights that understanding the decision context is a major factor for being able to generate true insights:

“I find it really difficult to reduce this just to technology. Technology is just a small part and the far more important part is the capability of the analyst […] but not to utilize the technology, but instead mainly to understand the context and to generate true insights from the analytics results […].” (Case 1)

The following quotation further corroborates this point:

“[…] you can’t just say I’m crunching the numbers – it is really crucial to capture the problem adequately and then to make the right proposition or to find the right solution approach.” (Case 4)

These statements highlight that understanding the decision context is one of the major requirements for being able to assess the value of insights that are generated and hence for effectively supporting organizational decision processes. A frequent assumption is that either the analysts have sufficient domain knowledge for judging the value of insights or the domain experts are capable of acquiring and analyzing all data by themselves. We find evidence that these assumptions do not seem to hold for non-routine decision scenarios. Due to the required specialization, we typically find division of labor between analytics specialists and decision makers. Analysts provide deep knowledge in analytics methods and technologies, whereas decision makers can contribute their domain expertise. On the one hand, we find evidence that capturing context should be a major capability of analysts. But on the other hand, several statements emphasized that it is challenging to achieve an understanding of the decision context and that analysts have to rely on the decision maker’s domain knowledge:

“[…] in business, there are just too many levers, too many aspects that are relevant. Therefore the collaboration [with domain experts] is definitively important from my point of view […].” (Case 4)

The following two quotations take the same line:

“Such [non-routine] situations are really challenging for analysts as they don’t have sufficient [domain] knowledge and the task is very unstructured. Typically, analysts don’t like those situations. Such situations are vague and there are many underlying assumptions that they don’t know [...].” (Case 10)

“[…] but managers just have a different view on the world and they try to include decision parameters into the decision process that are unknown to analysts.” (Case 8)

Hence, these statements underline the relevance of organizational information processing mechanisms for analysts in reducing the gap in their domain knowledge. Interestingly, we find evidence that a high level of analytic methodological and technological elaboration, which analysts need for their work with big data, can also induce more equivocality into the decision processes. This is particularly so when analytic elaboration creates a gap in understanding between the analyst and the decision maker, as noted in the following quotations:

"High analytic capability, for me this is not synonymous with the 'analytics crack' [...] those are important, but typically they have difficulties in communicating their results in an understandable manner, or in concentrating on the most essential parts, or just keeping it reasonably simple. At the end of the day management needs to understand this." (Case 1)

"[...] [analysts] have their own way of working. They go very much into details and probably don't see the overall picture. When they prepare this as a basis for a decision, decision makers often have great difficulties in assessing it." (Case 3)

In summary, these statements underline the relevance of organizational information processing mechanisms, which integrate understanding between analysts and decision makers.

3.4.3 Information Processing Mechanisms in Different Decision Contexts

In this section, we emphasize how and to what extent organizations combine data-centric and organizational information processing mechanisms in the context of different decision types. For this purpose, Figure 3.3 provides an aggregated overview of the phase-specific usage of mechanisms in the investigated cases for the decision types Q1-Q4.

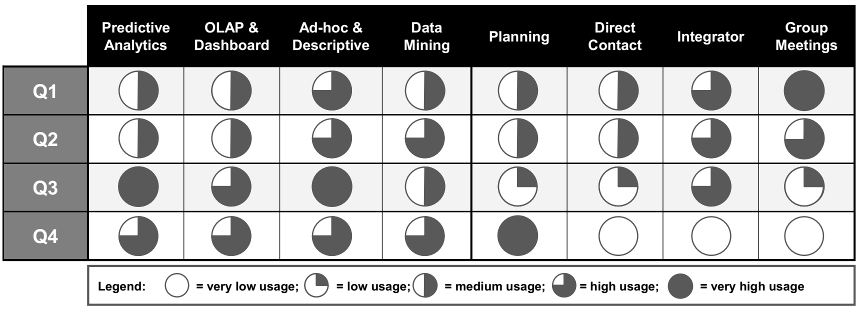


Figure 3.3: Extent of Mechanism Usage by Decision Type

For data-centric mechanisms, we find that in all decision types, organizations relied to a relatively high degree on descriptive analytics and ad-hoc queries. Those are fundamental BI&A capabilities, and hence their usage in all decision types is not surprising. For predictive analytics, as well as OLAP and dashboards, we find higher levels of usage for decision types that are less non-routine (Q3 & Q4). This indicates that in those situations where the decision context is not plagued by ambiguity or equivocality, organizations try to harness data through more structured and predictive approaches. Nevertheless, these approaches are also used in the other decision scenarios, but more selectively. For data mining, we observe medium usage for Q1 and Q3 and high usage for Q2 and Q4. We would have expected higher levels of usage of data mining approaches for non-routine situations (Q1 & Q2) due to the exploratory capacities of these approaches. Instead, however, the level of usage is relatively low in non-routine and uncertain decision scenarios. This implies that organizations do not rely solely on data-centric approaches but instead harness the capacities of organizational information processing mechanisms in such situations.

For organizational information processing mechanisms, we observe different patterns. The group meeting and direct contact mechanisms exhibit decreasing usage patterns. The group mechanism is used extensively in Q1 decision types, and its usage decreases as decisions become more routine and certain. Similarly, the usage of direct contact decreases, with the extent of usage ranging from medium to low. The usage of the integrator mechanism is high in all decision contexts that are either non-routine or uncertain. Hence, the integrator mechanism seems to play a particularly important role, as it spans a wide range of different decision types. Finally, we find that planning is used in all decision scenarios. Notably, we observe a very high reliance on planning for Q4 decision types, and in the three cases that we investigated, planning was the main organizational mechanism that was utilized.

In summary, we have discovered that planning plays a main role in decision scenarios that are routine and certain, whereas group mechanisms are used in non-routine and uncertain situations. Between those two extremes, we found that the integrator mechanism spans a wider range of decision types. In the following, we provide more insights about these mechanisms.

The previous section showed that capturing the domain context is crucial in decision processes and that it can be challenging from an analyst's perspective. Furthermore, we discovered that high elaboration in analytics can induce a gap in understanding and therefore equivocality in situations where decision makers have limited analytics knowledge. It was noted that 'analytics cracks' are often not well equipped for fostering this understanding. This is where the analytic integrator role comes into play to bridge the gap. Throughout the cases, we find evidence for the importance of this role and its tasks:

"Hence, we have division of labor in a way. We have analysts who focus on requirements management, on visualization and on consulting [decision makers], and we have analysts who focus on really performing the analysis, utilizing our analytics tools, experimenting with different analytical methods […]." (Case 1)

"[…] understanding the decision procedures is of high importance for the decision maker in order to be able to make a decision. […] I invested a lot of time in order to explain the analytical approach to the decision makers." (Case 2)

The group mechanism can be characterized as establishing an interdisciplinary analytical team consisting of domain and analytics experts who work together to support a specific decision process. The purpose of these teams is to create a working environment in which analysts and domain experts can contribute their relative expertise. The following quotations highlight the purpose and utility of interdisciplinary analytical teams:

"In our case, it is not one analyst who is working on a particular decision process, but typically three, sometimes even more. We involve the decision makers and domain experts right from the beginning. Consequently this goes hand in hand and everybody can contribute according to his strengths." (Case 1)

"Developing the solution ideas and alternatives, this comes mainly from marketing and sales […] and we go jointly through the whole decision process […]." (Case 4)

"Analysts and decision makers are co-located in one room […] and they are doing different types of simulations. The analysts contribute their knowledge and the decision makers contribute their knowledge […]." (Case 8)

The planning mechanism was found to be utilized throughout the different decision types, and therefore we contrast planning for the Q1 and Q4 decision types. In uncertain, non-routine decision scenarios we find high-level planning, as indicated by the following quotation:

"You really go into a requirements discussion. There you elicit the concrete requirements and this is very very important. Requirements at this stage are not: Look at this and do this analysis, using this method. It's more like answer questions A, B and C and we need solution alternatives and recommendations how to react and what to expect." (Case 1)

In contrast, planning is performed in detail in routine and low-uncertainty decision scenarios, and there is a major emphasis on exception handling, which is performed by human decision makers:

"The discount suggestion is generated by the BI&A system [...] and you can either accept it completely or go into the detailed aspects." (Case 10)

"[…] despite all the mass data that are handled and calculated, there is still the human decider from product control. Product control is the department that conducts the complete process […] they have high relevance for the whole value added process." (Case 10)

3.4.4 Dynamics of Information Processing Mechanism Composition

This section provides more detailed insights into how and to what extent data-centric and organizational mechanisms are utilized in different decision scenarios. Figures 3.4-3.6 show results at a decision-process level, which allows making inferences about dynamics between phases. Figures 3.4-3.6 present the levels of uncertainty and equivocality reduction per decision process phase for each case. The reductions are achieved through a phase-specific composition of data-centric and organizational information processing mechanisms. The extent of uncertainty and equivocality reduction is calculated as a linear combination of mechanisms. In the following representations, we assume 1 to be the lowest weight and 7 to be the highest. Additionally, the proportions of data-centric and organizational mechanisms are shown.

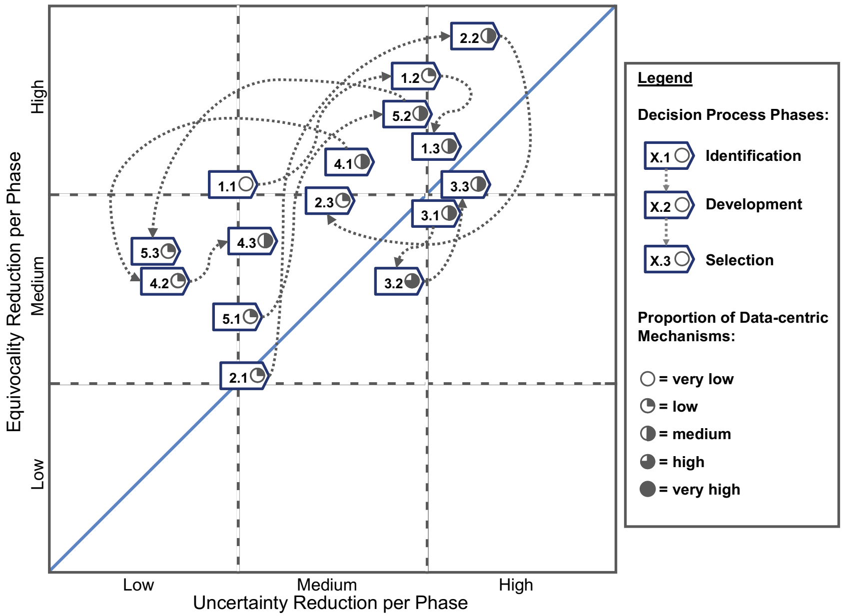


Figure 3.4: Mechanism Composition and Dynamics (Q1)

Figure 3.4 provides an overview of the five cases in Q1 (high non-routine and high uncertainty). Several interesting observations can be made based on the details of those decision processes. First, we find that the majority of process phases are located above the diagonal, and hence the focus of information processing lies on equivocality reduction throughout these decision processes. Looking at the proportions of mechanisms utilized, we find that in about half of the observed phases, organizational mechanisms play a more dominant role. In the other half, organizational and data-centric mechanisms are balanced. Additionally, this representation shows the relatively high level of dynamics between the process phases. We observe large jumps between process phases, and subsequent phases are not located in the same quadrants. This indicates that the focus of information processing behavior changes from phase to phase, which leads to adaptations in the mix of organizational and data-centric mechanisms. Therefore, dynamic mechanism composition seems to play an important role in the decision scenarios in Q1. Case 3 represents an exception, as analysts could rely heavily on data from an online-sales channel. In comparison to the other cases, the proportions of data-centric mechanisms is higher and more stable throughout the process, and we find decreased dynamics and more balanced information processing with respect to equivocality and uncertainty.

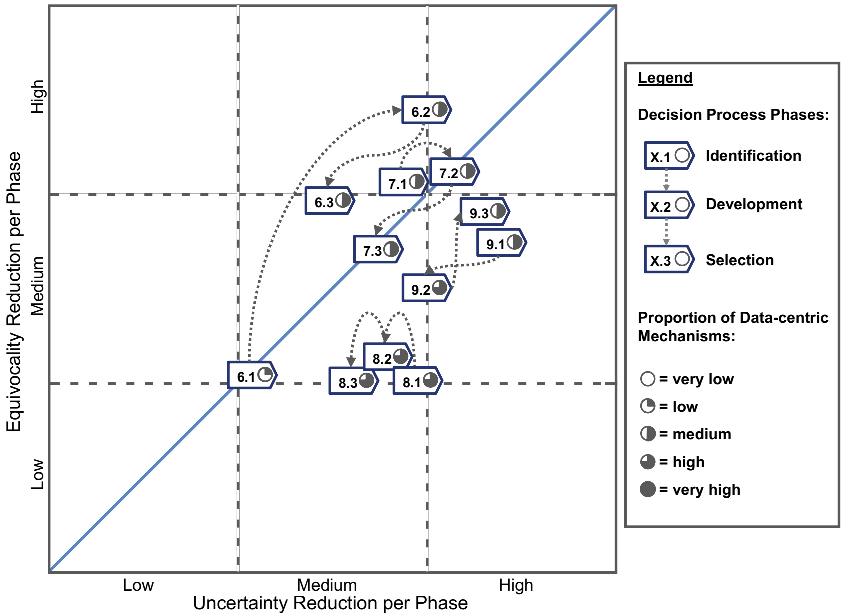


Figure 3.5: Mechanism Composition and Dynamics (Q2 & Q3)

Figure 3.5 comprises cases 6 and 7 from Q2 (high non-routine and low uncertainty) and cases 8 and 9 from Q3 (low non-routine and high uncertainty). Comparing these groups, we find that the cases from Q2 lie on the diagonal or above it, which indicates a slight focus on equivocality reduction, while cases from Q3 are located below the diagonal, which implies an information processing focus on uncertainty reduction. Hence for both groups, the primary need for information processing is addressed. Interestingly, in comparison to the Q1 cases, we find a higher and more stable level of reliance on data-centric mechanisms. The Q3 cases exhibit higher levels of data-centric mechanism usage than do the Q2 cases. Additionally, we find a tendency for reduced inter-phase dynamics in comparison to the cases from Q1. Comparison of the two groups represented in Figure 3.5 shows that subsequent process phases from cases that are more non-routine (Q2) have a higher level of mechanism composition dynamics than those that are uncertain (Q3). Although the Q3 cases exhibit some movement, they mainly remain in the same quadrant, which means that the dynamics of the composition of their information processing mechanisms remains at a low level.

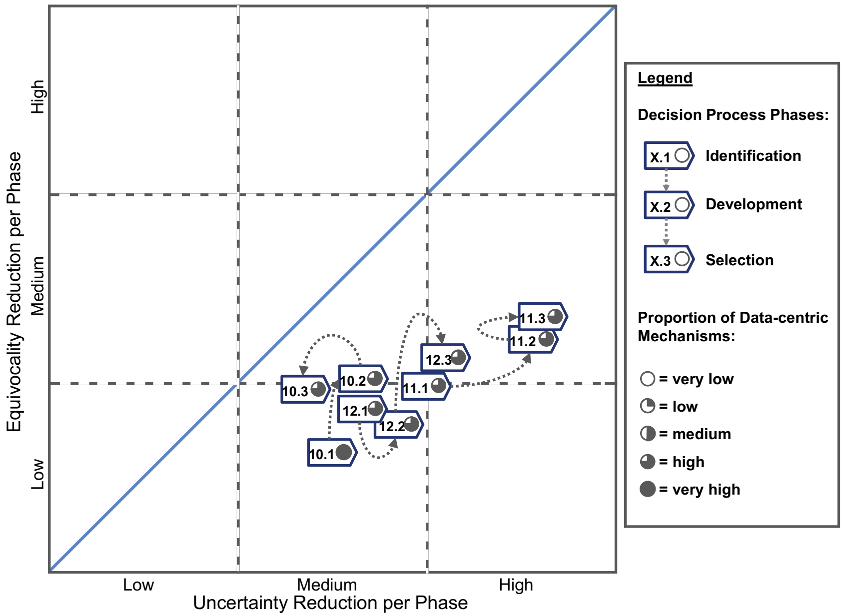


Figure 3.6: Mechanism Composition and Dynamics (Q4)

Figure 3.6 presents the cases for the decision types that are characterized by low levels of non-routine and uncertainty (Q4). In all of these cases, the decision process phases are clearly located below the diagonal, which means that the focus of information processing lies in reducing uncertainty. Looking at the mix of mechanisms, we find that data-centric mechanisms are predominantly utilized. Their level of utilization is high and stable throughout the phases of the decision processes. Additionally, subsequent decision process phases are located close together. Both aspects indicate a low level of composition dynamics for the information processing mechanisms. It seems that in stable scenarios, decision stakeholders rely on a relatively constant composition of mechanisms, with a focus on data-centric mechanisms.

3.5 Discussion of Results and Conclusion

In this paper, we have investigated the underexplored decision process perspective on BI&A and big data. Using information processing theory as a lens, we conducted a multiple case study to gain a better understanding of the composition of data-centric and organizational information processing mechanisms, as well as facets of big data, in the context of different decision types. We discuss the theoretical and practical implications of our research results in the following subsections.

3.5.1 Theoretical Implications

Based on information processing theory, we developed a conception that considers the composition of data-centric and organizational information processing mechanisms for the context of BI&A and big data. Using this conception, we investigated different types of decision processes with respect to non-routine and uncertainty. To our knowledge, this is the first study that applies information processing theory to BI&A-supported decision processes in a multiple case study approach. In contrast to previous theoretical conceptions (Daft and Lengel, 1986; Galbraith, 1974; Polites, 2006; Tushman and Nadler, 1978) and single case approaches (Goodhue et al., 1992; Zack, 2007) to information processing, the conception we use has allowed us to infer empirically grounded insights for the different types of BI&A-supported decision processes.

We provide insights about the complementary relationship of data-centric and organizational mechanisms in the context of BI&A-supported decision processes. We find that the high level of task specialization in BI&A-supported decision processes and the resulting knowledge gaps between decision makers and analysts create a need for complementing data-centric mechanisms with organizational ones. Hence, a combination of the two types of information processing mechanisms is needed for effective integration of analytic capabilities with domain-specific knowledge. Such integration has been considered crucial for realizing value from BI&A and big data (Viaene, 2013). In this regard, we find that neglecting organizational mechanisms not only reduces the capacity for handling equivocality, but can actually lead to an increase of equivocality in decision processes and hence impede their effectiveness.

Considering the different types of decision processes, we contribute insights about the decision-type-specific relevance of the utilized facets of big data and the information processing mechanisms. Concerning the underlying data basis, we find indications that utilization of all three facets increases with decreasing non-routine of the decision context. The most extensive utilization of the three facets is observed in cases with low levels of uncertainty and non-routine. Furthermore, we observe that throughout the cases that exhibit high levels of non-routine or uncertainty, there is an emphasis on data variety. A possible explanation could be that utilizing a variety of sources is associated with a focus on gaining broad coverage and integrating different perspectives on the decision context. This implies a priority of addressing equivocality in such decision scenarios. This finding is further underlined through insights about the composition of information processing mechanisms. We observe that data-centric mechanisms are complemented by organizational mechanisms and that their composition varies across different decision types. In cases that exhibit high levels of non-routine or uncertainty, we find a high reliance on complementary organizational mechanisms that primarily aim at reducing equivocality. This further corroborates previous research results, which suggest that equivocality will induce further uncertainty if not handled appropriately (Daft and

Lengel, 1986, p. 558) and should therefore be reduced beforehand (Zack, 2007, p. 1667). Within the set of organizational information processing mechanisms, the analytic integrator role is particularly noteworthy, as it is utilized throughout the different decision types to bridge understanding gaps between decision makers and analytics experts. The creation of interdisciplinary analytic teams that collaborate throughout the decision processes is another mechanism that is extensively used with increasing non-routine and uncertainty of the decision process. The planning mechanism was used to varying extents in the investigated cases, and interestingly, even for routine and certain decision scenarios, this organizational mechanism was used in the context of exception handling.

Additionally, our study's results make a contribution by providing phase-specific insights about the dynamics of mechanism composition and utilization that have not previously been discussed in the research literature. In decision processes involving high levels of non-routine and uncertainty, we observe a major focus on equivocality reduction throughout the process phases, as well as a higher reliance on organizational information processing mechanisms. This again emphasizes the priority of dealing with equivocality. The inter-phase dynamics of mechanism composition are high in those cases. Consistent with information processing theory, we find, concerning decision processes that involve either non-routine or uncertainty, that the former focus more on equivocality reduction and the latter on uncertainty reduction. In both decision types, reliance on data-centric mechanisms increases and inter-phase dynamics decrease with decreasing non-routine. Finally, decision processes in scenarios with low levels of non-routine and uncertainty are mainly data-centric throughout all phases of the decision processes and exhibit low levels of inter-phase dynamics.

3.5.2 Practical Implications

The results from our study shed light on information processing mechanisms and their phase-specific composition and dynamics and therefore also have some relevant practical implications. The conceptions of decision types and information processing mechanisms that have been provided give useful guidance for characterizing organizational decisions. We consider an improved understanding of different decision contexts and the required information processing mechanisms to be crucial for effective utilization of big data. In particular, in non-routine decision contexts, organizations have to depend on the dynamic composition of mechanisms and hence should be proficient in a wide range of data-centric and organizational mechanisms. Furthermore, our results indicate that organizations that want to utilize big data for their decision processes should first focus on reducing equivocality. Initially focusing on data variety can be a viable path in this respect, particularly when combined with organizational mechanisms that can help integrate insights gained from different sources. Furthermore, we find that the collaboration between decision makers and analysts within organizational decision processes needs to be actively managed in order to prevent gaps in understanding. A feasible strategy in this regard can be to institutionalize analytic integrators who bridge the gap between domain experts and analytics specialists. Analytic integrators typically differ from data scientists and analysts in their skill sets; they are typically experts in requirements management and visualization, as well as the communication of analytics results.

3.5.3 Limitations and Directions for Future Research

Although we performed a multiple case study aiming for more generalizable results, there is a need for further discussion and validation of our findings. A major limitation of this study arises from its reliance on the single key-informant method. We tried to compensate for this reliance through data triangulation, but nevertheless this research could be extended by complementing the perspectives of the different roles of participants in decision processes, such as decision makers. Furthermore, our case study organizations come from more traditional industries, and a comparison with Internet-based organizations would be very interesting. Another limitation is related to our conception of mechanism composition, as we assumed linear combinations in our qualitative study. Investigating and validating the functional relationships as well as mechanism-specific weights in a quantitative approach would be valuable.

Finally, our research results yield the following propositions that should be further validated by future research: (a) When BI&A matches the utilization of big data facets with the characteristics of the decision context, the support of a decision process will be more successful. (b) A decision process's capability for reducing equivocality and uncertainty arises from a linear combination of its information processing mechanisms. (c) Decision processes exhibit higher degrees of reliance on organizational information processing mechanisms with increasing levels of non-routine and uncertainty. (d) Neglecting organizational information processing mechanisms increasingly impedes the effectiveness of decision processes with increasing levels of non-routine and uncertainty. (e) The composition of information processing mechanisms exhibits higher inter-phase dynamics with increasing levels of non-routine and uncertainty.

This paper is intended as a step towards improving our understanding of the organizational decision context and its impact on the quality of BI&A support of decision processes in big data scenarios, and we hope that it will encourage further research in this direction.

4 Study C: Perspectives on Collaboration Procedures and Politics during the Support of Decision Processes with Business Intelligence and Analytics[3]

4.1 Introduction

Raising the level of decision quality in managerial decision processes by utilizing business intelligence and analytics (BI&A) is a crucial task, but the realization of the expected benefits is often challenging (Clark et al., 2007; Davenport, 2010; Polites, 2006; Watson et al., 2002). BI&A comprises a set of data collection, integration, and analytics technologies, which aim at improving data processing and analysis procedures along the information value chain (Chaudhuri et al., 2011; Chen et al., 2012; Dinter, 2013; Koutsoukis and Mitra, 2003; Watson, 2010). These technologies equip BI&A-experts (i.e., analysts or data scientists) with the technological capabilities for supplying decision makers with high quality information (Davenport and Harris, 2007; Viaene, 2013). Recent research findings suggest that the extent of benefits and improved decision quality, from supplying decision processes with high quality information, does not only depend on the BI&A technology that is utilized within an organization, but also on organizational factors and characteristics of decision processes (Davenport, 2010; Işık et al., 2013; Popovič et al., 2012, 2014; Sharma et al., 2014).

