Big Data and Information Processing in Organizational Decision Processes

A Multiple Case Study

The article presents results from a multiple case study in which we investigate different types of BI&A-supported decision processes. A conception of data-centric and organizational information processing mechanisms for the context of BI&A and big data is developed. The paper shows how different facets of big data and compositions of information processing mechanisms are utilized in different types of BI&A-supported decision processes. With decision processes increasingly becoming non-routine and more uncertain, a tendency towards a decreasing utilization of big data facets and data-centric mechanisms, as well as a complementary increase in reliance on organizational mechanisms is observed. Furthermore, the dynamics of mechanisms composition rises with increasing non-routine and uncertainty.

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The Authors

Dipl.-Wirtsch.-Ing.
Martin Kowalczyk (✉)
Prof. Dr. Peter Buxmann
Fachgebiet Wirtschaftsinformatik
Software Business & Information Management
Technische Universität Darmstadt
Hochschulstr. 1
64289 Darmstadt
Germany
kowalczyk@is.tu-darmstadt.de
buxmann@is.tu-darmstadt.de

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1 Introduction

In recent years, data-centric approaches such as big data and related approaches from business intelligence and analytics (BI&A) have attracted a considerable amount of attention in both the academic and the business communities (Buhl et al. 2013; Chen et al. 2012; LaValle et al. 2011). This 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), 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. With regards to this, in order to realize the expected benefits of data-centric approaches, 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 in industry, the question of whether this results in improved 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 approach, we investigate four different types of BI&A-supported decision processes from organizations operating in 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. Subsequently, we present results from the case study. The article ends with a discussion of the research findings and limitations, as well as directions for future research.

2 Theoretical Background

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 has become 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 to be 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), however the utility of this dimension is considered to be highly 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 to improve data processing procedures and thereby increase 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.

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 the 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.

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 **Fig. 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 the accurate prediction of recurring or well-understood issues (Chaudhuri et al. 2011, p. 97). This means that equivocality has been reduced beforehand.

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

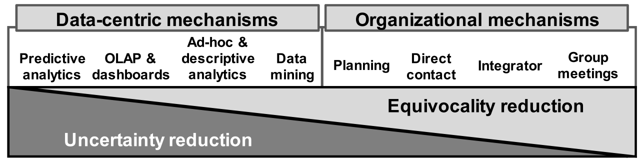

Fig. 1 Overview of information processing mechanisms

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 these 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 **Fig. 1**, the mechanisms' contribution to uncertainty and equivocality reduction varies. 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 Research Approach

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 that case studies lack 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.

3.2 Data Collection

To maintain reliability throughout the course of our study, a case study pro-

Table 1 Overview of investigated cases

Case ID	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

tocol and database were set up before data collection was begun. 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 Overview of Cases

Table 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.

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 **Fig. 2**). We were able to obtain at least two cases per quadrant.

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

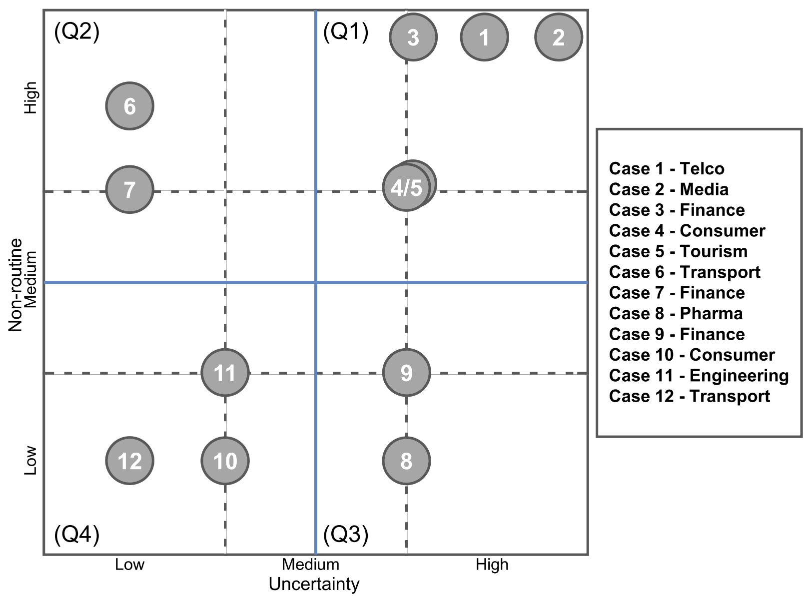

Fig. 2 Categorization of decision types

service. During the decision process, different scenarios about how to react were modeled. These 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 stated 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 the 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. Furthermore, the effects of the newly developed models on profits were 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.

Table 2 Overview of data variety, volume, and velocity per case

Decision type	Case ID	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

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.

4 Empirical Results

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

4.1 Big Data in Different Decision Contexts

Table 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 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.

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.

4.2 Relation Between 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 [. . .] however, not only 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.

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, **Fig. 3** provides an aggregated overview of the