Reviews of prior research on data-centric decision support, and BI&A in particular, identify a major focus on the technological perspective and find that organizational aspects related to decision processes have only been considered narrowly (Arnott and Pervan, 2008, 2014; Sharma et al., 2014; Shollo and Kautz, 2010). In this regard, our research addresses two main research gaps concerning organizational aspects of BI&A-supported decision processes.

The first gap pertains to the effects of decision makers' political behavior and procedural rationality on the use of information and the quality of decision outcomes. Concerning this, insights from management research on decision processes indicate that political behavior and procedural rationality affect decision outcomes (Dean and Sharfman, 1993a, 1996; Eisenhardt and Zbaracki, 1992; Elbanna and Child, 2007). Accordingly, research on data-centric decision support has explicitly called for further investigating the effects of these characteristics in the context of BI&A support (Shollo and Galliers, 2013).

[3] This is the accepted author's version of the following article: Kowalczyk, M. and Buxmann, P. (2015a), "Perspectives on Collaboration Procedures and Politics during the Support of Decision Processes with Business Intelligence & Analytics", European Conference on Information Systems 2015. The definitive publisher-authenticated version is available online at: http://aisel.aisnet.org/ecis2015_cr/109.

M. Kowalczyk, *The Support of Decision Processes with Business Intelligence and Analytics*, DOI 10.1007/978-3-658-19230-3_4

The second gap concerns the collaboration between analysts and decision makers in BI&A-supported decision processes and focuses on its effects on decision processes and their outcomes. Despite being a relevant topic in practice, the effects of collaboration procedures among analysts and decision makers have been marginally considered in prior research (Viaene, 2013). Therefore, more research in the context of BI&A-supported decision processes has been explicitly called for (Sharma et al., 2014). For examining collaboration procedures between analysts and decision makers we build on an ambidextrous conception, which considers process rigor and agility as two main procedural characteristics (Gibson and Birkinshaw, 2004; Lee et al., 2010). Thus, ambidexterity characterizes the capacity to combine both procedural characteristics within the collaboration between analysts and decision makers, in the context of BI&A-supported decision processes.

The combined examination of both gaps allows this research to address the theoretically neglected interplay between the supply of high quality information and characteristics of collaboration procedures between analysts and decision makers, as well as implications for decision outcomes. Thus, our research is guided by the following research question: How do characteristics of collaboration procedures affect BI&A-supported decision processes and the quality of their outcomes? In order to address this question we investigate ambidexterity of collaboration procedures and its complementing effects with information quality. Furthermore, we examine its influence on political behavior and procedural rationality, as well as the quality of decision outcomes in BI&A-supported decision processes. Because decision process ambidexterity and information quality haven't been studied together, their interaction in shaping political behavior, procedural rationality and resulting decision quality remains theoretically underdeveloped. These gaps also have substantial practical relevance, because they pertain to how analysts can improve collaboration procedures with decision makers and thus augment the impact of their analytic work for improving decision outcomes.

In order to address the identified gaps, in-depth research on BI&A-supported decision processes is required. Using a multiple case study approach, we investigate eleven managerial decision processes that were supported by BI&A. With this paper we strive to make three main contributions. We contribute to the first research gap by (i) investigating how different extents of political behavior and procedural rationality in BI&A-supported decision processes result in varying levels of decision quality, despite the availability of high quality information. We contribute to the second research gap by (ii) examining process rigor and agility as characteristics of ambidextrous collaboration procedures, as well as investigating their effects on BI&A-supported decision processes. Furthermore (iii) we provide evidence on the complementing relationship between ambidexterity and information quality in shaping political behavior, procedural rationality and resulting decision outcomes.

This paper is structured as follows. In the next section we discuss the theoretical background of BI&A, decision processes and ambidexterity. Then, we describe details of our multiple case study design and data analysis. Subsequently, we present results from the multiple case study. The article closes with a discussion of theoretical and practical contributions, limitations, and future directions.

4.2 Theoretical Background

This section focuses on BI&A support of decision processes and further elaborates on relevant aspects from related management research for characterizing the organizational context of decision processes.

4.2.1 Business Intelligence and Analytics (BI&A) and Information Quality

From a technological point of view, business intelligence and analytics (BI&A) originates from data-centric approaches like database management and data warehousing and it combines different data collection, integration, and analytics technologies (Arnott and Pervan, 2014; Chaudhuri et al., 2011; Chen et al., 2012; Watson, 2010). BI&A encompasses technological support for data collection and integration (ETL), which is the basis for achieving and maintaining high data quality. Additionally, BI&A provides capabilities for basic analytics (e.g., ad-hoc queries and descriptive statistics) and advanced analytics (e.g., data mining and predictive modelling) (Chaudhuri et al., 2011; Watson, 2010).

The underlying decision making paradigm of BI&A is strongly focused on a technological perspective in which improving the procedures of data processing and analysis plays a central role. BI&A systems aim at providing support for the complete data processing and analysis value chain with the purpose of ultimately improving the quality of information that is available for decision making (Dinter, 2013; Koutsoukis and Mitra, 2003; Popovič et al., 2012). This technological perspective has been found to not sufficiently consider the organizational decision process context of BI&A (Arnott and Pervan, 2008, 2014; Davenport, 2010; Sharma et al., 2014; Shollo and Kautz, 2010). Understanding the organizational context of decision processes is crucial as it affects the realization of the benefits from improved information quality that is delivered by BI&A systems (Popovič et al., 2012; Sharma et al., 2014). In this regard, research on BI&A started investigating organizational aspects related to decision processes, like organizational information processing (Kowalczyk and Buxmann, 2014; Shollo and Galliers, 2013), analytical culture, information-sharing values and information use (Popovič et al., 2012, 2014) and factors related to the decision environment (Işık et al., 2013).

This research contributes to the field by investigating ambidexterity of collaboration procedures between analysts and decision makers in BI&A-supported decision processes and by linking it to the established concepts of political behavior and procedural rationality from management research.

4.2.2 Political Behavior and Procedural Rationality in Decision Processes

In management research, decision processes have been often studied on the basis of a three phase conception, which includes the (i) identification of an issue, the (ii) development of solution alternatives and the (iii) selection of one solution (Mintzberg et al., 1976; Simon, 1960). Management research on decision processes distinguishes between political behavior and rationality of procedures as two main characteristics that affect the effectiveness of information usage in decision processes (Dean and Sharfman, 1993a; Eisenhardt and Zbaracki, 1992; Papadakis and Barwise, 1998). Both characteristics are considered as important, and a major focus has been on studying the outcomes of decisions that vary in terms of political behavior and rationality of procedures (Elbanna, 2006; Papadakis and Barwise, 1998).

The rationality of decision processes is a central topic in decision making theory and practice (Papadakis and Barwise, 1998). For characterizing rationality in the context of decision processes, previous research has developed a series of more specific constructs of rationality, which are derived from the rational model of decision making (Simon, 1978). Different notions of rationality in decision processes include comprehensiveness (Fredrickson, 1984; Papadakis et al., 1998), decisional rationality (Schwenk, 1995), and procedural rationality (Dean and Sharfman, 1996). The conception of procedural rationality in decision processes is defined as the extent to which decision makers' behavior involves gathering information that is relevant to the decision and relying upon analysis in making the decision (Dean and Sharfman, 1993a, 1996). Hence, procedural rationality characterizes the extent of information use throughout the phases of decision processes. This includes validating an issue, developing solution alternatives and forming expectations about them, as well as making the final decision (Dean and Sharfman, 1993a). The emphasis on the use of information in this 'procedural' conception of rationality renders it suitable for our research, as information use is considered to be crucial for profiting from high quality information that is supplied by BI&A (Popovič et al., 2014; Shollo and Galliers, 2013).

The perspective of political behavior in decision processes assumes that decisions are the result of a process in which decision makers have different goals and try to influence the decision process outcome, so that their own goals will be pursued (Pfeffer, 1992). This interaction of interests, conflict and power characterizes the political nature of decision processes and describes the way in which managers often make decisions (Eisenhardt and Zbaracki, 1992). The conception of political behavior can be defined as activities that use power and other resources to pursue own interests and preferred outcomes in situations with uncertainty about choices (Dean and Sharfman, 1996). According to this conception, control over information can be a possible source of power. From this point of view, problem definition, data collection, alternatives development and evaluation of the latter can be regarded as weapons that are used to distort effective information usage in order to manipulate decision outcomes, rather than instruments that deliver facts for decision making (Dean and Sharfman, 1993a). Therefore, in this research we consider political behavior as the use of power by decision makers to pursue own interests or goals, which might affect the use of information supplied by BI&A (Shollo and Galliers, 2013).

Dean and Sharfman (1993a) investigated the relation between procedural rationality and political behavior in decision processes. They argue that the extent, to which information is used systematically, is conceptually different from political behavior and found both characteristics to be uncorrelated. This means that procedural rationality and political behavior are two distinct dimensions of decision processes. Thus, decision processes can be both – procedurally rational and political – or neither (Dean and Sharfman, 1993a). The empirical results on the impact of procedural rationality on decision outcomes provide evidence for a positive relationship (Elbanna and Child, 2007; Nutt, 2005, 2008; Papadakis et al., 2010). In contrast, the empirical evidence on political behavior mainly supports a negative relationship (Elbanna, 2006; Elbanna and Child, 2007). Reasons that account for this negative relationship include a lack of open discussions and information sharing among decision makers or even distortion of information (Pfeffer, 1992). This may result in dependence on incomplete information and decision making without an understanding of environmental constraints (Dean and Sharfman, 1996). Furthermore, political behavior is considered to be time-consuming and may delay decisions, which can result in loss of opportunities and profit (Pfeffer, 1992). In summary, findings from literature suggest that positive decision outcomes depend on a favorable ratio between procedural rationality and political behavior, which means that the former exceeds the latter (Dean and Sharfman, 1993a).

4.2.3 Collaboration Procedures and Ambidexterity in Decision Processes

The success of BI&A-supported decision processes depends on the collaboration between analysts and decision makers (Sharma et al., 2014; Viaene, 2013). Analysts are experts who utilize the technological capabilities of BI&A systems in order to address the information needs of decision makers by supplying them with high quality information and insights (Harris et al., 2010; Viaene, 2013).

Prior research has found that managerial decision processes are often semi-structured or unstructured and characterized by nonroutineness. This means that typically adaptations of the procedures are needed and process steps within and between the process phases are often performed iteratively (Eisenhardt and Zbaracki, 1992; Gorry and Scott Morton, 1971; Mintzberg et al., 1976; Nutt, 2008). This implies that information needs, as well as data processing and analytics requirements can change frequently throughout managerial decision processes, which makes these decision contexts particularly challenging.

For the work of analysts to support managerial decision processes this means that they have to cope with changing information needs in addition to the varying levels of political behavior and procedural rationality, which were discussed in the previous section. The dynamics of decision processes demand adaptability in providing high quality information and effective analytical support in order to be able to improve the extent of procedural rationality. Potentially conflicting goals and interests among decision stakeholders demand alignment in order to be able to establish effective collaboration and to attenuate effects of political behavior. This means that requirements regarding adaptability and alignment are induced in the context of BI&A-supported decision processes.

Simultaneously fulfilling these potentially conflicting requirements has been often considered as difficult. Organizational ambidexterity provides a useful theoretical lens on coping with such conflicting demands (Gibson and Birkinshaw, 2004; Raisch and Birkinshaw, 2008). Based on a general conception of alignment and adaptability (Gibson and Birkinshaw, 2004), a process-oriented conception, which considers agility and rigor in development processes was derived in research (Lee et al., 2010). The general notion of alignment describes the coherence among all the patterns of activities and their working together towards the same goals (Gibson and Birkinshaw, 2004). The derived conception of rigor is defined as the adherence to pre-defined, formal, and structured processes, as well as explicit definitions of roles, activities, work products and methods (Lee et al., 2010). In general terms, adaptability defines the capacity to quickly reconfigure activities to cope with changing demands in the task environment (Gibson and Birkinshaw, 2004). Consistently, agility defines the process capability to effectively sense and respond to changing requirements (Lee et al., 2010; Lee and Xia, 2010). Ambidexterity describes the capability to combine capacities from both dimensions and the ideal state has been characterized as balance and excellence in both dimensions (Cao et al., 2009; Gibson and Birkinshaw, 2004).

In this research we rely on the process-oriented dimensions of ambidexterity (i.e., rigor and agility) for characterizing collaboration procedures between analysts and decision makers in the context of BI&A-supported decision processes. We furthermore investigate their effects on political behavior and procedural rationality, as well as decision outcomes in BI&A-supported decision processes.

4.3 Research Method

Researching BI&A-supported decision processes requires in-depth analysis of a complex phenomenon. Therefore, we considered the case study approach to be suitable for our research (Benbasat et al., 1987; Dubé and Paré, 2003; Seaman, 1999; Yin, 2003). The units of analysis of our study are decision processes that were supported by BI&A. We utilize a multiple case study approach and our design applies replication logic. This setup allowed us to attain a deep empirical grounding and immersion into multiple organizational decision processes. This helped establishing more valid and general results than it would be possible from a single case study (Miles and Huberman, 1994; Yin, 2003). The following sections provide further details on research design, data collection and analysis procedures.

4.3.1 Research Design

In this research we investigate eleven decision processes and these cases were selected following a theoretical and literal replication logic (Dubé and Paré, 2003; Yin, 2003). For achieving literal replication, we selected decisions that were characterized as being non-routine and we ensured that the basic corporate and technological context of the investigated decision processes were similar. This means that all case study companies were large firms and that in the investigated decisions, decision makers relied on BI&A support, which was provided by analysts. Furthermore, the decision processes had to be completed, because we were interested in gaining insights on the distinct phases and their characteristics, as well as on decision quality. We addressed potential sector-specific influences by selecting a broad set of firms from different industry sectors. For theoretical replication, we primarily aimed at investigating decision processes with varying levels of process agility and rigor, as well as distinguishing different levels of achieved decision quality. This allowed us comparing the obtained insights across the cases. Our research design relies on the perspective of BI&A-experts (i.e. BI&A unit leads, data scientists or analysts). These experts typically support all phases of a decision process and have deep insights into aspects related to data, analysis and the actual decision making. Hence, focusing data collection on their perspective helped us maximizing the visibility on the investigated decision processes.

4.3.2 Data Collection

In order to support data collection and assure reliability we created a case study protocol and database. There we defined the objectives and data collection procedures for our study. During data collection we utilized multiple sources of evidence for data triangulation, which helped us to enhance the validity of our findings (Yin, 2003). This means that we conducted in-depth expert interviews, collected additional documents where possible, and gathered complementary data by using a follow-up questionnaire in order to increase the reliability and validity of our findings (Eisenhardt, 1989; Yin, 2003).

We identified participants by searching for suitable expert profiles on social networks for professionals. For the expert interviews we developed a semi-structured interview guide with open-ended questions. The guidelines were tested and refined in the context of two pilot interviews. The final version encompasses three parts. The first part inquires the educational background, professional experience and current organizational role of the expert. The second part deals with general information about the BI&A technology and the investigated decision process. Finally, the third and major part of the interview deals with one specific decision process, which was supported by the interviewed expert. For capturing the expert knowledge regarding the investigated decision processes we followed a key-informant approach (Bagozzi et al., 1991). During the interviews we explored the three phases of the decision processes in detail, by encouraging the experts to speak openly (Ericsson and Simon, 1993) and by applying the laddering technique for asking successive questions (Reynolds and Olson, 2001).

As a complementing means of data collection, the interviewed experts completed a follow-up questionnaire, with the purpose of collecting data for cross-validation and quantification. All characteristics were measured using multi-item, seven-point Likert scales and we mainly used existing scales or adapted them to our research context. Scales of agility and rigor use four items each (Lee et al., 2010) and were adapted to the research context under study. Information quality was measured using eleven items according to Popovič et al. (2012). Relying on established management literature we assessed political behavior and procedural rationality with four items each (Dean and Sharfman, 1993a, 1996; Elbanna and Child, 2007) and decision quality with three items (i.e., goal achievement, realized decision value, overall quality of decision) (Dean and Sharfman, 1993a, 1996; Nutt, 2008).

The case study interviews were conducted during a time period of four month in the second half of 2013. The majority of the interviews was performed as face-to-face meetings and few also on the telephone. On average one case meeting lasted two hours. The average interview time accounts for approximately 75 minutes and the remainder of the time was used for presentations or demonstrations by the participants and in most cases for filling out the questionnaire. In all cases the interviews were audio recorded. In summary, this research approach yielded a rich combination of qualitative and quantitative data that provides substantial depth and breadth for data analysis.

4.3.3 Case Overview

Table 4.1 provides an overview of the investigated cases and presents details on the industry of case firms, the interviewed experts and the decisions that were investigated in the case study. The average professional BI&A-experience of the interviewed experts amounts to more than ten years. Characterization of the investigated cases as comparable managerial decisions is based on decision contents and the ratings of the nonroutineness of the decisions. All investigated decisions exhibit increased ratings of nonroutineness, which vary between five and seven. Decision contents include issues like reacting on new competitors (Case 01, Case 11), major segmentation and product portfolio related decisions (Case 02, Cases 04-06, Cases 09-10), introduction of new risk models (Case 03, Case 08) and substantial changes to the constitution of a fleet (Case 07). Decision quality ratings were provided by interviewees and these ratings, as well as the assignment into three groups was corroborated with qualitative descriptions from the interviews. In all cases the organizations relied on BI&A systems from major BI&A vendors. The average ratings of information quality for the three phases of the investigated decision processes are rather high and vary between five and six for all cases.

Table 4.1: Case Overview

Case ID	Industry	Interviewee Role	Experience (Years)	Decision Content	Avg.Info-Quality	Non-routine.	Dec. Quality
1	Telco	BA unit head	>10	Reaction to new competitor	5.7	7.0	High (7.0)
2	Media	Analyst	18	Product portfolio (pricing)	5.1	7.0	High (6.0)
3	Finance	Analyst	>10	Introduction of new risk models	5.9	5.0	High (6.0)
4	Consumer	BA unit head	6	Product portfolio (product mix)	6.0	5.0	High (6.7)
5	Tourism	BI unit head	14	New product development	5.9	5.0	High (6.3)
6	Finance	Analyst	>15	Product portfolio segmentation	5.3	7.0	High (6.0)
7	Logistics	Analyst	5	Fleet constitution	5.6	6.0	Med. (5.3)
8	Finance	Analyst	>10	Introduction of new risk models	5.0	5.0	Med. (4.7)
9	Logistics	Analyst	>12	Product portfolio (pricing)	5.4	6.0	Med. (5.0)
10	Telco	BA unit head	6	Product portfolio (constitution)	5.0	6.0	Low (1.5)
11	Telco	Analyst	> 15	Reaction to new competitor	5.3	7.0	Low (1.0)

Note: Scales for Avg. Information Quality, Decision Nonroutineness and Decision Quality: 1-7;
Decision Quality: 7.0 ≥ High ≥ 6.0 > Medium > 3.0 ≥ Low ≥ 1.0

4.3.4 Data Analysis

Before starting data analysis, the audio files were transcribed. The case transcripts represent the main raw data that we used during analysis. The subsequent data analysis procedure followed established recommendations for qualitative data analysis (Corbin and Strauss, 2008; Miles and Huberman, 1994). First, transcripts were coded, by using a list of codes that has been defined based on existing literature on decision processes (Corbin and Strauss, 2008; Ericsson and Simon, 1993; Miles and Huberman, 1994). We utilized first-level coding for assigning codes to all statements that reflected statements on agility, rigor, procedural rationality, political behavior and their effects. The coding process was performed iteratively (Miles and Huberman, 1994). Next, we focused on conceptual links and interrelations between the identified and coded segments. Here we relied on an inductive procedure that allowed relationships to emerge from the data (Corbin and Strauss, 2008). Then we conducted case comparisons by utilizing techniques for cross-case analysis (Miles and Huberman, 1994). In this step we compared cases with regard to similar concepts and relationships. Moreover, qualitative data from the interviews and quantitative data from the questionnaires were analyzed jointly and checked for consistency. At all intermediate steps during analysis the results were discussed among the authors with the purpose to create a common understanding, as well as convergence on joint interpretations.

4.4 Results

The presented results are based on a comparative analysis of the investigated decisions. Subsequently, we examine case-specific compositions of political behavior and procedural rationality and discuss their impact on decision quality. Next, we focus on ambidexterity and elucidate the effects of rigor and agility on BI&A-supported decision processes. Finally, we integrate these perspectives and present evidence on how ambidexterity complements information quality for achieving decision quality.

4.4.1 Impact of Political Behavior and Procedural Rationality

The major value that BI&A systems deliver, in an organizational context, is related to an improvement in data processing and analysis capacities, which creates the basis for usage of high quality information in decision processes. Based on the results from the comparative analysis of cases, we find that achieving high levels of information quality is a necessary, but not sufficient condition for achieving high decision quality in decision processes. More specifically, we found that despite having relatively high information quality in all cases, the actual decision quality varies (see Table 4.1). Cross-case analysis yielded two main categories of factors that influence the extent of political behavior and procedural rationality, which in turn can derogate the positive impact of information quality on decision quality.

The first category of factors originates from the organizational level and deals with the locus of analytics support. Analysts can be organized in a centralized or decentralized manner. This induces a trade-off between effectiveness of decision support, which requires analysts to have domain-specific knowledge, and transparency, which requires analysts to act independently. This tension turns out to increase the potential for an unfavorably unbalanced ratio between political behavior and procedural rationality, as summarized in the following expert statements:

“I know many companies that have decentralized BI&A units, […]. Of course every local BI&A unit generates insights that let their unit shine. Even if analytics are used for optimization or improvement, this typically only happens in the local unit and hence there is mainly local optimization.” (Case 1)

“[…] ‘one version of truth’, there are endless stories. If you don’t have it, every business unit creates its own numbers and then you can challenge the numbers of others if you don’t like them.” (Case 11)

The second category of factors addresses the individual level and deals with conflicting goals and personal motivations. These were found to be a hindrance, even if decision stakeholders utilize the same high quality information, as highlighted by the following expert statements:

"In situations in which analysts or several decision makers utilize the same information, but pursue different goals, this does not help […] as soon as we are coping with interpreting analytics results […] this is where most political games happen." (Case 8)

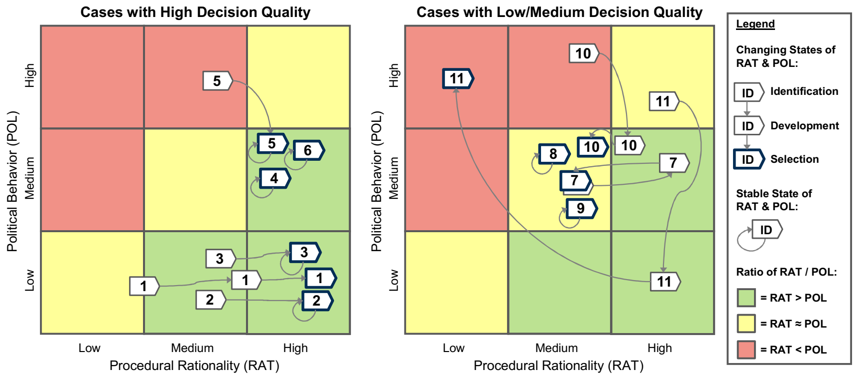
"Political behavior, such as withholding information, represents a risk from the decision maker perspective, as complete and valid facts and background information are needed […] this is particularly dangerous if personal goals are not aligned with organizational goals." (Case 4)

Furthermore, participants noted that often information availability and quality is not the actual problem, but that instead rational or objective procedures for working with the information are lacking:

"I don't think that with today's amounts of data there is a problem with information availability, it's rather that these things are often seen subjectively, which can lead to wrong decisions." (Case 6)

In summary, these factors affect the extents and ratio of political behavior and procedural rationality in decision processes and hence should impact decision quality. Next, we therefore take a closer look at political behavior and procedural rationality in the investigated decision processes. Figure 4.1 gives an overview of the phase-specific ratings for both characteristics. We aggregate the ratings from the seven point scales to three levels ($7.0 \geq$ high $\geq 5.0 >$ medium $> 3.0 \geq$ low ≥ 1.0) in order to enhance ease of interpretation. Additionally, we group decision processes that achieved high (left) and low/medium (right) decision quality. Decision process phases that are mainly characterized by procedural rationality are located below the quadrants of the diagonal and those that are mainly political are located above the diagonal. Based on previous findings (Dean and Sharfman, 1993a; Papadakis et al., 2010), cases located in quadrants below the diagonal should mainly exhibit high decision quality and those above the diagonal low decision quality. For cases in quadrants along the diagonal, medium levels of decision quality are feasible, as these process phases are exposed to both characteristics.

For cases with high decision quality we mainly find high extents of procedural rationality and these are maintained or even improved throughout the course of these decision processes. In particular, procedural rationality exceeds the extent of political behavior in most of the investigated decision process phases and we thus find favorable ratios of both characteristics. For cases with low/medium decision quality, we mainly find more balanced ratings of procedural rationality and political behavior. Here, higher extents of procedural rationality can be only found sporadically during some of the investigated development phases. In contrast to cases with high decision quality, particularly the selection phases are characterized by higher levels of political behavior. Overall, in these cases we find less favorable ratios of procedural rationality and political behavior. To summarize, the investigated cases exhibit patterns that confirm predictions that can be made based on literature. Interestingly, the results imply that already moderate levels of political behavior can impede the quality of decision results.



Notes: Cases with High Decision Quality (Left) and Low/Medium Decision Quality (Right).

Figure 4.1: Procedural Rationality and Political Behavior in Decision Processes

We describe case 11 in more detail, as it exhibits the highest extent of political behavior and the ratio with procedural rationality changes throughout the decision process phases. Case 11 deals with reacting to new competition and the decision process was triggered by brand management. The analyst was issued to develop a market model in order to make predictions about customer retention and for evaluating different strategies on how brand management should act with regard to the newly entered competition. A further goal that was perused was to highlight the value contribution of brand management, in order to strengthen its position within the company. The analyst collected information requirements from brand management and withdrew from interactions for developing the analytic model and recommendations. During the development phase the interaction with brand management was limited, which seems to have allowed for raising the extent of procedural rationality of the decision process. In the selection phase the model and the derived analytic advice were presented to brand management. Although the analytic results were perceived to have high quality, the suggestions for coping with the new competition were rejected. The main reasons of brand management for neglecting the analytic advice were concerns regarding worsening its internal position, as the advice contradicted to its current strategy. Additionally, it implied a low value contribution of brand management. Thus brand management decided to continue with its current strategy and forbid communicating the results from this analysis. In the long run, dealing with the newly entered competition ended up on the top-management agenda and their changes to the company strategy proved the rejected analytic advice to be right.

In summary, we find that despite high quality information and analytic results the outcomes of BI&A-supported decision processes can be severely affected by political behavior and procedural rationality. Solely focusing on the supply of information seems not to be sufficient, as noted in the next quote:

"Generally speaking, you could state that availability of better information leads to better decisions, but this is rather very simplistic. I think it's more like a saturation curve, until a certain degree information gains increasing utility, but then this reduces [...] then it's crucial how you make the decision, based on the information and the procedures." (Case 11)

This statement accentuates the relevance of procedural aspects in complementing the supply of information in decision processes. Next, we therefore focus on characteristics of collaboration procedures.

4.4.2 Decision Process Rigor and Agility as Dimensions of Ambidexterity

This section presents insights on rigor and agility as the two main characteristics of ambidextrous collaboration procedures between decision makers and analysts in BI&A-supported decision processes. We examine the effects of rigor and agility in the context of the investigated decision processes. Based on the comparative case analysis, five properties of BI&A-supported decision process emerged, which are positively or negatively affected by rigor and agility. Table 4.2 gives an overview of the identified properties and effects by providing representative quotes from the expert interviews. Whereas the first two properties (rights and roles clarity, transparency) mainly cover the need for alignment in decision processes in order to control the extent of political behavior, the latter three (adaptability, efficiency and effectiveness) primarily deal with improving procedural rationality in decision processes.

Rigor was associated with the clarity of rights and roles, which was described as positive in the context of decision processes, because responsibilities can be defined explicitly and independence of analysts in the organizational context can be ensured. This helps providing balanced perspectives on analysis and interpretation of results. Additionally, the creation of transparency concerning decision and analytic procedures through rigor was described as the major mechanism for being able to reduce the extent of political behavior. In this regard, process rigor was also associated with positive influence on efficiency of BI&A-supported decision processes. In contrast, rigor was found to have drawbacks regarding the required adaptability of analytic procedures in decision processes. Concerning the effectiveness of decision process support we received mixed results. Rigor was found to contribute to effectiveness. But at the same time, very high levels of rigor were associated with negative effects, particularly when high formality was impeding collaboration between analysts and decision makers.

Table 4.2: Effects of Rigor and Agility on Decision Processes

Dec. Process Properties	**Effects of Rigor**	**Effects of Agility**
Rights and Roles Clarity	*(+) "In the area of analytics and insights generation, we have explicit publishing rights. [..] we can independently publish our insights and all decision makers have access. Hence, we are neutral, independent and transparent and we can make insights available to everyone." (Case 1)* *(+) "[...] formality allows that analysis does not remain one sided [...] that all relevant stakeholders are involved into the process in a timely manner." (Case 8)*	*(-) "In agile collaboration this is rather difficult, personally I would consider a well-defined selection of decision stakeholders, with clearly defined roles, as necessary. Agile collaboration contributes rather little in this direction." (Case 3)*
Transparency	*(+) "[...] the clear advantage is that a lot is documented. It's always clear how you get to the results and with whom they have been discussed, this helps [dealing with politics]." (Case 1)*	*(-) "The more flexible you are, the more opportunities exist for making the process less transparent. There you can introduce large political influences." (Case 9)* *(+) "[With agility] you have significantly increased speed of information flowing into the decision process [...] this also allows for earlier intervention in such processes [...]." (Case 8)*
Adaptability	*(-) "If adaptability is needed in a problem context, then rigor could be a hindrance, because I won't have the flexibility to adapt the process as required." (Case 7)*	*(+) "[...] during model development, if data are changed or for example facets of the analysis change, then agility is fundamental in such a context." (Case 11)*
Efficiency	*(+) "[...] positive effects, particularly on decision speed and also on the avoidance of friction losses between stakeholders, because the procedures are clearly defined. I think that there is also more precision in interpretation." (Case 7)*	*(-) "But agility has to be used in a structured and rigorous manner, otherwise you lose track of what you are actually doing.", "[..]halfway through the process you realize that this needs major changes, then it was badly defined from the beginning [..]." (Case 2)*
Effectiveness	*(+) "If a decision is traceable and measurable, then this raises decision quality." (Case 2)* *(-) "This is a very structured process, which is important for us, but for decision makers this is really very formal and is partially seen as a barrier for working with us." (Case 1)*	*(+) "From my point of view, agility has a positive effect, because adaptability is important for the results, so that the results provide relevant evidence." (Case 7)* *(-) "I often experienced that in cases where different perceptions prevail, the analytic insights are often neglected in decision making and instead discussions about aspects like governance model and responsibilities emerge." (Case 6)*

For agility, the major benefit that was identified was the flexibility to adapt procedures to changing information requirements. Achieving an adequate level of adaptability was regarded as the basis for realizing effective analytic decision support. Overall, agility was found to be lacking with regard to rights and roles clarity. Statements concerning transparency were mixed. On the one hand, high levels of adaptability were considered as dangerous due to missing definition of procedures, diminishing reproducibility and consequently increased opportunities for political behavior. On the other hand, increasing the speed of information infusion and close collaboration with decision makers were seen as possibilities to gain consensus and more control over the decision process. Although agility was associated with speed in analytic procedures, high extents of agility were also linked to negative influences on decision process efficiency, when process structure was missing. Concerning effectiveness, agility was mainly attributed positive influence and was seen as the basis for achieving relevant analytic insights for supporting the decision processes. But also negative influences were mentioned, particularly for situations where absence of process structure can derogate the usage of relevant analytic results.

In summary, findings from the investigated cases suggest that rigor and agility seem to have advantages and drawbacks concerning their effects on decision processes. Consequently, a notion of balance between both characteristics was described as being most beneficial. But it was also considered as challenging to achieve, as explained in this quotation:

"This is somehow a paradox between both capabilities. On the one hand I can stay flexible, but then I lose formality and on the other hand I can make this so formal that I won't be flexible." (Case 9)

The importance of this balance between rigor and agility for BI&A support of decision processes is summarized and highlighted in the following expert statement:

"I believe that you need the right balance. [...] you need the defined process for transparency, structure and also efficiency. And you need agility for achieving result quality and effectiveness." (Case 1)

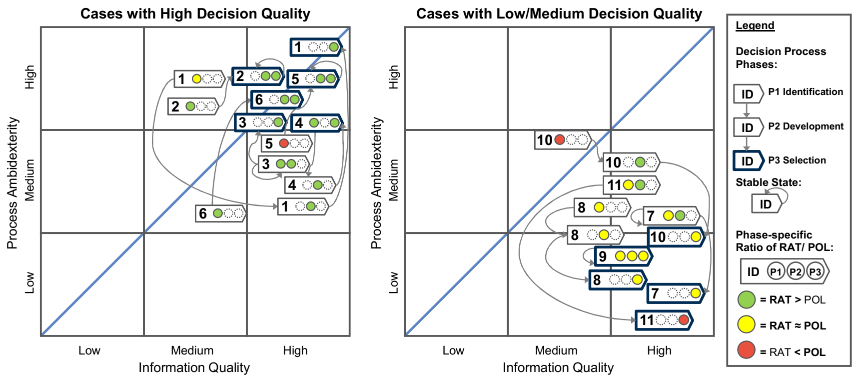
This notion of balance between rigor and agility has been previously conceptualized as ambidexterity (Lee et al., 2010). We use this conceptualization of ambidexterity in order to investigate the procedural dimension of the collaboration between analysts and decision makers jointly with information quality.

4.4.3 Complementarity of Information Quality and Ambidexterity

In this section we integrate the previously developed perspectives. We present evidence on how ambidexterity in BI&A-supported decision processes complements information quality in shaping favorable ratios of procedural rationality and political behavior, for achieving decision quality. Figure 4.2 integrates the phase-specific ratings of process ambidexterity and information quality for the investigated decision processes. We operationalized ambidexterity as product of the ratings of rigor and agility (Cao et al., 2009; Gibson and Birkinshaw, 2004). All ratings of ambidexterity and information quality are phase-specific and we again reduced the scales to three levels. Additionally, for each phase of the decision process, the phase-specific ratios of procedural rationality and political behavior are depicted.

For information quality we find that it was relatively high in all cases and decision process phases. The lowest values can be found mainly in the first phases (identification) of the investigated decision processes. Information quality improves or is maintained at a high level throughout the second phases (development). In the final phases (selection) we find high ratings in all cases. Hence, in most cases high quality information was available, but nevertheless decision quality varies strongly.

Comparing both groups of cases yields further interesting insights. We find that cases with high decision quality exhibit mostly high ratings of ambidexterity. The ratings of information quality and process ambidexterity are fairly balanced and this balance tends to be maintained or improved throughout the process phases. In the final decision process phases (selection) all cases can be found relatively close to the diagonal and the upper right corner. In the set of the cases with high decision quality, only two phases (identification phases of cases 1 and 5) are characterized by increased levels of political behavior, although information quality and ambidexterity are relatively high. An explanation for this might be that in the initial phases, the mode of collaboration between decision makers and analysts has not yet been established and hence increased levels of political behavior can occur. In both cases this changes in subsequent phases and these are to a higher extent characterized by procedural rationality.



Notes: Cases with High Decision Quality (Left) and Low/Medium Decision Quality (Right).

Figure 4.2: Effects of Information Quality and Ambidexterity in Decision Processes

In contrast, the set of cases with low/medium decision quality exhibits an unbalanced pattern between information quality and process ambidexterity. Most phases are located below the diagonal and we can observe a tendency for decreasing balance throughout the decision process phases. Particularly, in the selection phases we find the most unbalanced combinations between ambidexterity and information quality, with a focus on the latter. The majority of process phases is characterized by increased levels of political behavior. Prevalence of procedural rationality can be only found in the development phases of three cases (cases 7, 10 and 11). This interesting pattern can be explained by a reduced extent of interaction between decision makers and analysts during the development phase. After identifying and specifying the problem, analysts withdrew from the interaction with decision makers and focused on data analysis, which allowed them to raise the extent of perceived procedural rationality. Unfortunately, due to a lack of process ambidexterity, this effect seems not to be sustainable. Upon sharing analysis results with decision makers, the level of political behavior rose again during the selection phase and influenced decision quality negatively.

4.5 Discussion and Conclusion

This research investigated the organizational context of BI&A-supported decision processes. In the following, we discuss theoretical and practical implications, as well as directions for future research.

4.5.1 Discussion of Key Findings

With this study we strived to contribute to existing research by going beyond the prevailing technological perspective and by explicitly addressing decision processes and the organizational perspective of decision support with BI&A (Arnott and Pervan, 2008; Sharma et al., 2014; Shollo and Kautz, 2010). Our multiple case study of BI&A-supported decision processes offers the following contributions.

This research integrates established conceptions of political behavior and procedural rationality from decision process research into the context of BI&A support. Investigating compositions of political behavior and procedural rationality in BI&A-supported decision processes provided further evidence that achieving high levels of information quality is a necessary, but not sufficient condition for achieving high decision quality (Popovič et al., 2014; Shollo and Galliers, 2013). In the investigated cases we mainly observed medium and low levels of political behavior. Considering the research context, which deals with BI&A, this might not be surprising and is consistent with previous research on decision processes (Dean and Sharfman, 1993b; Eisenhardt and Zbaracki, 1992). The interesting implication is that despite having high quality information, already moderate levels of political behavior can impair decision process outcomes, particularly if politics prevail through multiple decision process phases.

Furthermore, we focused on the characteristics of collaboration procedures between analysts and decision makers in the investigated decision processes. The more distinctive theoretical contribution of this research refers to the complementing relation between ambidexterity and information quality in BI&A-supported decision processes. In this regard, our study provides insights on the need for both, process rigor and agility during the collaboration between analysts and decision makers in BI&A-supported decision processes. Through cross-case analysis of qualitative and quantitative data we provide initial empirical support for the complementing relation between information quality and ambidexterity, as well as for its implications on political behavior, procedural rationality and the outcomes of decision processes. We find that ambidexterity and information quality are essential for realizing the benefits of BI&A and achieving decision quality. Identifying the complementing effect of ambidexterity does not only allow for extending the reference theory foundation of decision support systems research, but also represents a novel contribution to management research by combining both streams of research (Papadakis et al., 2010). The results of this study provide valuable insights on how to design collaboration procedures in order to cope with varying extents of procedural rationality and political behavior in BI&A-supported decision processes.

These insights are also of considerable practical significance, because they highlight the factors that are relevant for improving decision processes and their outcomes. In particular, the results suggest that delivering technological and analytics support for achieving high quality information and analytic recommendations is not sufficient. Instead ambidexterity of collaboration procedures between analysts and decision makers has to be actively pursued and managed throughout decision processes, in order to assure that analytic insights generate the intended impact and benefits. This suggests that establishing collaboration procedures between analysts and decision makers should be guided by principles for achieving rigor and agility in decision processes. Our findings imply that maintaining rigor and agility throughout the collaboration can help achieving favorable ratios of procedural rationality and political behavior, which positively affects the outcomes of decision processes. Thus our results provide guidance on how to design procedures in order to improve BI&A-supported decision processes and their outcomes.

4.5.2 Limitations and Future Research

We presented results on BI&A support in decision processes from firms located across different industries. Using a multiple case study approach we strived for more general results than those that can be achieved with a single case study. Nevertheless, there is still further need for discussion and validation of the research findings. Limitations arise from reliance on the key-informant method, ex-post data collection and potential associated biases. Although taking the perspective of analysts was beneficial with respect to visibility on the investigated decision processes, this research would benefit from investigations of complementing decision makers' perspectives, in order to validate the findings.

We found that ambidexterity of collaboration procedures affects decision processes. This relationship should be investigated further, as it seems to be viable for the usage of information and the effectiveness of decision support in organizational contexts. Another interesting aspect that would require further research is the saturation effect for supplying information quality, which could be investigated under different conditions and decision process contexts. In this regard, a larger empirical basis of BI&A-supported decision processes would be of great value. We hope that by adding a perspective that goes beyond the technological view we can actuate further related research in this direction.

5 Study D: An Ambidextrous Perspective on Business Intelligence and Analytics Support in Decision Processes[4]

5.1 Introduction

Data-centric decision support is vital for managerial decision making in organizational decision processes. Business intelligence and analytics (BI&A) equips analytics experts (i.e., analysts or data scientists) with the technological capabilities to support decision processes with reliable information and analytic insights (Chaudhuri et al., 2011; Chen et al., 2012; Davenport and Harris, 2007; Davenport and Patil, 2012). The added value of BI&A is based on increasing the utilization of "data-driven" decision making and thus improving decision quality and organizational performance (Brynjolfsson et al., 2011; McAfee and Brynjolfsson, 2012; Pfeffer and Sutton, 2006). However, realization of these benefits is not assured, and the very nature of organizational decision processes poses challenges for effective BI&A support.

First, the reality of organizational decision processes has often been characterized as nonroutine and ill-structured (Eisenhardt and Zbaracki, 1992; Elbanna and Child, 2007; Mintzberg et al., 1976; Nutt, 2008). In these situations, ambiguity prevails and the right questions are not always obvious at the outset. Rather, questions and solution alternatives are developed as part of the decision process and are subject to change (Eisenhardt and Zbaracki, 1992; Mintzberg et al., 1976). As a consequence, data processing and analytics requirements can change frequently (Viaene and Van den Bunder, 2011). To achieve effective decision support in such nonroutine processes, the analysts who are involved must be able to adjust to these changes and, as a consequence, must maintain a high degree of adaptability and flexibility in their procedures.

Second, effective decision support with BI&A requires analysts to have a high level of specialization in analytics, which is different from the domain knowledge of decision makers, and this leads to further challenges (Viaene, 2013). Specifically, a high degree of analytics elaboration often makes it difficult for decision makers to assess the quality of the analytic advice they receive, due to their lack of analytics knowledge (Viaene, 2013; Viaene and Van den Bunder, 2011). Findings from the cognitive sciences suggest that such knowledge gaps induce information asymmetries, and these can lead decision makers to neglect analysts' advice and to instead overly rely on their own assessment of the decision situation (Bonaccio

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M. Kowalczyk, *The Support of Decision Processes with Business Intelligence and Analytics*, DOI 10.1007/978-3-658-19230-3_5

and Dalal, 2006; Yaniv and Kleinberger, 2000). To mitigate this risk, analysts are supposed to provide transparency and alignment with decision makers regarding their procedures and goals in deriving the analytic advice (Sniezek and van Swol, 2001; van Swol and Sniezek, 2005). This means that analysts have to ensure the rigor of their procedures in order to achieve coherence and traceability in the decision support that they provide.

In summary, analysts face decision process requirements that appear to be conflicting, or at least difficult to achieve simultaneously. Failure to meet these conflicting demands can thwart the potential benefits of BI&A support. However, despite their critical importance for the success of BI&A support, prior research has not considered these conflicting demands and their implications for managerial decision making. Therefore, in-depth research on this topic is required in order to gain a better understanding of the challenges that analysts face in supporting decision processes with BI&A. Organizational ambidexterity describes the capability of managing conflicting demands and as such provides a useful theoretical lens for our research (Gibson and Birkinshaw, 2004; Raisch and Birkinshaw, 2008). We use a multiple case study approach to investigate BI&A support of managerial decision making and thus respond to the identified need for research on actual decision processes (Arnott and Pervan, 2008, 2014; Sharma et al., 2014).

This paper makes several contributions. (1) We characterize and present previously unexplored tensions that pose a challenge for analysts' ability to provide effective BI&A support in organizational decision processes. (2) We provide insights into the tactics that analysts use to successfully manage those tensions, i.e., tactics that facilitate ambidexterity. (3) Through an investigation of decision processes with varying levels of ambidexterity, we provide initial evidence concerning the effects of ambidexterity by examining its impact on decision quality as well as its influence on decision makers' reliance on rationality and intuition in decision making. (4) Grounded in these empirical findings, we propose a theory of ambidexterity in decision support that addresses how this ambidexterity can be facilitated and how it affects decision outcomes. These contributions have great practical significance, as analysts need to be aware of the tensions and tactics in order to ensure the effectiveness and utilization of their BI&A support.

The remainder of this paper is structured as follows. In Section 2, we discuss the theoretical background for BI&A, conceptions of decision making, and organizational ambidexterity. In Section 3, we describe the details of our empirical study design and the data analysis procedure for our multiple case study research approach. In Section 4, we present the results from the multiple case study. Finally, in Section 5, we close with a discussion of the study's findings and limitations as well as possible directions for future research.

5.2 Theoretical Background

This section provides on overview of BI&A and presents conceptions of decision making that have been developed in management and cognitive sciences. It also elaborates on the challenging requirements that organizational decision processes pose for realizing effective BI&A support and introduces conceptions of ambidexterity from management and information systems research.

5.2.1 Data-centric Decision Support with Business Intelligence and Analytics

BI&A, which has its origins in data-centric approaches such as data warehousing, comprises a number of data collection, integration, and analytics technologies (Arnott and Pervan, 2014; Chaudhuri et al., 2011; Watson, 2010). BI&A systems aim to improve data processing in order to increase the quality of the information that is available for decision making (Chaudhuri et al., 2011; Popovič et al., 2012). In this regard, BI&A encompasses a number of basic analytics capabilities, such as online analytical processing, ad hoc queries, and descriptive statistics, as well as advanced analytics capabilities for data mining, prediction, and optimization (Arnott and Pervan, 2014; Chaudhuri et al., 2011; Davenport and Harris, 2007; Watson, 2010).

With an increasing level of analytics capabilities, the utilization of BI&A for delivering data-centric decision support becomes a specialized task, which requires analytics experts – for instance, data scientists or analysts – to support managerial decision makers (Davenport and Harris, 2007; Viaene, 2013). Hence, analytic advances induce a knowledge gap between analysts, who specialize in analytics, and decision makers, who have domain-specific knowledge (Viaene, 2013). Due to their lack of analytics knowledge, decision makers have to rely on analysts in the context of BI&A-supported decision processes. At the same time, analysts depend on the domain-specific knowledge of decision makers for developing relevant analytic insights and advice. As a consequence, effective BI&A support requires collaboration between analysts and decision makers (Sharma et al., 2014; Viaene, 2013).

Prior research on decision support has mainly assumed decision contexts in which decisions are made by either isolated, individual decision makers or groups of equal, undifferentiated decision makers (Arnott, 2010; Arnott and Pervan, 2008). The implications of specialization, collaboration, and an uneven distribution of decision-making power between decision makers and analysts has not been adequately considered in the literature, despite being highly relevant in practice (Sharma et al., 2014; Viaene, 2013; Viaene and Van den Bunder, 2011). Our research investigates such decision-making setups from the underexplored perspective of analysts, focusing on the challenges that arise for effective utilization of BI&A in organizational decision processes.

5.2.2 Conceptions of Decision Making in Management and Cognitive Sciences

Insights from management and cognitive sciences provide the foundation for a better understanding of the challenges for effective BI&A support of organizational decision processes. In both research areas, interrelated conceptions have been developed that distinguish between more rational and more intuitive modes of information processing and decision making (Akinci and Sadler-Smith, 2012; Dane and Pratt, 2007; Hodgkinson et al., 2009). Whereas management research distinguishes between rationality and intuition as two main properties that can characterize decision processes (Elbanna, 2006; Khatri and Ng, 2000; Mintzberg, 1994; Shapiro and Spence, 1997), cognitive sciences investigate associated cognitive processes under the designation “dual-process theories” (Chaiken et al., 1989; Evans, 2008; Kahneman and Frederick, 2002). We will focus on relations between the two domains and discuss their implications for decision processes.

Although there are variations among dual-process theories, they all distinguish between cognitive processes that are fast, automatic, effortless, and associative and those that are slow, controlled, effortful, and deductive (Evans, 2008; Kahneman and Frederick, 2002). A widely adopted practice in the cognitive sciences designates these two modes of processing as “System 1” and “System 2” (Kahneman and Frederick, 2002; Stanovich and West, 2000). System 1 and System 2 are viewed as working concurrently. System 1 is assumed to quickly propose intuitive answers to decision problems, while System 2 is supposed to control the quality of these proposals (Kahneman and Frederick, 2002). However, this is not always the case, as the rational reasoning associated with System 2 requires considerable cognitive effort, and such effort is considered to be limited by human cognitive capacity. Rather, individuals tend to use heuristics or mental shortcuts as adjuncts to System 1 in order to reduce the effort involved in processing difficult tasks. These heuristics have been found to lead to different kinds of systematic errors and to result in biased decision making (Tversky and Kahneman, 1974).

In this context, intuition is regarded as decision making that retains a hypothesized proposal from System 1 without control by System 2 (Kahneman and Frederick, 2002). Hence, intuitive judgment is based on System 1 processing and arrives at decisions through informal reasoning without the use of analytical methods or deliberative calculation (Kahneman and Tversky, 1982). In contrast, rational decision making relates to System 2 processing and includes the acquisition of information through conscious reasoning and deliberative analytical thought (Sadler-Smith and Shefy, 2004). In sum, dual-process theories offer cognitive explanations for an interaction between intuition and rational analysis in managerial decision making (Hodgkinson et al., 2009).

In management research, the rationality of decision processes has been investigated both theoretically and empirically (Dean and Sharfman, 1993b; Eisenhardt and Zbaracki, 1992; Elbanna, 2006; Hutzschenreuter and Kleindienst, 2006). Rationality has been characterized as systematic information gathering and reliance on analysis for the purpose of decision making (Dean and Sharfman, 1993b, 1996; Elbanna, 2006; Papadakis et al., 1998). Existing evidence about the relationship between rationality and the quality of decision outcomes mainly supports a positive relationship (Dean and Sharfman, 1996; Elbanna and Child, 2007; Nutt, 2008). Nevertheless, the presumption that only rationality should be considered in decision making research has been called into question (Eisenhardt and Zbaracki, 1992; Mintzberg, 1994).

Intuition has been proposed as providing an alternative approach to managerial decision making, particularly for decisions involving ambiguous or uncertain situations. These situations are characterized as having excessive cognitive processing requirements, entailing that decision makers might not be able to utilize rational processes (Khatri and Ng, 2000; Miller and Ireland, 2005; Sadler-Smith and Shefy, 2004; Shapiro and Spence, 1997). Intuition has been defined as an interplay between knowing and sensing, which allows understanding to be attained without explicit analytical inferences (Hodgkinson et al., 2009; Miller and Ireland, 2005; Sadler-Smith and Shefy, 2004). Very few studies have investigated the direct relationship between intuition and decision outcomes, and those that have done so provide an inconclusive picture. Intuition has been found to have a positive effect on decision outcomes in unstable decision environments and a negative effect in stable decision environments (Khatri and Ng, 2000). Furthermore, intuition has been found to significantly increase the occurrence of major unexpected, negative decision outcomes (Elbanna et al., 2013). In consequence, intuition is seen as a "troublesome decision tool" (Miller and Ireland, 2005), and most authors caution that sole reliance on intuition creates a risk in the decision making process (Elbanna et al., 2013; Elbanna and Child, 2007; Shapiro and Spence, 1997; Sinclair and Ashkanasy, 2005). Based on these findings, some researchers suggest the possibility of interactions between intuition and rationality as components of decision making (Miller and Ireland, 2005; Sadler-Smith and Shefy, 2004; Woiceshyn, 2009).

The implications of interactions between intuition and rationality in the context of BI&A-supported decision processes remain unexplored, and our understanding of their effects on decision outcomes is limited. From the analyst's perspective, the goal is to deliver analytic insights that will be utilized by decision makers in the decision process (Viaene, 2013). Hence, analysts aim at raising the level of rationality in managerial decision making and thus improving decision quality. However, as will be discussed in the next section, task specialization and the constitution of decision processes pose challenges for analysts' effectively contributing to these ends.

5.2.3 Decision Processes and Challenges for Effective BI&A Support

The effectiveness of the BI&A support that analysts provide to decision makers faces challenges stemming from specialization and the constitution of organizational decision processes.

The constitution of a decision process is related to the structure and perceived ambiguity of the decision situation. It is important to note that owing to the nonroutine character of managerial decisions, related tasks are subject to frequent changes and have often been found to be iterative (Eisenhardt and Zbaracki, 1992; Mintzberg et al., 1976; Nutt, 2008). This has immediate consequences for BI&A support of decision processes. More specifically, analysts often find themselves in nonroutine decision situations that are ambiguous, with the appropriate questions not obvious at the outset. As a consequence, early definition of information needs can be difficult, and data processing and analytics requirements can change frequently throughout the decision process. These circumstances require analysts to maintain a high degree of flexibility and adaptability in the procedures they utilize in order to effectively support decision makers. Failure to achieve this adaptability typically leads to defective analytic procedures and ineffective solutions (Viaene and Van den Bunder, 2011). This is a critical issue, because research has found that decision makers revert to intuitive decision making in uncertain or ambiguous decision situations (Khatri and Ng, 2000; Miller and Ireland, 2005; Sadler-Smith and Shefy, 2004; Shapiro and Spence, 1997). Hence, if analysts cannot deliver effective analytic advice, they won't be capable of raising the level of rationality in such decision situations – and the probability that the decisions will be based mainly on intuition might even increase. Therefore, adaptability is a crucial requirement that poses a challenge for analysts in providing effective BI&A support.

Specialization in BI&A-supported decision processes requires collaboration between the analysts, who contribute analytics capabilities, and the decision makers, who contribute domain-specific knowledge (Sharma et al., 2014; Viaene, 2013; Viaene and Van den Bunder, 2011). To develop relevant analytic insights, analysts must integrate their analytics capabilities with the domain-specific knowledge of decision makers (Viaene, 2013). Complicating the situation, in most organizations, such collaboration is embedded in formalized roles and hierarchies in which decision-making power is seldom distributed equally (Huber, 1990; Sharma et al., 2014).

The cognitive sciences investigate the implications of such decision-making setups under the "judge-advisor system" (JAS) paradigm (Bonaccio and Dalal, 2006; Sniezek and Buckley, 1995) and provide insights about advice utilization and discounting (Bonaccio and Dalal, 2006; van Swol and Sniezek, 2005). From the analyst's perspective, developing analytic advice is not enough, because decision makers frequently have difficulty assessing the quality of analytic advice due to their lack of analytics knowledge (Viaene and Van den Bunder, 2011). The persistence of such knowledge gaps can induce information asymmetries and uncertainty, which can lead decision makers to neglect advice and instead rely on their own experience (Bonaccio and Dalal, 2006). This “egocentric advice discounting,” in which decision makers tend to overemphasize their own evaluation of a decision problem, is one of the most robust findings of the JAS literature (Bonaccio and Dalal, 2006; Yaniv and Kleinberger, 2000). Researchers have found that advice discounting occurs mainly because decision makers have access to their internal justifications when making a particular decision, but not to their advisors’ procedures, evidence, and reasoning (Yaniv and Kleinberger, 2000). Hence, evaluation of the advice becomes difficult and uncertain for them. Findings from JAS research suggest that creating transparency and trust might overcome such uncertainty (Sniezek and van Swol, 2001; van Swol and Sniezek, 2005).

In this regard, reducing knowledge gaps and related information asymmetries in BI&A-supported decision processes seems to be crucial for promoting the utilization of analytic advice. If these gaps persist, decision makers will most likely discount analytic advice and instead rely heavily on their experience-based assessments of decision problems, which decreases the potential for improving rationality – and increases the probability that these decisions will be based primarily on intuition. Hence, analysts need to be transparent about their goals and the procedures they use to derive their analytic advice if they want to demonstrate alignment with decision makers and thus create traceability and trust for their analytic advice. Consequently, BI&A support of decision processes necessitates well-structured and traceable procedures. Thus, analysts have the challenge of structuring their procedures adequately in order to align with the decision makers and provide transparency concerning their procedures and delivery of analytic advice.

In summary, analysts are confronted with decision process requirements that demand procedures that are adaptable and flexible, on the one hand, and that provide traceability and alignment, on the other. Simultaneous fulfillment of both needs has been considered difficult, and organizational ambidexterity has been suggested for approaching such conflicting demands (Gibson and Birkinshaw, 2004; Lee et al., 2010; Raisch and Birkinshaw, 2008).

5.2.4 Ambidexterity and Decision Processes

The previous sections showed that high demands are placed on analysts and BI&A support in decision processes. Approaching such processes from the perspective of ambidexterity can be useful for gaining insights about the relations between those demands. In general, ambidexterity concerns conflicting task requirements and induced tensions that are difficult to resolve. Previous research has identified various dichotomies involved in conflicting demands, such as alignment and adaptability (Gibson and Birkinshaw, 2004), rigor and agility (Lee et al., 2010), and efficiency and flexibility (Adler et al., 1999). Although the tensions that result cannot be entirely eliminated, successful organizations are capable of reconciling them by simultaneously dealing with the conflicting demands (Gibson and Birkinshaw, 2004; Raisch and Birkinshaw, 2008). Hence, ambidexterity has often been described as a means to manage such conflicting demands (Andriopoulos and Lewis, 2009).

Based on the demands of decision processes, the concepts of alignment and adaptability and the related process-oriented concepts of rigor and agility seem to be particularly relevant to our research. On the one hand, aspects of BI&A-supported decision processes involving information asymmetries are related to the alignment or rigor dimension. Process rigor has been defined as adherence to predefined, formal, and structured processes, which include explicit definitions of roles, activities, work products, and methods (Lee et al., 2010). Achieving rigor throughout a decision process can reduce knowledge gaps and information asymmetries by explicitly specifying procedures and thus increasing transparency and enhancing understanding. On the other hand, aspects of decision processes that concern the unstructured nature of those processes are related to the adaptability or agility dimension. Consistent with the literature, we consider agility to be the ability to effectively sense and respond to changing requirements (Lee et al., 2010; Lee and Xia, 2010). Hence, achieving agility is the basis for being able to effectively react to changing information requirements within decision processes.

Ambidexterity is the ability to combine capacities from two conflicting dimensions, and the ideal state has been characterized as a balance between the two, which requires excellence in both respects (Cao et al., 2009). Attaining such ambidextrous excellence is challenging. This research contributes to understanding how this goal can be achieved by providing detailed insights into the tensions that arise in decision processes. Analysts need to be aware of those tensions in order to ensure effective BI&A support and utilization of their analytic advice. Since we shed light on tactics that can be applied to cope with those tensions, our results also have considerable practical relevance.

5.3 Research Method

Investigation of BI&A-supported decision processes is rather complex and requires in-depth analysis of the phenomenon. We therefore decided that a multiple case study approach would be particularly suitable and applied replication logic to our study design (Dubé and Paré, 2003; Yin, 2003). Utilizing a series of cases allowed us to achieve results that are more valid and general than a single case study would have allowed (Eisenhardt, 1989; Yin, 2003). This setup enabled us to create a strong empirical foundation, to gain a deep understanding of multiple BI&A-supported organizational decision processes, and therefore to derive more elaborated insights (Eisenhardt, 1989; Miles and Huberman, 1994; Yin, 2003).

5.3.1 Research Design

We used a multiple case study approach to investigate eleven BI&A-supported decision processes, which we selected based on a theoretical and literal replication logic (Dubé and Paré, 2003; Yin, 2003). To achieve literal replication, we examined firms with similar organizational contexts (i.e., large firms) that have used BI&A systems in their decision processes (see Table 5.1). Furthermore, we investigated cases in which the decision processes had been completed prior to the study's commencement, as we were interested in gaining insights into decision process performance and the quality of the resulting decision. In order to address potential sector-specific influences, we examined firms that operate in different industry sectors (see Table 5.1). We primarily aimed to investigate decision processes with different levels of agility and rigor in order to achieve theoretical replication. Additionally, we distinguished between the processes based on their resulting decision quality, which allowed us to contrast the analysis results.

Investigation of BI&A-supported decision processes would have been possible from the perspective of decision makers or analysts. The advantage of the latter is that analysts have deep insights into the analytics that are used for supporting decisions and they typically have also achieved an understanding of the decision makers' requirements. Furthermore, they have insights about how their analytic solution is taken into consideration during decision making and how it contributes to the decision outcome. Therefore, in order to maximize insights into the different tasks involved in the decision processes, we based our research design on the analyst perspective.

5.3.2 Data Collection

Before commencing our data collection, we drew up a case study protocol in order to assure reliability during the execution of the study. The protocol defined the objectives of our study and the data collection process. Utilizing multiple sources of evidence for data triangulation helped us enhance the validity of our findings (Yin, 2003). In this regard, we conducted in-depth expert interviews, collected additional documentation where possible, and gathered complementary quantitative data using a follow-up survey in order to increase the reliability and validity of our findings (Eisenhardt, 1989; Yin, 2003).

We decided to use the key informant method in capturing information from the expert interviews (Bagozzi et al., 1991). To identify participants who could share their experiences from real decision processes, we relied on social networks for professionals and searched for senior BI&A experts (see Table 5.1).

For the expert interviews, we developed a semistructured interview guide. We conducted two pilot interviews to refine this guide. The major part of the interview concerned a specific decision process that the interviewed analyst had supported with BI&A. In order to explore the decision processes in detail, we encouraged the experts to speak openly about everything that came to their minds (Ericsson and Simon, 1993) and, where appropriate, we used the laddering technique to pose successive questions (Reynolds and Olson, 2001). To complement this means of data collection, we set up a structured survey to assess characteristics of the decision processes. The measurements in the survey were based on established literature in the IS and management fields and used seven-point Likert scales. Scales for measuring agility and rigor (Lee et al., 2010) were adapted to our research context. For assessing procedural rationality (Dean and Sharfman, 1993b, 1996; Elbanna and Child, 2007; Elbanna and Younies, 2008) and intuition (Dean and Sharfman, 1996; Elbanna, 2006) as well as decision and outcome characteristics (Dean and Sharfman, 1993b, 1996; Elbanna and Child, 2007; Nutt, 2008), we relied on related management literature.

The case study interviews were conducted over a period of four months, beginning in July 2013. Most of the interviews were performed as face-to-face meetings, and the rest were conducted over the telephone. On average, each case meeting lasted two hours. In all cases, the interviews were audio recorded. Overall, this research approach yielded a rich combination of qualitative and quantitative data that provide a substantial depth and breadth for the data analysis.

5.3.3 Case Overview

Table 5.1 presents a summary of the investigated cases, including characteristics of the decisions, the organizations, and the roles that were involved. All of the decisions we investigated were major decisions within the organizations. They all required executive-level or higher management involvement and were all rated as nonroutine. The decision problems included reacting to new competition (Cases 1 and 11), major segmentation and product portfolio decisions (Cases 2, 4, 5, 6, 9, and 10), the introduction of new risk models (Cases 3 and 8), and substantial changes to the fleet constitution (Case 7). The decisions were supported by senior BI&A experts. On average, the interviewed experts had more than ten years of BI&A-related professional experience. The technological BI&A maturity in these cases was relatively high, and most of the organizations utilized standard, state-of-the-art, BI&A solutions from one of the major vendors.

Table 5.1: Overview of Investigated Cases

Organization Characteristics				Decision Characteristics				Interviewee Characteristics	
Case ID	**Industry**	**Size of Org.**	**BI&A Technology Maturity**	**Decision Content**	**Non-routineness**	**Decision Maker Level**	**Decision Quality**	**Analyst Role**	**Experience**
1	Telecom.	Very Large	Standard BI&A	Reaction to new competitor	High (1.0)	Executive (C-Level)	High (1.0)	BA Unit Leader	>10 Years
2	Media	Large	Standard BI & Custom BA	Product portfolio (pricing)	High (1.0)	Executive (C-Level)	High (0.86)	Analyst	18 Years
3	Finance	Very Large	Standard BI&A	Introduction of new risk models	High (0.71)	Executive (C-Level)	High (0.86)	Analyst	>10 Years
4	Consumer	Very Large	Standard BI&A	Product portfolio (product mix)	High (0.71)	Executive (C-Level)	High (0.95)	BA Unit Leader	6 Years
5	Tourism	Very Large	Standard BI & Custom BA	Product development	High (0.71)	Executive (C-Level)	High (0.90)	BI Unit Leader	14 Years
6	Finance	Large	Standard BI&A	Product portfolio segmentation	High (1.0)	Executive (C-Level)	High (0.86)	Analyst	>15 Years
7	Logistics	Large	Standard BI&A	Fleet constitution	High (0.86)	Executive (C-Level)	Medium (0.76)	Analyst	5 Years
8	Finance	Very Large	Standard BI&A	Introduction of new risk models	High (0.71)	Executive (C-Level)	Medium (0.67)	Analyst	>10 Years
9	Logistics	Very Large	Standard BI&A	Product portfolio (pricing)	High (0.86)	Executive (C-Level)	Medium (0.71)	Analyst	>12 Years
10	Telecom.	Very Large	Standard BI & Custom BA	Product portfolio (constitution)	High (0.86)	Product Manager	Low (0.21)	BA Unit Leader	6 Years
11	Telecom.	Very Large	Standard BI & Custom BA	Reaction to new competitor	High (1.0)	Brand Manager	Low (0.14)	Analyst	>15 Years

Notes: Decision Nonroutineness: 1.0 ≥ High ≥ 0.7 > Medium > 0.3 ≥ Low ≥ 0; Decision Quality: 1.0 ≥ High ≥ 0.8 > Medium ≥ 0.5 > Low ≥ 0; BI&A Tech. Maturity: Standard = Solutions from major BI&A vendors such as SAS, IBM, Oracle, or SAP; Custom BA = Solutions partially based on custom coding, Excel, or R; Orga.Size: Large = employees > 250 / revenue > 50 m€, Very Large = employees > 1000 / revenue > 500 m€

5.3.4 Data Analysis

The audio files were transcribed, producing an average of nineteen pages of transcript per case. The transcriptions made up the main raw data and were used to identify specific tensions related to BI&A support and the tactics analysts used to address them. We used software for qualitative data analysis to support the coding process. We analyzed our data in four main steps, following established recommendations for qualitative data analysis (Corbin and

Strauss, 2008; Miles and Huberman, 1994), and we discussed the intermediate results obtained during the analysis in order to ensure a common understanding.

In the first step, we identified initial categories using in vivo coding to generate first-order codes (Corbin and Strauss, 2008). More specifically, we used short conceptual descriptions of sections of the transcripts that referred to tensions occurring in the decision process or to approaches for dealing with those tensions. In the second step, we focused on conceptual links between the identified first-order codes in order to group them into adequate second-order topics. We relied on an inductive procedure that allowed concepts and relationships to emerge from the data (Corbin and Strauss, 2008). In the third step, we used cross-case analysis techniques to conduct case comparisons (Miles and Huberman, 1994). We compared the cases with regard to similar concepts and relationships. We also compared interview data with data from the survey with respect to the ratings of the decision processes and their outcomes in order to corroborate the quantitative data with the qualitative descriptions. In the final step of our analysis, we aggregated the identified concepts towards a theory that is grounded in our data and empirical findings (Eisenhardt, 1989). For this purpose we relied on inductive integration of the concepts resulting from the cross-case analysis (Corbin and Strauss, 2008; Eisenhardt, 1989; Kuechler and Vaishnavi, 2012), as well as on triangulation of perspectives (Kuechler and Vaishnavi, 2012). This allowed us to develop a mid-range theory of ambidexterity in decision support for the purposes of explanation and prediction (Gregor, 2006; Kuechler and Vaishnavi, 2012). The theory is represented by means of a conceptual model that includes the identified concepts and their relationships, as well as derived propositions.

5.4 Results

The analysis of BI&A-supported decision processes across the investigated cases reveals several interesting findings. First, we provide detailed insights into the tensions that challenge effective BI&A support and that appeared to be highly robust across the cases. Analysts need to reconcile these tensions if they want to provide effective analytic support for decision makers. We shed light on the tactics they use for this purpose and how they achieve ambidexterity through these means. Next, we present an assessment of the ambidexterity that was achieved in each case, and we outline its relation to the quality of the decisions and the managerial decision making. Finally, we propose a theory of ambidexterity in decision support that integrates the presented results.

5.4.1 Tensions and Tactics

Using comparative case analysis, we identified six major tensions and also discovered viable tactics for coping with those tensions. Figure 5.1 provides an overview of the tensions that analysts have to address in order to provide effective BI&A support in organizational decision processes and summarizes the tactics they use for coping with those tensions. In what follows, we present these tensions and tactics in more detail. We also provide exemplary quotes that enhance the understanding of these tensions and tactics and highlight their most important aspects.

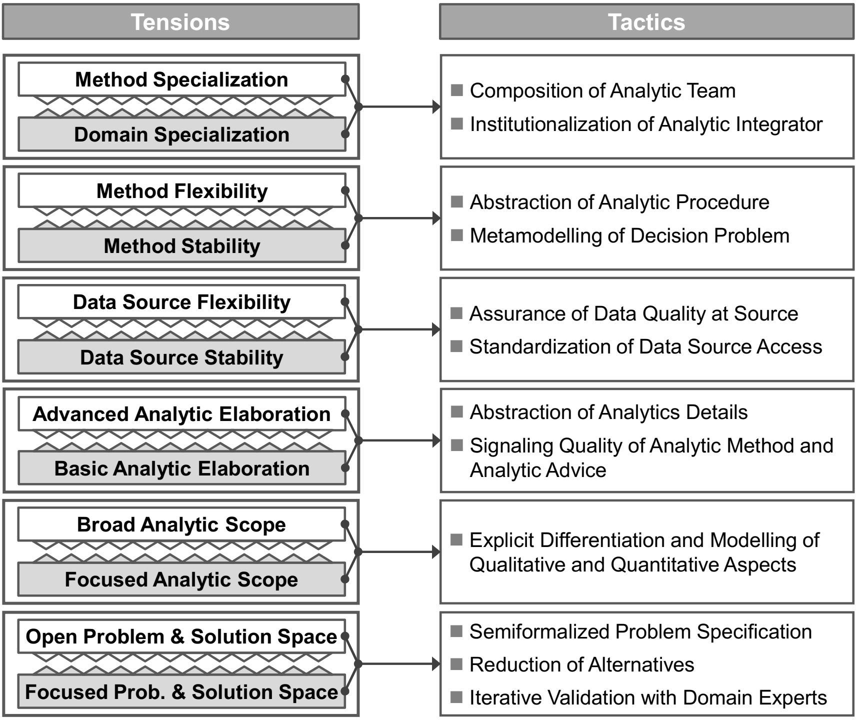


Figure 5.1: Overview of Tensions and Tactics

5.4.1.1 Method and domain specialization

The first general tension, which involves the specialization in analytics, is the tension between method and domain specialization. Method specialization means that the analyst has a high level of proficiency in BI&A methods and technologies. This is a prerequisite for effective decision support, and having a broad specialization in BI&A allows analysts to quickly adapt to changes in nonroutine decision contexts. The expert from Case 5 described this advantage as follows:

"Our great advantage was our extensive knowledge of the structure and content of our data. This allowed us to inform our colleagues about possibilities very early on. It allowed us to indicate which combinations were possible for drawing specific conclusions, […]." (Case 5)

In contrast, domain specialization means that analysts are focused on a problem domain, which provides them with deeper problem-specific knowledge but often restricts the scope of their BI&A proficiency. Having knowledge about the decision maker's problem domain is crucial:

"[...] the problem is that you have to be close to the business to answer dedicated questions. I don't think that a centralized unit would have been capable of developing such a model, as they wouldn't have known the details that were needed for developing it." (Case 11)

Being capable of combining the two types of specialization has been noted as vital for effective decision support. However, combining them is considered very challenging:

"[...] the ideal for our analysts is to combine the two [capabilities] [...], but that's actually barely possible." (Case 1)

We found two main tactics that are used to manage this tension. These tactics are to compose analytic teams and to explicitly establish an analytic integrator role. Analytic teams are cross-functional and consist of analytics and domain experts who collaborate on supporting a specific decision process. The purpose of these teams is to create a working environment in which analysts and domain experts can contribute and combine their expertise, as described in the following:

"In our case, not just one analyst works on a decision process, but typically three, sometimes even more. We involve the decision makers and domain experts right from the beginning. This goes hand in hand and everybody can contribute according to their strengths." (Case 1)

The analytic integrator role is designed to bridge the knowledge gaps between analytics experts and decision makers. Hence, the analytic integrator role differs from that of the analysts or data scientists and requires a skill set that specifically focuses on managing requirements, explaining analytic procedures and visualizations, and communicating analytic results:

"We have analysts who focus on managing requirements, on visualization, and on consulting [the decision maker] and we have analysts who focus on actually performing the analysis, utilizing our analytics tools, and experimenting with different analytical methods [...]." (Case 1)

5.4.1.2 Method flexibility and stability

The second and third tensions both stem from analysts' need to flexibly experiment with different analytic methods and data sources and to simultaneously maintain an adequate level of rigor in order to reduce information asymmetries with respect to decision makers. The second tension distinguishes between method flexibility and stability. Method flexibility is needed in nonroutine decision contexts because analysts are often unable to prescribe the best analytic procedures at the outset. Consequently, experimentation is necessary for developing a suitable approach to solving the problem. The following statement summarizes the importance of method flexibility:

"[...] we work flexibly and try out different methods, and by no means do we want to state from the start which approach is best suited for solving the problem." (Case 11)

In contrast, a certain level of method stability is necessary throughout the decision process in order to maintain transparency and hence manage the information asymmetries that can otherwise develop between analysts and decision makers. The following quotation summarizes these needs:

"If you have an established process, a specified method, and everybody knows what you are talking about, this creates a certain degree of transparency about how results were developed [...]." (Case 2)

Therefore, the simultaneous need for method flexibility and method stability creates a tension, as the following statement elaborates:

*"In cases with several iterations, the decision maker cannot always conceive whether there is actually an improvement in quality [...] this has to be well-defined. You typically need two or three iterations; if you need five, then the whole thing is probably poorly defined." (*Case 3)

We noticed that analysts used abstraction as a tactic to cope with this tension. Analysts try to abstract from the details of the analytic procedure while working with decision makers. This allows them to achieve a certain level of flexibility while maintaining the transparency and traceability of their procedures at a higher level of abstraction. They do this by metamodeling the decision problem at a question level that is relevant to the decision maker:

"You try to keep the core of the question similar and [...] you build hierarchical models, which ensure that the highest level of questions remain similar." (Case 2)

5.4.1.3 Data source flexibility and stability

The third tension, which concerns the data sources, is between data flexibility and data stability. Analysts have to rely on various internal and external data sources to effectively support decision processes. In nonroutine situations, there is a particularly high probability that the required data sources are not immediately available and need to be flexibly integrated into the decision process:

"[...] everything occurred quickly; there were no formalized processes. When something was missing in the warehouse, you had to get it there somehow. The integration of new sources was done in the department [...] but the quality was never validated outside of it." (Case 8)

Data source flexibility is advantageous in nonroutine decision contexts, but data source stability also has to be considered. A lack of data source stability is associated with negative consequences regarding data quality and transparency, as summarized in the following quote:

"[...] when you have to act fast [...] the wrong data can easily be extracted or combined [...] in cases where rapid changes have to be made, data quality is often not considered." (Case 8)

Data source stability relates to the use of validated data sources. Relying on high quality data sources can help reduce information asymmetries and mistrust. This is especially true if these sources are regarded as reliable and their information is traceable for decision makers:

"If all stakeholders involved in the decision process have knowledge about all utilized methods and data sources [...] the procedure becomes controllable at any point in time [...]." (Case 2)

In summary, the conflicting demands related to data source flexibility and stability introduce a further tension. We identified two main tactics for coping with this tension. The first involves moving data quality management from the BI&A system to the (internal) source systems and thus maintaining high data quality for internal data. This improves analysts' flexibility when reacting to changing information needs in decision processes, as the following statements highlight:

"Data quality originates from where the data are created, and it is not possible to develop quality after the fact [...] data quality issues need to be pushed back to the source systems [...]."(Case 5)

"The more complete your warehouse infrastructure is, the more flexibility you have to react to changes in requirements. This presumes that the data quality is assured." (Case 5)

The second tactic involves increasing the standardization of access to data sources in order to improve the quality of data access, which affects traceability and the analytics quality:

"Typically, analysts [...] obtain their data by themselves. Through a little bit of standardization [...] we are now able to spend 20% of our time on data collection and 80% on data analysis, and not the other way around. This has a very positive impact on analysis quality." (Case 1)

5.4.1.4 Advanced and basic analytic elaboration

The tension related to analytics elaboration concerns a fundamental design choice that analysts have to make, namely, a choice between utilizing advanced or basic analytic approaches. This design choice relates to the analytic approaches used throughout the decision process, as well as to the mode of delivering and communicating the analytic results. Use of advanced analytics gives analysts the opportunity to potentially gain new insights or improve the validity of results; consequently, they usually try to harness the best available approaches:

"Analysts typically aim at utilizing the best available models, those with the most advantages from their point of view." (Case 3)

Despite the benefits that can be realized through advanced analytics, this increases the information asymmetry between decision makers and analysts and therefore poses a challenge. Determining the extent of analytics elaboration should not be based only on considerations related to the analytic quality, but should also consider decision makers' comprehension:

"An important precondition for decision making or for influencing it, apart from data quality, system quality, and analytic capability, is management understanding. For me, this is the crucial dimension. […] if management does not understand it, then they won't use it." (Case 2)

This particularly relates to the mode of delivering and communicating the final analytic results. Making use of the analytic models allows for an interactive evaluation of solution alternatives during which assumptions can be challenged and variables can be adapted. Such a procedure can be advantageous in terms of addressing the nonroutine decision context and the traceability of the recommendations obtained, but it also requires an advanced understanding of the analytics:

"If the decision maker is a specialist, the results are rather dynamic. Then we meet and together examine the effects of changing inputs and conditions. If we are mandated by management, the dynamics are typically reduced to three scenarios in total." (Case 1)

For dealing with the tension of analytics elaboration, analysts rely on the abstraction of analytics details in combination with a means to signal quality. During collaboration in the decision process, abstraction allows analysts to maintain flexibility regarding the extent of analytics elaboration while simultaneously enhancing the understanding, as noted in the following quote:

"We provide solution proposals in the form: 'We think that we can answer your questions in the following ways,' but this is less oriented toward the details of the analytics in use." (Case 1)

In their delivery of analytic results, analysts also rely on abstraction by providing analytic advice to decision makers. Such analytic advice is directed towards the goals and questions that were defined during modelling of the problem. This allows analysts to clearly communicate results:

"Using the specified decision tree, we systematically went through the different aspects, and we explained the validity of the results. […] we didn't show the complete calculations, but the figures that were presented provided enough details to assess the final result." (Case 2)

Additionally, analysts use means for signaling quality. For analytic methods, this involves providing successful cases of application, as summarized in the following expert statement:

"I provided examples of previous applications of the analytical approaches [that is, of] how they performed, just to create a better understanding of and trust in the methods." (Case 2)

In order to convey the trustworthiness of their analytic results, analysts also rely on signaling the quality of their analytic advice. Signaling quality includes demonstrating problem understanding and providing insights into assumptions, model validity, and data, as well as responding to decision makers' intuitions and involving domain experts in the presentation of analytic results. The following quote summarizes the main aspects of such signaling:

"Accordingly, we had to state the problem clearly once more, so as not to just present the solution, but to clearly characterize the situation, and not only to deliver the numbers, but also the views from Marketing and Sales." (Case 4)

5.4.1.5 Broad and focused analytic scope

Analytic scope is another general design choice that analysts have to consider for each decision scenario. On the one hand, focused use of analytics allows for maintaining a very manageable analytic scope, which can help analysts cope with information asymmetries. On the other hand, while considering a broader scope might be more adequate for covering the problem space, it can lead to more complex models and induce further gaps in understanding. Moreover, it might become difficult to holistically model all relevant aspects, as the following quote emphasizes:

"I think it's very important to obtain a holistic picture and to make the decision based on all available facts. This also involves aspects that BI&A cannot cover a hundred percent." (Case 7)

The major tactic that analysts use to address this challenge is to explicitly identify, differentiate, and model qualitative and quantitative aspects of the decision scenario. This enables them to broadly cover the problem space and to simultaneously deliver fact-based information for the most important aspects. The following statement provides an overview of this tactic:

"[…] we developed a decision tree, which required rather strategic work in order to describe all the influencing factors for the pricing decision. On the one hand, there was a quantitative part, […] but then there was also a lot of qualitative work, which was quite laborious." (Case 2)

5.4.1.6 Open and focused problem and solution space

Support of decision processes involves validation and specification of the decision issue. Furthermore, analysts have to support exploration of alternative solutions in order to create a basis for decision making. Both types of tasks simultaneously require focus and openness. From the analyst perspective, early and detailed specification provides the opportunity to derive clear information requirements and allows focusing the BI&A support at an early stage. Similarly, a focused solution space aims at reducing the number of alternatives early on. Clear specifications and a focused problem space enable an increase in the alignment and transparency of the analytic procedures, which, according to the following expert quotation, can be considered advantageous:

"When you are developing scenarios, they should not overlap. Instead, you try to design distinct scenarios, and it is not by chance that one designs three alternatives. Simply, left, right, and in the middle, and I think this is beneficial for decision making." (Case 2)

In contrast, relying on emergent problem specifications and an open solution space provides flexibility for adapting to a nonroutine context. This creates opportunities to validate decision issues from different points of view and to have a more comprehensive as well as explorative search for alternative solutions, as the following expert statement suggests:

"[...] but I think it is really crucial, [...] to remain open at this stage and to listen carefully to the different perspectives, to collaborate with the other units [...]." (Case 4)

At the same time, this strategy increases the potential for misalignment between the analyst and the decision maker by introducing more options that have to be considered, which reduces clarity. To address this conflict, three main tactics were described. First, decision issues and information requirements are specified using semiformalized approaches, in order to define the problem at a goal-and-questions level, as stated in the following expert quotation:

"In this context, we had discussions with the decision makers regarding the goals, and they wanted to know what we could additionally draw from the data." (Case 5)

Such an approach seems to provide enough rigor to establish the subsequent directions. Second, during the search for and development of alternatives, analysts provide explicit rationales for the inclusion or exclusion of the various alternatives, thereby restricting their number:

"[...] it was not like 'those are the numbers and this is the alternative,' but the numbers provided a good tendency and we then predefined two scenarios and continued working on them." (Case 4)

Third, involving domain experts in the validation activities during the development of alternative solutions and the reduction of the number of alternatives complements the other two tactics:

"It is really important to discuss the whole thing at intermediate steps. Like, 'We have some first ideas,' and then we discuss whether we could take any other route. [...] this helps to sig-

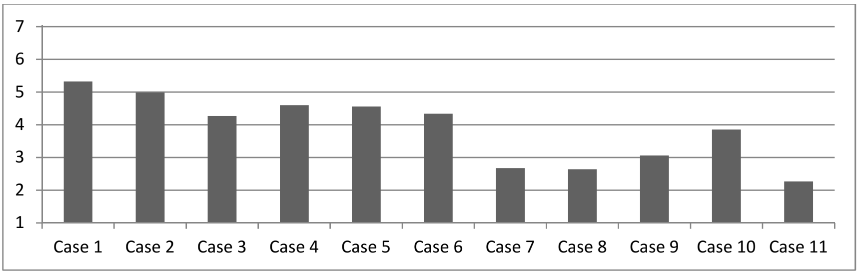
nificantly improve the quality of the decision process and, eventually, decision quality." (Case 1)

5.4.2 Ambidexterity in BI&A-Supported Decision Processes

The previous section introduced the tensions that analysts need to address in order to deliver effective BI&A support. It also presented the tactics that analysts use to resolve these tensions and thus to achieve ambidexterity. In what follows, we first show that ambidexterity affects decision quality. In this context, we also explore the extents of procedural rationality and intuition that characterize decision making within the investigated decision processes. Finally, we integrate our empirical findings by proposing a theory of ambidexterity in decision support.

5.4.2.1 Ambidexterity and the quality of decision process outcomes

In the context of BI&A support within the investigated cases, the conflicting task requirements revolved around needs for process rigor (i.e., traceability, structure, and stability) and agility (i.e., flexibility and adaptability). Consistent with the literature, we assess ambidexterity as a product of the ratings of rigor and agility (Cao et al., 2009; Gibson and Birkinshaw, 2004) that were provided by the interviewees. Hence, we obtain the levels of ambidexterity that were achieved in the investigated cases (see Figure 5.2). This provides initial evidence about the impact of ambidexterity on decision outcomes.



Notes: Cases with High (1–6) and Medium/Low (7–11) Decision Quality.

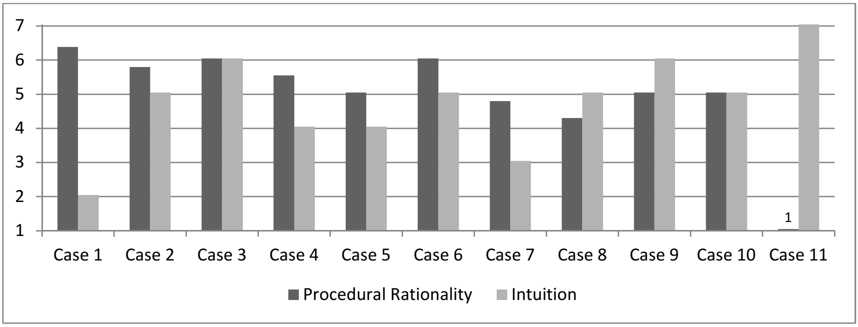
Figure 5.2: Ambidexterity in Decision Processes

A comparison of the cases that realized high-quality decisions (Cases 1–6) with those that achieved medium- or low-quality decisions (Cases 7–11) shows that the high-quality decision cases exhibit higher ratings of ambidexterity than the less successful cases. The rating of Case 10 seems to be an exception, but the reason for this increased rating lies in the multiplication of highly unbalanced dimensions (agility > rigor), which overrates the actual ambidexterity. Thus, the main finding implies that achievement of an ambidextrous combination of rigor and agility seems to have a positive impact on the success of decision processes. This further confirms that ambidexterity should be considered as relevant and advantageous for decision support.

5.4.2.2 Procedural rationality and intuition in decision processes

Figure 5.3 presents the interviewees' assessments of the magnitudes of procedural rationality and intuition that characterized the decision making within the investigated decision processes.

We find that, to a certain extent, both rationality and intuition play a role in decision making. An interesting observation arises from comparison of the cases that realized high-quality decisions (Cases 1–6) with those that achieved medium- or low-quality decisions (Cases 7–11). For the high-quality decision cases, we observe that the ratings for rationality are the same as or higher than those for intuition. In comparison, we mainly find relatively lower ratings for rationality in the less successful decision cases. Additionally, intuition seemed to play a more important role in the latter cases, and it even exceeded rationality in three cases (8, 9, and 11).



Notes: Cases with High (1–6) and Medium/Low (7–11) Decision Quality.

Figure 5.3: Procedural Rationality and Intuition of Decision Making

These observations imply that in nonroutine decision scenarios, the relationship or ratio between procedural rationality and intuition seems to be of relevance. Notably, rationality seems to exceed the utilization of intuition in cases that exhibit higher levels of ambidexterity, and these cases tend to result in higher quality decision outcomes. In contrast, intuition turns out to be more influential in medium- and low-quality decisions (except for Case 7), and these cases were characterized by lower levels of ambidexterity as well as lower decision quality.

5.4.2.3 A theory of ambidexterity in decision support

In order to integrate the empirical findings from this research, we propose a theory of ambidexterity in decision support, which we developed through inductive analysis of the case study data. These results and propositions are based on the replication logic of our multiple case study design. This means that the proposed model for a theory of ambidexterity in decision support (see Figure 5.4) is grounded in replicated empirical findings and can thus provide an explanation of how ambidexterity can be facilitated and how it affects decision outcomes. Furthermore, we derive testable propositions for the identified concepts and their relationships.

Overall, this theory of ambidexterity in decision support suggests that improving analysts' ability to cope with the tensions in decision processes will facilitate ambidexterity, which in turn will lead to higher decision quality (see Figure 5.4).

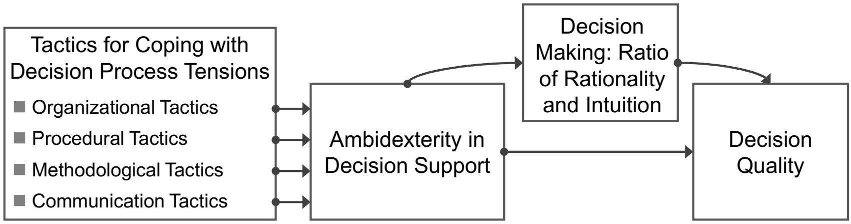


Figure 5.4: Model of the Theory of Ambidexterity in Decision Support

Based on the empirical results of our study, the theory differentiates between four types of tactics for coping with decision process tensions and thus achieving ambidexterity. Organizational tactics (i.e., analytic team, analytic integrator, assurance of data quality, standardization of data source access) address the setup of the working environment for BI&A support. Procedural tactics (i.e., abstraction of the analytic procedure, iterative validation) deal with the process of collaboration between analysts and decision makers. Methodological tactics (i.e., metamodeling, differentiation of qualitative and quantitative aspects, semiformal specification, reduction of alternatives) concern the practices and approaches that analysts utilize during their collaboration with decision makers. Finally, communication tactics (i.e., abstraction of analytics details, quality signaling) comprise means for shaping the direct personal interactions of analysts with decision makers.

In sum, the following proposition can be derived for achieving ambidexterity:

(P1) Increasing utilization of organizational, procedural, methodological, and communication tactics will raise the level of ambidexterity in decision support and improve coping with decision process tensions.

Additionally, the proposed theory distinguishes between direct and indirect effects of ambidexterity on the quality of decision outcomes. The results from our analysis suggest that ambidexterity in the support of decision processes has a positive direct influence on decision quality. Thus, it can be considered as basis for the development of high quality decision support. This direct effect of ambidexterity is stated in the following proposition:

(P2) Increasing the level of ambidexterity in the support of decision processes will result in better decision quality.

The proposed indirect effect of ambidexterity relates to its influence on the extents of procedural rationality and intuition utilized during decision making. The results presented in the previous section suggest that ambidexterity increases the relative extent of procedural rationality compared to intuition, which improves decision makers' utilization of analytic results during decision making. This should have a positive influence on the quality of decision outcomes. Therefore, the indirect effect of ambidexterity is identified in two propositions: *(P3) Increasing the level of ambidexterity in the support of decision processes will result in a higher ratio of procedural rationality to intuition.*

(P4) A higher ratio of procedural rationality to intuition will result in better decision quality.

The implications of this theory of ambidexterity may be substantial for organizations aspiring to become more analytic in their decision making, because it highlights the need for capabilities that go beyond establishing a BI&A technology in order to improve the quality of decision making.

5.5 Discussion and Conclusions

This section discusses the theoretical and practical implications of the presented results, as well as their limitations. Furthermore it outlines opportunities for future research.

5.5.1 Implications for Research

Utilizing the underexplored perspective of analytics experts, this research examined the conflicting demands that arise with regard to the analytic support of decision processes with BI&A. We propose ambidexterity as a theoretical lens for investigating the conflicting task requirements, and our research makes four contributions that have considerable theoretical implications for BI&A, as well as DSS and managerial decision making research.

First, we identify and provide in-depth insights into six tensions surrounding BI&A support that arose during the decision processes we investigated. These tensions are related to the skill specialization of analytics experts, the simultaneous need for flexibility and stability in their analytic methods and data sources, design choices regarding the elaboration and scope of the analytic approach, and the openness of the problem specification and the solution space. These tensions can impede BI&A support by threatening the effectiveness and utilization of the analytic insights that analysts supply during decision processes to raise the rationality of managerial decision making. By focusing on these challenges arising from collaboration between different specialized roles in the decision processes (i.e., analysts and decision makers), which are highly relevant in practice (Sharma et al., 2014; Viaene, 2013; Viaene and Van den Bunder, 2011), these findings provide a much needed complementary perspective on the organizational context of decision support and decision making.

Second, in addition to characterizing the tensions that arise during the decision processes, we identify a set of tactics that analysts use to successfully manage these tensions. These tactics concern organizational, procedural, and methodological aspects of decision support, as well as communication with decision makers. Besides providing valuable insights and guidance for managing the tensions that arise in decision processes, these findings emphasize that achieving effective decision support requires more than choosing the best available technological solution. Previous research has considered it important to extend BI&A and decision support research beyond such a technological perspective in order to strengthen the relevance of our research field for managerial decision makers and analytics experts (Arnott and Pervan, 2008, 2014; Sharma et al., 2014).

Third, this research not only presents the tactics that are used to achieve ambidexterity in decision processes, but also examines the relationship between ambidexterity and the quality of decision outcomes. The assessment of ambidexterity across the investigated decision processes suggests that decision processes that achieve higher levels of ambidexterity also realize higher decision quality. To the best of our knowledge, this study is the first to explicitly establish this link. In this context, we also explicitly consider the potential influence of ambidexterity on managerial decision-making behavior. We conceptualized managerial decision making in terms of the extent of the managers' reliance on intuition and on rational analysis. We found that, to a certain extent, intuition played a role in all of the investigated decision processes. This is not surprising, considering managerial research findings (Akinci and Sadler-Smith, 2012; Hodgkinson et al., 2009; Khatri and Ng, 2000; Sinclair and Ashkanasy, 2005; Woiceshyn, 2009) and the nonroutine character of these decisions. The far more interesting finding concerns the ratio of procedural rationality to the use of intuition. Cases with high levels of ambidexterity exhibit high decision quality, and in these cases we found that the extent of rationality used tends to exceed that of intuition. In contrast, less successful cases with lower levels of ambidexterity mainly exhibit patterns in which reliance on intuition exceeds procedural rationality. This finding supports a notion of complementary interaction between the two dimensions (Miller and Ireland, 2005; Sadler-Smith and Shefy, 2004; Woiceshyn, 2009) and thus suggests that ambidexterity could play a role in shaping the ratio between procedural rationality and intuition. In summary, these observed effects of ambidexterity underscore its relevance for decision support research and highlight the importance of understanding and effectively managing the identified tensions.

Fourth, we develop and propose a theory of ambidexterity in decision support based on the empirical findings from this research. This includes the derivation of testable propositions for the identified concepts and their relationships. The presented theoretical model allows an explanation of how ambidexterity can be achieved or improved through the utilization of different types of tactics (i.e., organizational, procedural, methodological, and communicative) that we identified in this research. Furthermore, it suggests that ambidexterity affects the quality of decision outcomes through direct and indirect effects. Ambidexterity should have a positive direct influence on decision quality by contributing to the development of BI&A decision support that effectively addresses the decision problem. Furthermore, it should have a positive indirect effect by improving decision makers' utilization of analytic results during decision making and thus raising the relative extent of procedural rationality, which contributes to improved decision quality.

5.5.2 Implications for Practice

The results of this study also have considerable practical significance and make the following contributions. For analytics experts, our results not only highlight the tensions of which they need to be aware in order to deliver effective BI&A support, but also suggest tactics for coping with these tensions. By distinguishing different types of tactics (i.e., organizational, procedural, methodological, and communicative), our results provide guidance on how to systematically improve decision processes and their outcomes. Communication, methodological, and procedural tactics can be readily applied by analysts to balance task-related requirements of adaptability and rigor in their collaboration with decision makers. In contrast, for organizational tactics, an institutionalization of the associated practices at the organizational level would be advisable.

Turning to decision makers, the findings suggest that they need to be aware that despite the challenges that come with analytic specialization and nonroutine decisions, overdependence on intuition in decision making is risky. In contrast, the introduction of ambidextrous tactics within the organization can improve decision makers' utilization of analytic advice and thus help them scrutinize intuitive hypotheses during decision making. This will contribute to mitigating the risks of biased decision making and should therefore also raise the quality of decision making.

5.5.3 Limitations and Future Research Directions

We have presented results from a multiple case study of BI&A support in decision processes, and we conclude by noting the following limitations as well as directions for future research. We decided to use a multiple case study approach because it enabled us to deliver more general results than would have been possible had we conducted a single case study. Nevertheless, there is still a need to further discuss and validate the research findings. One limitation of this study is that it relies on the single key informant method, for which we tried to compensate by using data triangulation. Although choosing the analyst's point of view yielded several benefits, investigating the perspectives of other stakeholders could extend this research, and it would be valuable to replicate this study from the decision maker's point of view. A larger empirical basis of BI&A-supported decision processes would also be of great value. Our current setup was too limited, in terms of the number of cases and interviews, to achieve high measurement validity and to explore cultural or domain-specific aspects. Additionally, quantitative research to test the suggested theory of ambidexterity and to address the presented propositions would be of great interest. We hope that by adding ambidexterity to the theoretical base of DSS research, we will actuate further decision-support-related research that can benefit from this perspective.

6 Study E: Business Intelligence and Analytics – Decision Quality and Insights on Analytics Specialization and Information Processing Modes[5]

6.1 Introduction

Business intelligence and analytics (BI&A) provides the technological capabilities for data collection, integration, and analysis with the purpose of supplying decision processes with high quality information and new analytic business insights (Chaudhuri et al., 2011; Chen et al., 2012; Davenport and Harris, 2007; Dinter, 2013; Watson, 2010). While the supply of high quality information and the generation of analytic insights have the potential for improving managerial decision making, they must be used effectively in decision processes in order to live up to this potential (Pfeffer and Sutton, 2006; Popovič et al., 2014; Shollo and Galliers, 2013). Hence, leveraging the benefits of BI&A does not only depend on establishing a technological infrastructure, but also on the organization and characteristics of decision processes in which BI&A is deployed (Davenport, 2010; Işık et al., 2013; Popovič et al., 2012, 2014; Sharma et al., 2014).

Successful analytic support of decision making typically depends on the collaboration between analytics experts (i.e., analysts or data scientists), who supply high quality information and analytic advice, and domain experts (i.e., decision makers), who utilize these inputs for decision making (Davenport and Patil, 2012; Viaene, 2013). Analyses of practitioners reports repeatedly suggests that problems of realizing effective decision support with BI&A, are grounded in the high degree of specialization between analytics experts and decision makers (Viaene, 2013; Viaene and Van den Bunder, 2011). For instance, due to this specialization, decision makers may lack the analytics expertise to understand analytic advice, which could undermine the effective use of analytic insights. Concerning this, findings from psychology research suggest that such lacking comprehension can reduce the acceptance of advice and furthermore increase the impact of factors related to the qualities of personal interaction (e.g., trustworthiness) within decision processes (Bonaccio and Dalal, 2006).

While utilizing BI&A raises the level of analytics elaboration and establishes analysts as mediators between information and its use by decision makers, the resulting implications for decision processes remain largely unexplored. Achieving better understanding of the effects of BI&A on decision processes has been identified as a precondition for conceiving how to

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improve decision outcomes and consequently organizational performance. Therefore, more research in this direction has been explicitly called for (Kowalczyk et al., 2013; Sharma et al., 2014). Moreover, reviews of research on decision support systems and BI&A recommend further investigations regarding decision makers' actual utilization of information or analytics results in decision making processes and its consequences for decision outcomes (Arnott and Pervan, 2008, 2014; Shollo and Kautz, 2010). In departure from prior research, this study explicitly considers the implications that result from specialization in BI&A-supported decision processes. Moreover, our research approach investigates the relation between the supply of information, a decision maker's mode of information use, and the resulting quality of decision outcomes.

For this purpose we build on the heuristic-systematic model (HSM) of information processing (Chaiken, 1980; Chaiken et al., 1989), as a theoretical lens for our research. This perspective allows us achieving a better understanding of the mechanisms that shape decision makers' use of information and utilization of analytic advice. The HSM distinguishes between a systematic and a heuristic mode of information processing. Whereas systematic processing is analytic and makes extensive use of information, heuristic processing is characterized by the application of simple inferential rules in making a decision (Chaiken et al., 1989). We argue that HSM provides a valuable perspective for investigating the effects of BI&A on decision making and the quality of decision outcomes. Therefore, we first propose how information quality and the extent of analytics elaboration influence a decision maker's mode of information processing behavior. Second, we theorize how the decision maker's mode of information processing behavior and qualities of personal interaction with analysts affect the adoption of analytic advice, as well as the quality of decision outcomes. These theoretical propositions are tested using quantitative data obtained from 136 BI&A-supported decisions.

This study strives to make three contributions. First, it highlights a tension between the supply of high quality information and analytics elaboration in BI&A-supported decision processes, by showing how the former enhances and the latter reduces a decision maker's capacity to process analytic results. Second, it sheds light on how a decision maker's dealings with information (i.e., rather systematic or heuristic) and the qualities of personal interaction with analysts are crucial for the utilization of analytic results in task-specialized decision making processes. Finally, it demonstrates how information processing and utilization determine the quality of decision outcomes. These findings are also of high practical relevance, because they highlight how to establish effective usage of BI&A that converts into improved decision outcomes.

The remainder of the paper is structured as follows. The next section provides the theoretical background for our research and hypotheses are developed afterwards. Subsequent sections provide details on data collection, analyses, and results. The article concludes with a discussion of findings and contributions, as well as their implications for theory and practice.

6.2 Theoretical Background

This section elaborates on the theoretical background of our research and focuses on the levels of analytics elaboration in BI&A and specialization in BI&A-supported decision processes. Furthermore we introduce the heuristic–systematic model (HSM) as a theoretical lens for our research.

6.2.1 Business Intelligence & Analytics

From a general technical point of view, business intelligence and analytics (BI&A) comprises a set of data collection, integration, and analytics technologies (Arnott and Pervan, 2014; Chaudhuri et al., 2011; Watson, 2010). In this research, we differentiate between basic versus advanced functionalities of BI&A (Davenport and Harris, 2007; LaValle et al., 2011; Watson, 2010). As will be argued below, this distinction should affect the decision process significantly. Basic analytics capabilities include functionalities like online analytical processing (OLAP), ad-hoc queries, simple descriptive statistics, and predefined reports or dashboards. Advanced analytics comprise functionalities that include data mining (e.g. neural nets, classification and regression trees, support vector machines), advanced statistical analysis (e.g. regression modeling, time-series analysis, factor analysis, forecasting, sensitivity analysis), and simulation or optimization approaches (e.g. solver approaches, heuristics, Monte Carlo simulation, agent-based modeling) (Davenport and Harris, 2007; Watson, 2010). Whereas basic analytics represent relatively common means of data analysis and hence should be easily understandable and assessable for most decision makers, advanced analytics comprise functionalities that require specialized skills. Advanced analytics are typically utilized by analysts or data scientists, who have the specialized knowledge for delivering potentially new business insights and analytic advice to decision makers (Davenport et al., 2010; Harris et al., 2010; Viaene, 2013).

6.2.2 Specialization in BI&A-Supported Decision Processes

Prior research has only marginally considered analytic specialization and its implications for BI&A support of decision making. Existing studies often assume that decisions are either made by individual decision makers or by groups of equal peers, who use a decision support technology (Arnott and Pervan, 2008). In contrast, in most organizations formalized hierarchies and roles exist, among which decision making power and analytic capabilities are rarely distributed equally (Bonaccio and Dalal, 2006; Huber, 1990). Similarly, the support of decision processes with BI&A depends on the collaboration between analytics experts, who develop analytic advice and decision makers, who utilize these inputs for decision making

(Davenport and Patil, 2012; Sharma et al., 2014; Viaene, 2013). Thus, existing research in the context of BI&A should be complemented by a perspective that considers specialization and collaboration to adequately represent the actual decision making processes. For example, with increasing levels of analytic elaboration the delivery of analytic advice can become increasingly difficult to understand by decision makers, due to limited analytics knowledge (LaValle et al., 2011; Viaene and Van den Bunder, 2011). In cognitive sciences, such gaps in understanding have been found to be a hindrance to the utilization of advice, as they induce information asymmetries and perceived uncertainty (Bonaccio and Dalal, 2006). As decision power lies with the decision maker, this can lead to disregard of (analytic) advice and strong reliance on the decision maker's domain experience for decision making (Yaniv and Kleinberger, 2000). In situations that are characterized by gaps in understanding between both roles, the qualities of personal interaction between decision maker and analyst should gain significance in their relevance for decision process outcomes (Bonaccio and Dalal, 2006; Sniezek and van Swol, 2001).

Investigating analytic specialization as part of the utilization of BI&A for supporting decision processes contributes to a major gap in information systems research, as the effects of BI&A use in the context of decision processes remain largely unexplored (Sharma et al., 2014). Concerning this, findings from cognitive sciences suggest that analytic specialization in BI&A-supported decision processes should have major implications on decision maker's processing of information and utilization of analytic advice. In consequence analytic specialization should also affect the overall success of BI&A support. Thus a better understanding of the mechanisms that shape decision makers' use of information and utilization of analytic advice in scenarios with analytics specializations is needed.

6.2.3 Heuristic–Systematic Model of Information Processing

In order to gain a better understanding of the impact of BI&A support on decision making and its outcomes, we require more insights about the influence of BI&A on decision makers' information processing behavior in the context of decision processes. In this regard, dual-process theories of cognitive information processing from psychology research provide a useful theoretical lens. In order to distinguish between different modes of decision makers' information processing, we propose that the heuristic–systematic model (HSM) (Chaiken, 1980; Chaiken et al., 1989) serves as a valuable perspective to gain a better understanding of effects of BI&A support on decision processes. HSM addresses contexts in which individuals "are exposed to information about themselves, other persons and events, and have to make decisions or formulate judgments about these entities" (Chaiken et al., 1989). This perspective renders HSM particularly suitable for research on BI&A-supported decision processes.

HSM theory argues that when individuals are faced with decision situations, they can process the information, which they receive in this context, by using two distinct modes – systematic or heuristic processing (Chaiken, 1980; Chaiken et al., 1989). Systematic processing is characterized by extensive analysis and scrutinizing of information for its relevance and importance to the decision task. Hence, systematic processing represents an information processing mode, which is analytic and makes extensive use of information, by integrating all useful information in forming a judgment or decision (Chaiken et al., 1989). In contrast, heuristic processing represents a rather limited processing mode in which only an incomplete subset of available information is accessed and processed. Information use is less analytic and characterized by the application of simple inferential rules or cognitive heuristics. These rules or heuristics can be understood as simple knowledge structures or frames that are used, consciously or unconsciously, in making a decision (Chaiken et al., 1989).

The HSM considers two major types of determinants – cognitive and motivational – that influence the mode of information processing in decision making (Chaiken et al., 1989). The main cognitive determinant is an individual's capacity for in-depth and systematic information processing. The HSM assumes that systematic processing is more demanding, with respect the required effort and capacity, than heuristic processing (Chaiken, 1980; Chaiken et al., 1989). In consequence the systematic mode is supposed to be more constrained by situational and individual factors that reduce the ability for in-depth information processing, like time pressure or lack of expertise. Hence, in decision situations where available capacity is low or limiting factors prevail, heuristic processing will have a major influence on decision making, due to its relative small requirements for capacity and effort (Chaiken et al., 1989).

Furthermore, the model considers individuals to be economy-minded and therefore trying to satisfy their information needs efficiently by using the principle of least effort (Chen and Chaiken, 1999). This links to the motivational aspects of information processing. The main motivational determinant is related to the extent of judgmental confidence an individual aspires to attain in a given decision scenario and the model asserts that individuals will exert whatever effort is required to attain a sufficient degree of confidence (Chen and Chaiken, 1999). This sufficiency principle is related to the personal importance of the decision situation. Importance of the decision situation elevates the amount of required judgmental confidence. In high involvement decision situations the need for reliability and accuracy exceeds potentially limiting effort constraints. In such situations, individuals were found to exhibit increasing reliance on systematic processing (Chaiken and Maheswaran, 1994) and to be increasingly sensitive to the reliability of statistically based information (Hazlewood and Chaiken, 1990).

The value of HSM for our research purpose lies in better explaining decision makers' information processing behavior in the context of BI&A-supported decision processes and thus addressing an identified need for research in this direction (Arnott and Pervan, 2014). Thus, the HSM does not only help to explain why analytic insights or advice are used to varying extents in decision making, but can also shed light on their impact on the quality of decision outcomes.

6.3 Research Model and Hypotheses

The heuristic–systematic model (HSM) of information processing provides the theoretical foundation for the research model proposed in Figure 6.1. In the forthcoming we theoretically develop and discuss (1) the effects of BI&A characteristics on decision maker information processing, (2) determinants of information processing and their effects on (3) information processing and decision quality.

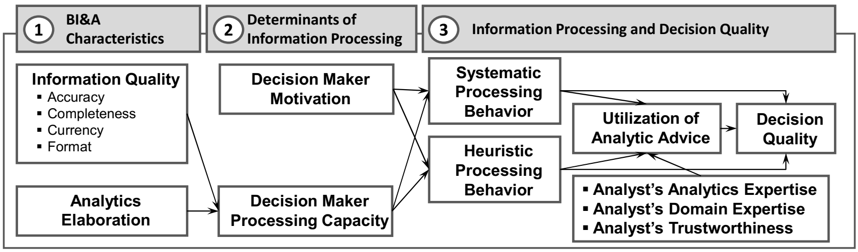


Figure 6.1: Conceptual Model

6.3.1 BI&A Characteristics and Decision Makers' Information Processing

The supply of high quality information and the utilization of analytics functionalities in order to generate potentially valuable analytic insights are two main benefits of BI&A (Davenport and Harris, 2007; Popovič et al., 2012; Sharma et al., 2014; Watson, 2010). In order to gain a better understanding of their impact on decision making, this study investigates their effects on the determinants of decision maker's information processing behavior. In particular, we analyze how information quality and analytics elaboration affect decision maker's information processing capacity.

Following Nelson and Todd (2005), we define information quality according to four quality dimensions, which include accuracy, completeness, currency, and format of information. Accuracy relates to the extent that information is correct, unambiguous, meaningful, believable, and consistent. Completeness describes the degree to which all relevant content is included and currency relates to the extent to which information is up-to-date. Finally, format addresses how well information is understandable and interpretable to its user. We define analytics elaboration as the extent to which advanced analytic approaches are used in the context of BI&A-supported decision processes (Chen et al., 2012; Davenport et al., 2010; Watson, 2010). Thereby, analytics elaboration should not be confused with the concept of task complexity, which has been defined as the degree of cognitive load or mental effort required to solve a problem (Payne, 1976). While both concepts might be correlated in some cases, such a correlation should depend on having a lack of task-specific analytic skills, which would result in a subjectively perceived complexity (Campbell, 1988). In the context of this research, we define decision maker's information processing capacity as the extent to which the decision maker is able to understand and use the analytic results for decision making (Kahlor et al., 2003; Trumbo, 2002).

Information quality has been investigated extensively in prior research and has been viewed as a desirable characteristic (Nelson and Todd, 2005), beneficial for the use of information (Popovič et al., 2012; Wixom and Todd, 2005) and decision making (Citroen, 2011; Raghunathan, 1999; Watson et al., 2002). Considering the dimensions of information quality, high quality information should decrease the cognitive effort required for understanding and processing of information. For instance, unambiguous and consistent information in high quality format should be more easily understandable than poor information items, which lack support of effective formatting (Chaiken and Maheswaran, 1994). In this regard, findings from research on information overload suggest that improving the quality of information positively affects the capacity for information processing of individuals (Jackson and Farzaneh, 2012; Schneider, 1987; Simpson and Prusak, 1995). Thus, we expect higher levels of information quality to have a positive effect on decision makers' processing capacity.

> *Hypothesis 1 (H1): Higher levels of information quality will have a positive effect on decision maker's information processing capacity.*

The effects of the use of advanced analytics haven't been investigated systematically so far. Although the use of advanced analytics has been associated with the generation of potentially valuable business insights (Davenport, 2010; Sharma et al., 2014), its specific effects on individuals' decision making capacities have remained unexplored so far. In contrast to the previous emphasis on benefits of advanced analytics, the next hypothesis relates to the idea that, besides their value potential, advanced analytics might also lead to negative consequences. In order to be able to effectively utilize advanced analytics, specialized skills are needed which are considered to go beyond common data analysis skills of decision makers from the business domain (Davenport et al., 2010; Harris et al., 2010; Viaene, 2013). In this context, high levels of analytics elaboration have been reported to possibly restrain decision makers' understanding of analytic results (LaValle et al., 2011; Viaene and Van den Bunder, 2011). In consequence, we expect that higher levels of analytics elaboration will have a constraining effect on decision maker's processing capacity.

> *Hypothesis 2 (H2): Higher levels of analytics elaboration will have a negative effect on decision maker's information processing capacity.*

6.3.2 Determinants of Information Processing

The HSM distinguishes between cognitive (i.e., information processing capacity) and motivational (i.e. personal importance or involvement) determinants of information processing behaviors in decision making (Chaiken et al., 1989). For the context of BI&A-supported decision processes, we investigate the influence of decision makers' information processing capacity and motivation on their mode of information processing behavior, which can be systematic or heuristic in nature, as outlined above.

We define a decision maker's motivation for information processing according to the importance and personal relevance of the decision (Barki and Hartwick, 1994). Following the definitions of information processing modes used in the HSM (Chaiken et al., 1989), we define systematic processing behavior as a comprehensive effort to analyze and understand information. Moreover, we define heuristic processing behavior as a limited effort to analyze and understand information.

The HSM considers systematic processing to be much more demanding, with respect to the required effort and cognitive capacity, than heuristic processing (Chaiken, 1980; Chaiken et al., 1989). Consistent with these assumptions experimental findings suggest that low capacity leads to heuristic processing, whereas high capacity is conducive to systematic processing (Chaiken and Maheswaran, 1994). Accordingly, we expect that higher levels of decision makers' information processing capacity should have a positive influence on the extent of systematic processing behavior and reduce the extent of heuristic processing behavior.

> *Hypothesis 3a (H3a): Higher levels of decision maker's information processing capacity will increase the extent of systematic processing behavior.*
>
> *Hypothesis 3b (H3b): Higher levels of decision maker's information processing capacity will decrease the extent of heuristic processing behavior.*

A decision maker's motivation is regarded as a relevant determinant, because the personal importance of a decision situation raises the need for confidence and thus reliability and accuracy of decision making (Chen and Chaiken, 1999). In this regard, experimental findings suggest that low motivation should result in heuristic processing, and high motivation induces systematic processing (Chaiken and Maheswaran, 1994). Therefore, in decision processes of high importance, it should be more likely that decision makers will undertake systematic processing behavior as opposed to relying on heuristic processing behavior.

> *Hypothesis 4a (H4a): Higher levels of decision maker's motivation will increase the extent of systematic processing behavior.*
>
> *Hypothesis 4b (H4b): Higher levels of decision maker's motivation will decrease the extent of heuristic processing behavior.*

6.3.3 Advice Utilization and Determinants of Decision Quality

The effective use of information or analytic results has been considered to be crucial for the success of BI&A support (Popovič et al., 2012, 2014) and also for the improvement of decision quality (Citroen, 2011; Davenport, 2010; Davenport et al., 2010; Sharma et al., 2014; Shollo and Kautz, 2010). In this research we explicitly establish and investigate the new perspective of decision makers' information processing behavior and the utilization of analytics results as determinants of decision quality.

Following conceptions from psychology, the utilization of analytic advice is defined as the extent to which decision makers follow the analytic advice that they receive from analysts (Bonaccio and Dalal, 2006). Advice utilization in decision making scenarios, which are comparable to BI&A-supported decision processes, has been previously investigated in psychology literature (Bonaccio and Dalal, 2006; Schrah et al., 2006; Sniezek and van Swol, 2001). For the context of BI&A support this means that it is not sufficient for analysts to just develop and deliver analytic advice; if decision makers do not have sufficient specialized analytics knowledge, then they can be expected having difficulties to adequately asses the quality of the analytic advice they receive. Such gaps in understanding can severely impede advice utilization as they introduce information asymmetry and perceived uncertainty for decision makers. This perceived uncertainty was found to influence decision makers to systematically discount advice that they receive and instead to overly rely on their own knowledge or experience (Sniezek and van Swol, 2001; Yaniv and Kleinberger, 2000). In this regard, systematic processing behavior assumes that information is processed carefully and comprehensively by decision makers, whereas heuristic processing behavior presumes limited information processing in which not all relevant information is considered (Chaiken et al., 1989). Systematic processing behavior was found to exhibit more capacity than heuristic processing behavior to change beliefs or attitudes concerning information that is received. Furthermore, attitudes developed from systematic processing behavior tend to be more persistent than those based on heuristic processing behavior (Eagly and Kulesa, 1997). Consequently, we expect systematic processing behavior to have a positive effect and heuristic processing behavior to have a negative effect on the decision maker's utilization of analytic advice.

> *Hypothesis 5a (H5a): Higher levels of systematic processing behavior will have a positive effect on the utilization of analytic advice.*
>
> *Hypothesis 5b (H5b): Higher levels of heuristic processing behavior will have a negative effect on the utilization of analytic advice.*

In decision processes, where decision makers receive analytic advice from analysts, their perception of the analyst, as source of the advice, should have an influence on the utilization of the advice. Therefore, we also include qualities of analysts' personal interaction with decision makers. In this regard, the HSM considers, in very general terms, the credibility of a source to be a message recipient's perception of a message source, without considering the content of the message as such (Chaiken, 1980). Source credibility has been mostly defined to consist of the two dimensions: expertise and trustworthiness. We therefore investigate the influence of analyst's expertise and trustworthiness on the utilization of analytic advice. Consistent with prior research, expertise refers to the perception of an analyst's capability of making correct assertions, and trustworthiness refers to the degree to which these assertions are perceived to be considered valid by the recipient of the information (Pornpitakpan, 2004; Watts Sussman and Siegal, 2003).

The importance of source credibility and its influence on advice or information adoption has been highlighted in IS research (Watts Sussman and Siegal, 2003). Previous research on the effects of credibility has mostly found that sources with high expertise and trustworthiness induce significant extents of persuasion on a recipient in direction of the presented advice or information (Pornpitakpan, 2004) and should consequently exhibit a positive influence on the utilization of analytic advice. In this study we consider trustworthiness and expertise as key dimensions of the qualities of analysts' personal interaction with decision makers. Additionally, due to the importance of specialization in BI&A-supported decision processes, we distinguish between domain and analytics expertise of analysts. For all three dimensions we expect a positive influence on the decision maker's utilization of analytic advice.

> *Hypothesis 6a (H6a): Higher levels of an analyst's analytics expertise will have a positive effect on the utilization of analytic advice.*
>
> *Hypothesis 6b (H6b): Higher levels of an analyst's domain expertise will have a positive effect on the utilization of analytic advice.*
>
> *Hypothesis 6c (H6c): Higher levels of an analyst's trustworthiness will have a positive effect on the utilization of analytic advice.*

The benefits of BI&A support are only realized, when the quality of decision process outcomes improves (Shollo and Kautz, 2010; Watson et al., 2002) In this regard, we investigate the effects of decision makers' processing behavior, as well as advice utilization on decision quality. The HSM suggests that systematic processing behavior, which is characterized by extensive analysis and scrutinizing of information with the purpose of achieving decision confidence (Chaiken, 1980; Chaiken et al., 1989), should lead to higher quality decision outcomes. Heuristic processing behavior as a limited processing mode, which relies on incomplete information (Chaiken, 1980; Chaiken et al., 1989), should lead to lower quality decision outcomes.

We further expect the utilization of analytic advice to have a positive influence on the quality of decision outcomes regardless of the mode of information processing. The reasoning for this is based on findings that the interaction with analysts and their analytic advice can bring decision makers to think of the decision problem in new ways (Schotter, 2003). Thus, such interactions can deliver additional information or decision alternatives that haven't been considered (Yaniv, 2004) or ameliorate framing effects (Druckman, 2001). Therefore we expect the following effects of processing modes and advice utilization on decision quality.

Hypothesis 7a (H7a): Higher levels of systematic processing behavior will have a positive effect on decision quality.

Hypothesis 7b (H7b): Higher levels of heuristic processing behavior will have a negative effect on decision quality.

Hypothesis 7c (H7c): Higher levels of utilization of analytic advice will have a positive effect on decision quality.

6.4 Methodology

6.4.1 Data Collection and Sample

To test our hypotheses, we conducted a survey in the BI&A context in 2014. As BI&A-supported decision processes depend on the collaboration between analysts and decision makers, investigating these decision processes could be approached from both perspectives. While we believe that both perspectives have their merits (and potential drawbacks), we considered several advantages of choosing the analyst perspective for this research. First, decision makers' assessments of their own dealings with analytic advice and resulting decision quality should be subject to considerable consistency and desirability bias. Further, analysts possess deep insights into the analytics that are used for supporting decision processes, as well as substantial understanding of the decision problem through analysis of decision makers' information requirements. Moreover, by presenting analytic advice to decision makers, they gain immediate feedback on how their analytic results are utilized by the decision maker and they witness how these contribute to the final decision outcome. This means that the analyst perspective is valuable for obtaining an external assessment of decision makers' information processing behavior, as well as of the decision outcome and its quality (Yammarino and Atwater, 1997).

In order to derive insights based on data from distinct BI&A-supported decisions, participants were asked to answer all questions with regard to one specific decision process from their professional career. The requirement for decisions to be eligible for the study was that the responding analyst had to choose a decision in which he provided BI&A support to a decision maker and we additionally asked for a short description of the supported decision. Thus all decisions in this sample involve task specialization and collaboration between analysts and decision makers. We did not place any further constraints on the types of decisions in order to obtain heterogeneous data and to enhance generalizability of our results. To be able to characterize and compare different types of decisions, we additionally collected ratings of organizational importance, uncertainty, nonroutineness, and time pressure.

To collect data on real decisions, recruitment took place via direct requests over professional networks such as LinkedIn. Among the participants of the survey, an iPad was raffled as an incentive to participate. Furthermore, a study report was offered to the individuals. Overall, we contacted 1197 professionals of which 408 agreed to participate in our study. 245 individuals started the survey, which eventually resulted in a final response of 136 completed questionnaires. The final response rate was 11%.

Data was well distributed with regard to industries, organizations, and decisions. As shown in Table 6.1, a broad range of different industries is included in our sample. Organizational size is rather large, which is not surprising for the BI&A context. The average BI&A-related professional experience was 7.2 years (SD = 4.7). 124 participants were male and 12 were female. Regarding the characteristics of the specific decision scenarios selected by the study participants, decisions were on average rated 5.1 on a 7-point scale of organizational importance (SD = 1.05). Furthermore, decisions were equally distributed regarding their uncertainty (mean = 4.39; SD = 1.24; 7-point scale), nonroutineness (mean = 4.07; SD = 1.52; 7-point scale), and time pressure (mean = 4.46; SD = 1.63; 7-point scale).

Table 6.1: Sample Structure by Industry, Number of Employees, and Annual Revenue

Industry (1/2)	(%)	Industry (2/2)	(%)	# Employees	(%)	Revenue (m €)	(%)
Basic resources	1.5	Media	8.1	Less than 50	2.2	Less than 10	3.0
Consumer goods	5.9	Chemicals	2.9	50–250	9.0	10-50	12.8
Health care	2.9	IT	7.4	251–500	10.4	51-100	7.5
Retail	7.4	Telco.	8.8	501–1000	11.2	101-500	17.3
Financials	16.9	Utilities	4.4	1001–5000	26.9	501-1000	16.5
Automobile	7.4	Electronics	3.7	More than 5000	40.3	More than 1000	42.9
Industrial eng.	5.1	Construction	0.7				
Travel	4.4	Other	12.5				

6.4.2 Operationalization and Measurement Properties

Where possible, we used established scales from information systems, management, and psychology research for measuring the constructs in this study. In some cases we had to adapt the scales to our research context. We did this by modifying the formulation of the item towards being applicable for BI&A-supported decision processes, but being cautious not to change the core of the respective concept. For our main measures we used seven-point Likert scales. Information quality was measured by using a reflective three-item scale in addition to the dimensions of information accuracy, completeness, currency, and format that were measured using three items each (Nelson and Todd, 2005; Wixom and Todd, 2005). For assessing analytics elaboration, a new scale had to be developed by synthesizing key concepts of advanced business analytics from a review of literature (Bose, 2009; Chaudhuri et al., 2011; Chen et al., 2012; Davenport et al., 2010; Davenport and Harris, 2007; Watson, 2010) and integrating them into a reflective five-item scale. Decision makers' information processing capacity was measured using a four-item reflective scale which was adopted from Kahlor et al. (2003) and Trumbo (2002) and adapted to the context under study. Decision maker involvement was assessed using a reflective nine-item scale for involvement (Barki and Hartwick, 1994). Systematic processing was assessed by a five-item reflective scale based on existing studies (Griffin et al., 2002; Trumbo and McComas, 2003) and adapted to our research context. Heuristic processing was measured using an existing three-item reflective scale (Elbanna and Younies, 2008; Khatri and Ng, 2000). Utilization of analytic advice was measured using a three-item scale, based on established scales of information adoption (Cheung et al., 2008; Filieri and McLeay, 2014; Watts Sussman and Siegal, 2003) and adapted to the context under study. Analyst's domain expertise, analytics expertise, and trustworthiness were measured with reflective five-item (five-point) scales (Ohanian, 1990). Decision quality was measured using a reflective four-item scale based on previous studies from management research on decision making processes (Amason, 1996; Nutt, 2008).

We included control variables for decision characteristics (organizational importance, uncertainty, nonroutineness, and time pressure) and decision maker expertise (domain and analytics competence) as these were found to influence cognitive information processing and decision outcomes (Chaiken et al., 1989; Watts et al., 2009). Competence was assessed with reflective two-item scales (Watts Sussman and Siegal, 2003). Measurements of organizational importance used a reflective three-item scale (Dean and Sharfman, 1993b), uncertainty and nonroutineness were based on reflective three-item scales (Dean and Sharfman, 1993b; Goodhue, 1995; Karimi et al., 2004), and time pressured was assessed with a reflective two-item scale (Fisher et al., 2003). Furthermore we controlled for effects of analytical decision making culture in the organization as this was found to influence the extent of information processing and use (Popovič et al., 2012, 2014). Therefore, a reflective four-item scale based on measurements from existing studies was used (Popovič et al., 2012; Sen et al., 2006).

For all reflective measures, standard quality criteria were computed in order to assess scale validity. In terms of reliability, all Cronbach's alpha values surpassed the recommended cutoff of .70 (MacKenzie et al., 2011). Composite reliabilities and average variances extracted (AVEs) were greater than .70 and .50 respectively as suggested (e.g., MacKenzie et al. 2011). We further assessed discriminant validity by following the recommendation by Fornell and Larcker, which states that the square root of AVEs must surpass all bivariate correlations between the construct and another variable (Fornell and Larcker, 1981). All variable pairs fulfilled this condition. These quality statistics as well as latent variable correlations are shown in Table 6.2. Further details on new or modified constructs and items can be found in the appendix.

Table 6.2: Latent Variable Statistics and Correlations

						Constructs														
		M	**SD**	**α**	**CR**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	**IQ_ac**	**5.61**	**1.11**	**.86**	**.94**	**.94**														
2	**IQ_co**	**5.10**	**1.28**	**.80**	**.89**	.58**	**.85**													
3	**IQ_cu**	**5.31**	**1.28**	**.86**	**.92**	.45**	.50**	**.89**												
4	**IQ_fo**	**5.13**	**1.28**	**.86**	**.92**	.44**	.47**	.41**	**.88**											
5	**IQ**	**5.49**	**1.06**	**.90**	**.94**	.62**	.61**	.64**	.65**	**.91**										
6	**AE**	**3.35**	**1.74**	**.86**	**.90**	-.03	.12	.07	.02	.080	**.80**									
7	**DM_mot**	**5.65**	**.89**	**.92**	**.94**	.15	.23**	.27**	.27**	.22**	.19*	**.79**								
8	**DM_pc**	**5.01**	**1.41**	**.91**	**.94**	.31**	.15	.24**	.17	.19*	-.27**	.27**	**.89**							
9	**SysProc**	**4.71**	**1.2**	**.87**	**.91**	.15	.19*	.23**	.19*	.29**	.07	.40**	.08	**.82**						
10	**HeuProc**	**4.42**	**1.25**	**.75**	**.85**	-.10	-.00	-.14	.14	-.09	.04	-.19*	-33**	-.04	**.81**					
11	**UAA**	**5.01**	**1.16**	**.92**	**.95**	.20*	.16	.26**	.07	.28**	.05	.29**	.20*	.44**	-.27**	**.93**				
12	**AN_DEx**	**3.61**	**.78**	**.92**	**.94**	.04	.27**	.20*	.01	.05	.21*	.31**	-.01	.25**	.01	.06	**.88**			
13	**AN_AEx**	**4.06**	**.62**	**.89**	**.90**	.21*	.27**	.10	.16	.21*	.11	.36**	.12	.20*	-.02	.10	.44**	**.81**		
14	**AN_T**	**4.30**	**.59**	**.87**	**.91**	.19*	.25**	.25**	.11	.17*	.07	.44**	.35**	.27**	-.16	.35**	.05	.30**	**.81**	
15	**DQ**	**5.28**	**1.03**	**.90**	**.93**	.20*	.29**	.36**	.25**	.30**	.19*	.47**	.29**	.52**	-.21*	.60**	.14	.31**	.46**	**.88**

Notes: The bold diagonal elements depict the square root of AVE for each latent variable, *p < 0.05, **p < 0.01, N = 136.

M = mean; SD = standard deviation; α = Cronbach's alpha; CR = composite reliability; IQ_ac = information accuracy; IQ_co = information completeness; IQ_cu = information currency; IQ_fo = information format; IQ = information quality; AE = analytics elaboration; DM_mot = decision maker motivation; DM_pc = decision maker processing capacity; SysProc = systematic processing behavior; HeuProc = heuristic processing behavior; UAA = utilization of analytic advice; AN_DEx = analyst domain expertise; AN_AEx = analyst analytics expertise; AN_T = analyst trustworthiness; DQ = decision quality.

We checked and controlled for common method bias by using the following standard procedures provided by Podsakoff et al. (2003). During data collection, we assured to all participants that their answers would be handled confidentially and anonymously and that no right or wrong answers existed. We further asked individuals to provide their answers as spontaneous as possible. Using established and validated scales (cf. analytics elaboration), we avoided bias stemming from ambiguous item wordings. As for statistical procedures, we used EFA in order to check whether a single factor would account for the majority of variance of all variables. This procedure extracted 18 factors with the first factor accounting for only 19.7% of the overall variance. We furthermore checked for common method bias by adding an unmeasured common method variable to the structural model following the procedures suggested by Liang et al. (2007). Results from these tests suggest that overall, common method bias should not have distorted our results significantly.

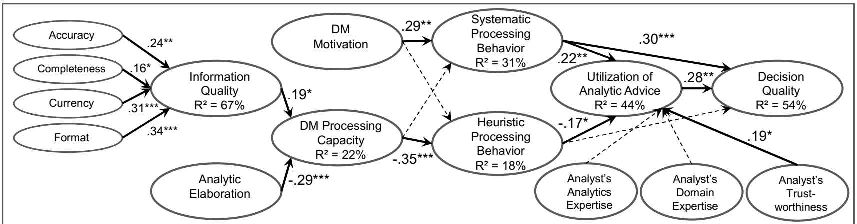
6.5 Results

We tested our model using partial least squares analysis (PLS) which suited our sample size as we were able to obtain data from 136 BI&A professionals (Cohen, 1992). Compared to covariance based SEM, PLS is less dependent on larger samples (e.g., Gefen et al., 2000). The model was calculated using the software package SmartPLS 3.0 (Ringle et al., 2014). Table 6.3 provides an overview of all study hypotheses and their levels of significance.

Table 6.3: Summary of Tested Hypotheses and Results

Hypothesis #	Variable Effects and Directions	Coefficient	Significance	Result
H1	Information Quality (+) → Processing Capacity	0.19*	0.024	Supported
H2	Analytics Elaboration (-) → Processing Capacity	-0.29***	0.000	Supported
H3a	Processing Capacity (+) → Systematic Processing	0.01	0.954	-
H3b	Processing Capacity (-) → Heuristic Processing	-0.35***	0.000	Supported
H4a	DM Motivation (+) → Systematic Processing	0.29**	0.002	Supported
H4b	DM Motivation (-) → Heuristic Processing	-0.10	0.274	-
H5a	Systematic Processing (+) → Advice Utilization	0.22**	0.004	Supported
H5b	Heuristic Processing (-) → Advice Utilization	-0.17*	0.021	Supported
H6a	Analytics Expertise (+) → Advice Utilization	0.06	0.597	-
H6b	Domain Expertise (+) → Advice Utilization	-0.05	0.609	-
H6c	Trustworthiness (+) → Advice Utilization	0.19*	0.020	Supported
H7a	Systematic Processing (+) → Decision Quality	0.30***	0.000	Supported
H7b	Heuristic Processing (-) → Decision Quality	-0.10	0.093	-
H7c	Advice Utilization (+) → Decision Quality	0.28**	0.003	Supported
Notes: * p <0.05; ** p <0.01; *** p <0.001				

Figure 6.2 displays the model results, path coefficients as well as R^2 of our dependent variables.



Notes: * p <0.05; ** p <0.01; *** p <0.001; bold lines - significant paths; dotted lines - non-significant paths

Figure 6.2: Model Results

Overall, our data confirmed the majority of our theoretical considerations. This shows that characteristics of the BI&A support significantly influence decision makers' modes of information processing which in turn affect the resulting decision quality. Furthermore, we found that the different characteristics of analysts' credibility vary in their influence.

6.6 Discussion

6.6.1 Implications for Research

The goal of this research was to examine the role of specialized analytics support and information processing in decision processes. In particular, we investigated the relations between the supply of information, decision makers' information processing behavior and the resulting quality of decision outcomes. We built on the heuristic–systematic model (HSM) of information processing (Chaiken, 1980; Chaiken et al., 1989) as a central explanatory mechanism for linking BI&A support and the quality of decision outcomes. Data from 136 BI&A-supported decisions was used to conduct partial least squares analysis regarding the proposed effects.

This research provides three major contributions, with considerable theoretical implications for BI&A research and the DSS field in general. First, we elucidate how raising the level of analytics elaboration in BI&A support of decisions can have negative effects on decision makers' information processing capacity. This new perspective should raise awareness of potentially negative influence of BI&A support in certain decision contexts. For information quality we found a positive influence on decision makers' information processing capacity. This provides a complementary perspective on the benefits and positive effects of information quality and confirms prior findings (Popovič et al., 2012, 2014; Raghunathan, 1999; Watson et al., 2002; Watts Sussman and Siegal, 2003; Wixom and Todd, 2005).

Second, based on the HSM we theorized how decision makers' systematic and heuristic information processing behaviors influence the utilization of analytic advice and we highlighted the role that analysts play in this context. Consistent with HSM theory, we find that systematic processing behavior contributes to advice utilization and heuristic processing behavior has a negative influence in this regard. Interestingly, we find that systematic processing behavior is determined by decision maker motivation, while the extent of heuristic processing behavior can be only reduced by a decision maker's information processing capacity. This emphasizes that analytic elaboration also induces a tension with regard to the utilization of analytic advice. The paths from decision maker's motivation, respectively capacity to heuristic, respectively systematic processing behavior turned out to be non-significant. This suggests that having processing capacity does not necessarily lead to more systematic processing and similarly, motivation alone does not seem be enough to reduce heuristic processing.

The findings of our study are particularly relevant with respect to the role of analytics experts and suggest that trustworthiness is a major significant factor for influencing the utilization of analytics, particularly when highly elaborated analytics approaches are used. The influences of domain and analytics expertise turned out to be non-significant. We suppose that the reason for this may be rooted in the measurement approach that requested a self-assessment of expertise from the participants, which resulted in little variance in the obtained ratings. By explicitly distinguishing these three dimensions we can partially confirm prior findings regarding source credibility (Watts Sussman and Siegal, 2003).

We consider our third contribution to be the most significant one. To the best of our knowledge, this study is the first to explicitly establish a link between characteristics of BI&A support (i.e., information quality and analytic elaboration), decision makers' information processing and utilization of analytic advice, and how these ultimately shape the quality of decision outcomes. We find that systematic processing behavior and the utilization of analytic advice both contribute significantly to decision quality. Hence, in the context of BI&A-supported decision processes, paths to successful decision making require systematic processing and the utilization of analytic advice by decision makers. Although the direct negative influence of heuristic processing behavior was only found to be significant at a 0.1 level, heuristic processing behavior nevertheless has an indirect negative consequence on decision quality. Its potential to weaken the utilization of analytic advice can translate to reduced decision quality.

6.6.2 Implications for Practice

Besides theoretical implications, our study is also of high practical relevance and contributes as follows. For analytics experts, our results suggest that, in order to be effective, they need to think about suitable levels of analytic elaboration for each decision context. They should try to mitigate the risk of using analytic approaches that totally overburden decision makers' capacity of understanding and using analytic results for decision making. Furthermore, in highly elaborated analytics contexts analysts should focus their attention not only on delivering excellent analytic advice, but also on their interaction with decision makers in order to build trustworthiness. This can be seen as a strategy for mitigating the risk that heuristic processing by decision makers induces for the utilization of analytic advice.

The implications for decision makers suggest that they have to be aware that, despite the challenges that come with analytic specialization, only systematic processing behavior leads to effective utilization of analytic advice and hence to significant improvements of decision quality. In contrast, strong reliance on heuristic processing behavior can endanger the effectiveness of BI&A initiatives and hence vaporize the potentials of analytic support for higher quality decision making.

Despite “data scientist being the sexiest job of the 21st century” and the current hype surrounding BI&A (Davenport and Patil, 2012), analytics experts and decision makers need to *jointly* convert the potentials of analytics into better decision making in order to harness the benefits of BI&A. If high quality information and analytic advice do not translate into better decision making, relying on analytics loses its value (Davenport, 2010; Sharma et al., 2014; Shollo and Kautz, 2010). The results from this research emphasize the quality of collaboration for augmenting the impact of BI&A.

6.6.3 Limitations and Future Research

Our study should be regarded in light of its limitations, which offer potential for future research. First, although formal requirements regarding sample size were met (Cohen, 1992), we admit that this research could profit from a larger sample. As the context of this study would not permit relying on a convenience sample, recruitment of professionals required one-by-one contacting. However, future studies should validate our results using increased sample sizes.

Investigating the consequences of the analytics elaboration presents a valuable step toward understanding possible challenges of BI&A usage. As could be shown in this study, highly elaborated procedures might eventually result in lower decision quality as they increase the chances of heuristic information processing on part of the decision maker. It would be worthwhile to investigate trade-offs regarding this characteristic as elaborate analytics should also lead to positive outcomes in some way.

The present research has argued that in decision processes characterized by task specialization, relationship characteristics should affect decision making. Testing for effects on decision makers’ utilization of analytical advice, only trustworthiness had a significant influence. We believe that further investigations of relationship characteristics in decision process contexts could be of high value.

7 Conclusion and Summary of Contributions

This thesis aimed to contribute to our comprehension of what constitutes successful BI&A-supported decision processes and how to establish effective BI&A support that involves collaboration between specialized roles (i.e., analytics experts and decision makers). Progress in understanding both of these aspects of BI&A support creates a foundation for designing and establishing BI&A-supported decision processes that result in improved decision making and higher quality decision outcomes.

The research presented in this thesis approached this aim by elucidating organizational and individual perspectives on BI&A-supported decision processes and by pursuing three research goals. The first research goal was to establish a foundation for investigating BI&A-supported decision processes from the organizational perspective and to validate the general research direction by providing an integrative perspective on the current state of the art regarding BI&A support of decision processes. Based on the insights gained from an analysis of the state of the art, this thesis then turned to its second and third research goals.

The second goal was to contribute to an understanding of what constitutes successful BI&A-supported decision processes that result in high-quality decision outcomes. Taking the organizational decision process perspective, the research related to this goal investigated how BI&A-supported decision processes and their procedural characteristics evolved throughout their various phases. The research also examined the use and composition of different kinds of information processing mechanisms in BI&A-supported decision processes.

The third goal was to achieve a better understanding of how to shape analytics experts' BI&A support for decision makers in order to be effective in improving the quality of decision making and decision outcomes. Focusing on the individual perspective, research related to this third goal examined factors that influence analytics experts' ability to provide effective BI&A support in the context of their collaboration with decision makers. The research also examined how analytics experts' BI&A support affects decision makers' information processing behaviors, as well as the quality of the decision making and the decision outcomes.

By addressing these three research goals and utilizing the two perspectives, this thesis contributes to recent calls for research concerning the use and effects of BI&A with regard to decision processes (Sharma et al., 2014) and decision making (Arnott and Pervan, 2014). The research goals were addressed by answering eight derived research questions and relying on a mix of qualitative and quantitative research approaches. In this regard, this thesis delivers several contributions that are of theoretical and managerial significance. The following sections summarize the most important theoretical and practical implications of the thesis. Detailed discussions of limitations and opportunities for future research can be found in the relevant main chapters of this thesis and will therefore not be repeated in this section.

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7.1 Theoretical Implications

Research on what constitutes successful BI&A-supported decision processes was presented in the third and fourth chapters of this thesis, with the following noteworthy theoretical contributions.

The third chapter focused on the composition of information processing mechanisms in BI&A-supported decision processes. Based on organizational information processing theory, this chapter developed a conceptual framework that takes into account data-centric and organizational information processing mechanisms. This framework is an adaptation and extension of organizational information processing theory for the context of BI&A-supported decision processes. The value of this framework for BI&A research is that it extends the prevailing data-centric conception of information processing (such as OLAP and ad-hoc queries) with a set of organizational mechanisms that rely on personal communication (such as direct contact and group meetings). Moreover, the conceptual framework proposes how these different mechanisms relate to one another.

This conceptual framework was used to investigate different types of BI&A-supported decision processes that varied with respect to nonroutineness and uncertainty. The analysis provided evidence for a complementary relationship of data-centric and organizational mechanisms due to the need for effective integration of analytics experts' analytic capabilities with decision makers' domain-specific knowledge in the context of BI&A-supported decision processes. Additionally, the results yielded detailed insights about variations in the composition of data-centric and organizational information processing mechanisms across decision processes that differed in their extents of nonroutineness and uncertainty. A major pattern that surfaced showed that with increasing levels of nonroutineness and uncertainty, there was a higher reliance on organizational mechanisms. The study also considered the characteristics of big data (i.e., volume, variety, and velocity) used by the data-centric mechanisms and found that the utilized data exhibited the highest ratings for volume, variety, and velocity in cases that had low levels of uncertainty and nonroutineness. These findings are consistent with prior research on information processing (Daft and Lengel, 1986; Zack, 2007) and confirm the importance of organizational information processing mechanisms for BI&A-supported decision processes. Furthermore, these findings contribute by elucidating patterns in the compositions of data-centric and organizational information processing mechanisms for the different types of BI&A-supported decision processes.

Beyond highlighting patterns in the composition of data-centric and organizational mechanisms in decision processes, this research also provided unique insights into the phase-specific dynamics of the mechanism composition throughout the phases of the investigated decision processes. The results suggest that inter-phase dynamics of the mechanism composition increase with the increasing nonroutineness and uncertainty of decision processes. Assessing such dynamics of the mechanism composition of decision processes contributes a new perspective for information processing theory that is of great value, as it goes beyond a static view of information processing mechanisms. The dynamic perspective shows that depending on the nonroutineness and uncertainty of a decision context, organizations may rely on a small and stable set of information processing mechanisms or may have to be proficient in combining a multitude of different information processing mechanisms.

Overall, the results presented in the third chapter address how data-centric and organizational information processing mechanisms are composed in decision processes and thus contribute to a better understanding of how these mechanisms should be incorporated in BI&A-supported decision processes.

The fourth chapter further contributes to our understanding of what constitutes successful decision processes by examining the influences of characteristics of collaboration procedures on the quality of the decision outcomes of BI&A-supported decision processes. Based on established characteristics used in management research on decision processes (i.e., political behavior and procedural rationality), the first finding from this study confirmed prior research results concerning information quality. The results show that supplying high quality information to decision processes is a necessary but not a sufficient condition for achieving high decision quality (Popovič et al., 2014; Shollo and Galliers, 2013). Explicit consideration of the effects of political behavior in the context of BI&A-supported decision processes represents a new perspective in information systems research related to decision support. The interesting implication of this analysis is that even when high quality information is supplied for decision processes, moderate levels of political behavior are already enough to have significant negative effects on the quality of the decision outcomes, particularly if politics prevail throughout the various decision process phases.

The more distinctive theoretical contribution of this research comes from an examination of the effects of decision process rigor and agility, two procedural characteristics that were derived from research on information systems development. Both characteristics were explored for their relevance in the context of BI&A-supported decision processes, and the analysis showed that achieving high levels of both rigor and agility (i.e., ambidextrous combinations of the two characteristics) was beneficial. More specifically, such ambidextrous combinations exhibited a complementary relationship to information quality, which turned out to have a positive influence on the ratio of procedural rationality to political behavior, as well as the quality of the resulting decision outcomes. Identification of this complementary relationship between procedural characteristics of BI&A-supported decision processes and information quality extends the theoretical basis of DSS research. Further, as this relationship affects the extent of decision makers' political behavior and procedural rationality, this also represents a new contribution to management research by combining the two streams of research. The value of this contribution lies in a better understanding of how the ratio of political behavior to procedural rationality can be controlled by establishing collaboration procedures that allow for simultaneously achieving rigor and agility in the context of BI&A-supported decision processes.

In sum, the findings presented in the fourth chapter provide insights about the circumstances under which the supply of high-quality information is effective in positively influencing decision outcomes. The findings indicate that simultaneously achieving decision process rigor and agility is essential in this regard. Hence, both characteristics can be considered as relevant for the design of BI&A-supported decision processes that will achieve high-quality decision outcomes.

The focus of this thesis then turned to an investigation of how analytics experts' BI&A support for decision makers should be shaped in order to be effective in improving the quality of decision making and decision outcomes. The fifth and sixth chapters, which address this, make the following research contributions.

The fifth chapter explored in detail analytics experts' collaborations with decision makers and identified a comprehensive set of conflicting requirements (e.g., a simultaneous need for flexibility and stability in the use of analytic methods and data sources) along with the resulting tensions that analytics experts must cope with as part of their BI&A support for decision makers. These tensions were found to threaten the success of BI&A support if left unresolved. Hence, this research contributes to the literature by identifying and characterizing this comprehensive set of tensions, which represent potential inhibitors of effective BI&A support. These tensions have been overlooked by prior research since it neglects the importance of the collaboration between specialized roles (i.e., analytics experts and decision makers) in the context of BI&A support.

In addition to identifying the conflicting task requirements and resulting tensions, this study also shed light on tactics that analytics experts use to successfully manage the conflicting task requirements. These tactics concern organizational, procedural, methodological, and communication aspects of analytics experts' decision support for decision makers. The capacity to successfully resolve conflicting task requirements has been conceptualized in prior research as ambidexterity (Gibson and Birkinshaw, 2004; Lee et al., 2010). The findings from this thesis's research contribute new in-depth insights into how to achieve ambidexterity in BI&A support. These new insights are valuable because they provide a better comprehension of how to achieve effective BI&A support through managing the tensions that arise as part of analytics experts' provision of BI&A support for decision makers.

This analysis of ambidexterity in BI&A support also examined the relationships between ambidexterity and decision makers' behavior in decision making (i.e., rational or intuitive), as well as the quality of the resulting decisions. Higher levels of ambidexterity were found to be conducive to improving decision making behavior and the quality of the decision outcomes. Finally, grounded in the study's empirical findings, this research contributes a theory of ambidexterity in decision support. The merits of this theory lie in explaining how ambidexterity can be facilitated and how it influences decision quality.

In sum, the research results presented in the fifth chapter address the challenges arising from the collaboration between specialized roles (i.e., analytics experts and decision makers) and provide a much needed complementary perspective on the organizational and social context of BI&A-supported decision making (Arnott and Pervan, 2014; Sharma et al., 2014; Viaene, 2013). This research highlights the conflicting task requirements that analytics experts need to address in order to enhance the effectiveness of their BI&A support and additionally the results provide guidance on tactics that can be applied towards this end.

The sixth chapter further considered analytics experts' collaboration with decision makers and explicitly focused on the advice giving that is part of analytics experts' BI&A support. Thus, in departure from prior research, this study explicitly investigated and quantified the effects caused by the specialization of analytics experts and decision makers in BI&A-supported decision processes. In particular, this research considered the effects of analytics experts' advice giving on the information processing behavior of decision makers and their utilization of analytic advice, as well as the resulting quality of the decision outcomes. The proposed effects and relations were tested with partial least squares analysis, and the results from this research yielded the following main insights and contributions.

This study provided evidence that increasing the quality of information in BI&A support for decision making enhances the availability of decision makers' information processing capacity, while increasing analytics elaboration reduces it. In general, the benefits and positive influences of high-quality information are well known from prior information systems research (Popovič et al., 2012, 2014; Watts Sussman and Siegal, 2003; Wixom and Todd, 2005). In contrast, the finding regarding the effect of analytics elaboration provides a new perspective. This is particularly relevant because increasing analytics elaboration was found to reduce the availability of information processing capacity, which in turn negatively affected decision makers' information processing behavior. Therefore, this finding contributes to existing research by raising awareness of the potentially negative effects of BI&A support on decision makers' information processing behavior in decision situations that involve advice giving as part of the analytics experts' BI&A support.

In addition, this study's findings show that decision makers' information processing behavior and their trust in analytics experts significantly influence their utilization of analytic advice. Systematic processing behavior and trust were found to promote the utilization of analytic advice, whereas heuristic behavior was found to impede advice utilization. Moreover, the empirical results show that systematic processing behavior and the utilization of analytic advice both significantly contribute to the quality of the decisions. These findings show that considering the social context and advice giving in BI&A support can deliver substantial new insights on how to improve the effectiveness of BI&A-supported decision making.

Further, this research establishes explicit relations between the characteristics of BI&A support (i.e., information quality and analytic elaboration), trust in the analytics expert, decision makers' information processing behavior, the utilization of analytic advice, and how these ultimately contribute to decision quality. This provides a much needed integrative perspective on the effects of BI&A support on decision making (Arnott and Pervan, 2014). This integrative perspective helps explaining how managerial decision making can be improved through BI&A support, and it elucidates relevant influencing factors that promote achievement of higher levels of advice utilization and higher quality decisions.

Overall, the findings presented in the sixth chapter provide insights about the factors that affect the effectiveness of analytics experts' BI&A support with regard to decision makers' utilization of advice and the resulting quality of the decisions. The findings show that in decision situations that involve analytics experts' advice giving as part of BI&A support, an adequate level of analytics elaboration, trust in the analytics expert, and systematic processing behavior, as well as decision makers' utilization of the analytic advice, are required for achieving high-quality decisions.

7.2 Practical Implications

In addition to the theoretical contributions, this thesis offers a number of relevant implications for practitioners. The structured literature review presented in the second chapter offers practitioners a summarizing overview of the state of the art in research on the effects of decision support technologies on the phases and characteristics of decision processes. Further, applying the evaluation framework that was used for the analysis of literature can provide a starting point for assessing and comparing decision processes in practice.

Regarding the questions of what constitutes successful BI&A-supported decision processes this thesis delivers a number of insights that can be used to guide the design of decision processes in practice. The findings on information processing mechanisms that were discussed in the third chapter provide guidance on distinguishing between different types of decisions and accordingly composing data-centric and organizational information processing mechanisms. The understanding of which mechanisms can be combined in different decision contexts is of high importance for the effective use of BI&A in decision processes. Further, the results suggest that reducing ambiguity and equivocality in the decision context should have priority for the purpose of utilizing data-centric decision support approaches. The findings on the dynamics in the composition of mechanisms suggest that, particularly in non-routine decision contexts, organizations should be proficient in a wide range of data-centric and organizational information processing mechanisms. Further, organizations have to be prepared for altering the composition of mechanisms throughout decision process phases.

The results presented in the fourth chapter of this thesis provided insights on decision process characteristics that are relevant for the design of effective BI&A-supported decision processes in organizations. The results indicate that the two procedural characteristics of rigor and agility have to be pursued simultaneously in the collaboration procedures between analytics experts and decision makers. The reason for this is that maintaining rigor and agility throughout the collaboration has been found to be conducive to achieving favorable ratios of procedural rationality and political behavior, which in turn positively affects the outcomes of decision processes. Thus, simultaneously pursuing rigor and agility in the design of decision processes can be seen as a major factor for assuring that information quality and associated analytic results generate the intended impact and benefits in BI&A-supported decision processes.

Concerning analytics experts' BI&A support for decision makers, this thesis sheds light on how to establish an effective collaboration that helps enhancing decision makers' utilization of analytic advice and improving the quality of decision outcomes. The fifth chapter of this thesis highlighted a series of tensions that analytics experts need to cope with in order to deliver effective BI&A support. Additionally, this research also identified different types of tactics (i.e., organizational, procedural, methodological, and communicative) that analytics experts can use for successfully coping with the tensions present during analytics experts' BI&A support for decision makers. The organizational tactics require an institutionalization of the presented practices on the organizational level. In contrast, the communication, methodological, and procedural tactics can be readily applied by analytics experts in their daily work.

Further, the results presented in the sixth chapter suggest that analytics experts should carefully match the level of analytics elaboration of their analytic approaches to each decision situation they support. In this regard, analytics experts should think about appropriate levels of analytic elaboration that help mitigating the risk of overburdening decision makers' capacity of understanding and using analytic results for decision making. Managing information quality can be conducive in this connection and should be particularly addressed in the context of using externally available large and heterogeneous (big) data sets. Often, these do not fulfill the same quality standards as data that is stored and quality assured in an organization's internal data bases. For the purpose of successfully collaborating with decision makers, analytics experts should also focus their attention on their joint interaction and personal relationship with decision makers in order to build trust. This can be seen as a viable strategy for mitigating the risk of excessive heuristic processing and its negative consequences for decision makers' utilization of analytic advice.

Finally, the presented findings recommend for decision makers that systematic processing behavior is a main prerequisite for effective advice utilization and improvement of decision quality, despite the challenges associated with analytics elaboration. In contrast, strong reliance on heuristic processing behavior reduces advice utilization and in consequence endangers the success of BI&A initiatives. Therefore decision makers should be interested in establishing collaboration environments that allow for their joint contribution with analytics experts towards transforming the potentials of BI&A into better decision making.

7.3 Conclusion

The research presented in this thesis investigated previously unexplored and complementary perspectives on the BI&A support of decision processes. This research has thereby contributed to a better comprehension of what constitutes successful BI&A-supported decision processes and how to establish effective BI&A support that involves collaboration between specialized roles (i.e., analytics experts and decision makers) for the purpose of improving the quality of decisions. From the organizational decision process perspective, the research considered how BI&A-supported decision processes evolve throughout their phases and focused in particular on the composition of different organizational and data-centric information processing mechanisms in decision processes. A promising direction for future research on the organizational perspective would be further validation of the proposed framework of organizational and data-centric information processing mechanisms, as well as quantification of the effects of the individual mechanisms. In this regard, an examination of how different compositions of information processing mechanisms in decision processes affect the political behavior of decision stakeholders would be of great value.

From the individual decision making perspective, the research addressed analytics experts' ability to provide effective BI&A support to decision makers. It investigated how analytics experts' BI&A support affects decision makers' information processing behaviors and the quality of the decisions they make. In this context, this thesis developed a theory of ambidexterity in decision support, which provides a multitude of opportunities for future research. It would be of great interest to test the proposed theoretical relations and quantify the contributions of tactics dedicated to facilitating ambidexterity and achieving improved decision quality. This thesis contributed another previously unexplored perspective on BI&A support by explicitly considering advice giving as part of analytics experts' BI&A support for decision makers and examining its effects on decision makers' information processing behaviors and the quality of the decision outcomes. The research results highlighted the importance of the social context of BI&A-supported decision making and thus open further research opportunities in this direction. In particular, characteristics of the relationships between analytics experts and decision makers can be expected to have multifaceted effects, and therefore further research on relationship characteristics in the context of decision processes should be of interest.

In sum, the insights and contributions provided in this thesis extend the theoretical basis of the decision support specialty in information systems research and offer various starting points for future empirical studies to further enrich our understanding of the role of BI&A support in decision processes. I hope that the theoretical extensions that were developed as part of this thesis's research agenda, along with the results achieved in the thesis, will actuate further decision-support-related research that can benefit from these new perspectives.

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Appendix

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A.2 Scales and Items (Study E)

Information Quality (IQ) (1 = strongly disagree; 7 = strongly agree)

[Nelson and Todd 2005; Wixom and Todd 2005]

Please rate the following characteristics of the information that was provided by the BI&A system as a basis for decision making in the considered decision process.

IQ_ac1 - The BI&A system produced correct information.

IQ_ac2* - There were few errors in the information obtained from the BI&A system.

IQ_ac3 - The information provided by the BI&A system was accurate.

IQ_co1 - The BI&A system provided a complete set of information.

IQ_co2 - The BI&A system produced comprehensive information.

IQ_co3 - The BI&A system provided all the information that was needed.

IQ_cu1 - The BI&A system provided the most recent information.

IQ_cu2 - The BI&A system produced the most current information.

IQ_cu3 - The information from the BI&A system was always up to date.

IQ_fo1 - The information provided by the BI&A system was well formatted.

IQ_fo2 - The information provided by the BI&A system was well laid out.

IQ_fo3 - The information provided by the BI&A system was clearly presented on the screen.

IQ_1** - Overall, I would give the information from the BI&A system high marks.

IQ_2** - Overall, I would give the information provided by the BI&A system a high rating in terms of quality.

IQ_3** - In general, the BI&A system provided high-quality information.

* Item was dropped from the analysis due to negative item loading

** Reflective indicators for information quality

Analytics Elaboration (AE) (1 = not at all; 7 = extensively)

[Self-developed, items based on extensive literature review]

Please indicate to which extent the following BI&A functionalities were used for supporting the decision.

AE1 - Data mining (e.g. neural nets, classification and regression trees, support vector machines)

AE2 - Advanced statistical analysis (e.g. regression modeling, time-series analysis, factor analysis, discriminant analysis, forecasting, sensitivity analysis)

AE3 - Simulation and optimization (e.g. solver approaches, heuristic approaches, Monte Carlo simulation, agent-based modeling)

Generally speaking, for supporting the decision we utilized the following analytic approaches:

AE4 - Predictive statistical modeling, optimization and simulation techniques

AE5 - Very advanced analytic approaches

Decision Maker Motivation (DM_mot)

[Barki and Hartwick 1994]

Please indicate your perception of the importance of the decision to the decision maker(s). The decision maker(s) considered the decision (to be) ….

DM_mot1 - (1) unimportant – (7) important

DM_ mot2 - (1) not needed – (7) needed

DM_ mot3 - (1) nonessential – (7) essential

DM_ mot4 - (1) trivial – (7) fundamental

DM_ mot5 - (1) insignificant – (7) significant

DM_ mot6 - (1) to mean nothing to them – (7) to mean a lot to them

DM_ mot7 - (1) of no concern to them – (7) of concern to them

DM_ mot8 - (1) irrelevant to them – (7) relevant to them

DM_ mot9 - (1) not to matter to them – (7) to matter to them

Decision Maker Processing Capacity* (DM_pc) (1 = strongly disagree; 7 = strongly agree)

[Kahlor et al. 2003; Trumbo 2002]

Please indicate the extent to which you agree or disagree with the following statements on your perception regarding the decision makers' ease of understanding and using of analytic results.

DM_pc1 - The delivered analytic result/information was difficult to understand for the decision maker(s).

DM_pc2 - The decision maker(s) had difficulties seeing how the analytic results/information fit together into an overall picture that made sense.

DM_pc3 - It took a lot of mental effort on part of the decision maker(s) to understand how the analytic results/information fit together.

DM_pc4 - The decision maker(s) didn't feel capable of understanding and using the analytic results/information that were needed in order to decide.

*Reverse coded according to Kahlor et al. (2003)

Systematic Processing Behavior (SysProc) (1 = strongly disagree; 7 = strongly agree)

[Griffin et al. 2002; Trumbo and McComas 2003]

Please indicate the extent to which you agree or disagree with the following statements concerning the decision process:

SysProc1 - The decision maker(s) made a strong effort to carefully examine the information presented on the question of the decision.

SysProc2 - In order to be completely informed about the decision topic, the decision maker(s) asked for multiple viewpoints on the issue.

SysProc3 - After thinking about the information on the decision topic, the decision maker(s) gained a broader understanding.

SysProc4 - The decision maker(s) read or listened to most of the provided information, even though they may not have agreed with its perspective.

SysProc5 - Receiving more viewpoints on this matter was perceived as better by the decision maker(s).

Heuristic Processing Behavior (HeuProc) (1 = not at all; 7 = extensively)

[Elbanna and Younies 2008; Khatri and Ng 2000]

Please rate the following aspects regarding the decision process:

HeuProc1 - To what extent did decision maker(s) rely basically on personal judgment?

HeuProc2 - To what extent did past experience play the main role in making this decision?

HeuProc3 - To what extent did decision maker(s) depend on a "gut feeling" to make the decision?

Utilization of Analytic Advice (UAA) (1 = strongly disagree; 7 = strongly agree)

[Cheung et al. 2008; Filieri and McLeay 2014; Watts Sussman and Siegal 2003]

Please indicate your agreement to the following statements regarding the decision maker(s) that were involved in the decision process:

UAA1 - The decision maker(s) closely followed the suggestions and decided in line with the recommendation.

UAA2 - The decision maker(s) agreed with the opinion suggested in the recommendation.

UAA3 - The decision maker(s) agreed with the action suggested in the recommendation.

Analyst Trustworthiness (AN_T)

[Ohanian 1990]

Please rate the following aspects from your perspective. Please rest assured that your answers will remain anonymous and will be only analyzed on an aggregated level, i.e. there won't be any analysis of individual ratings.

Which impression did you convey to the decision maker(s) during your collaboration on this decision? The decision maker(s) perceived me as …

AN_T1 - (1) Undependable – (7) Dependable

AN_T2 - (1) Dishonest – (7) Honest

AN_T3 - (1) Unreliable – (7) Reliable

AN_T4 - (1) Insincere – (7) Sincere

AN_T5 - (1) Untrustworthy – (7) Trustworthy

Analyst Analytics Expertise (AN_AEx)

[Ohanian 1990]

How would you characterize your expertise regarding the analytical procedures that were used to support the decision process?

AN_AEx1 - (1) Unknowledgeable – (7) Knowledgeable

AN_AEx2 - (1) Inexperienced – (7) Experienced

AN_AEx3 - (1) Not an expert – (7) Expert

AN_AEx4 - (1) Unqualified – (7) Qualified

AN_AEx5 - (1) Unskilled – (7) Skilled

Analyst Domain Expertise (AN_DEx)

[Ohanian 1990]

How would you characterize your knowledge concerning the domain / topic of the supported decision process?

AN_DEx1 - (1) Unknowledgeable – (7) Knowledgeable

AN_DEx2 - (1) Inexperienced – (7) Experienced

AN_DEx3 - (1) Not an expert – (7) Expert

AN_DEx4 - (1) Unqualified – (7) Qualified

AN_DEx5 - (1) Unskilled – (7) Skilled

Decision Quality (DQ) (1 = poor; 7 = excellent)

[Amason 1996; Nutt 2008]

Please characterize the decision that was made according to the following statements:

DQ1 - Overall, the decision value was …

DQ2 - The quality of the decision relative to its original intent was …

DQ3 - The quality of the decision given its effect on organizational performance was …

DQ4 - The overall quality of the decision was …

Organizational Decision Importance (dec_oi)

[Dean and Sharfman 1993]

Please indicate your perception of the importance of the decision to the organization.

dec_oi1 - How important was this decision to the company?
(1 = not at all important; 7 = very important)

dec_oi 2 - How serious would the consequences have been if something had gone wrong?
(1 = not at all serious; 7 = very serious)

dec_oi 3 - How serious would the consequences of delaying this decision have been?
(1 = not at all serious; 7 = very serious)

Decision Uncertainty (dec_un)

[Dean and Sharfman 1993; Goodhue 1995; Karimi et al. 2004]

Please indicate Please characterize the uncertainty of the decision task according to the following statements.

dec_un1 - During the decision process, how would you describe the need for additional information? (1 = had all relevant information; 7 = needed a great deal more information)

dec_un2 - How difficult was it to predict the outcomes of the various courses of action that were considered in making this decision? (1 = not at all; 7 = very difficult)

dec_un3 - Was there uncertainty regarding this decision, which created a need for information? (1 = not at all; 7 = very much)

Decision Nonroutineness (dec_nr) (1 = strongly disagree; 7 = strongly agree)

[Goodhue 1995; Karimi et al. 2004; Dean and Sharfman 1993]

Please indicate the extent to which you agree or disagree with the following statements about the decision task.

dec_nr1 - The decision task was a nonroutine business problem.

dec_nr2 - The decision task involved answering questions that have never been asked in quite that form before.

dec_nr3 - This decision task was not similar to others that we have dealt with in the past

Decision Time Pressure (dec_tp) (1 = strongly disagree; 7 = strongly agree)

[Fisher et al. 2003]

Please indicate the extent to which you agree or disagree with the following statements about the decision task.

dec_tp1 - The stakeholders involved in the decision process experienced time pressure to complete the decision task.

dec_tp2 - The decision had to be made under time pressure.

Analytic Decision Making Culture (ac) (1 = strongly disagree; 7 = strongly agree)

[Popovič et al. 2012; Sen et al. 2006]

Please indicate the extent to which you agree or disagree with the following statements:

ac1 - It is our organization's policy to incorporate available information within any decision-making process.

ac2 - In our organization, we consider the available information regardless of the type of decision to be taken.

ac3 - In our organization, we rely on facts in decision-making.

ac4 - In our organization fact-based decision-making is encouraged and rewarded.

BI&A System Quality (sq) (1 = strongly disagree; 7 = strongly agree)

[Nelson and Todd 2005; Wixom and Todd 2005]

Please indicate your agreement to the following statements regarding the overall quality of the BI&A-system that was used for supporting the decision making in the considered decision process. Please take into account aspects like integration, accessibility, flexibility, response time and reliability.

sq1 - Overall, the BI&A system was of high quality.

sq2 - In terms of system quality, I would rate the BI&A system highly.

sq3 - Overall, I would give the quality of the BI&A system a high rating.

Decision Maker's Domain / BI&A Competence (dm_dom/dm_bia)

[Watts Sussman and Siegal 2003]

Please rate the following aspects regarding the decision maker(s) that were involved in the decision process:

How knowledgeable were decision maker(s) about the topic of the decision?
(1 = not knowledgeable; 7 = knowledgeable)

To what extent were decision maker(s) experts on the topic of the decision?
(1 = not expert; 7 = expert)

How knowledgeable were decision maker(s) about Business Intelligence & Analytics?
(1 = not knowledgeable; 7 = knowledgeable)

To what extent were decision maker(s) experts on Business Intelligence & Analytics?
(1 = not expert; 7 = expert)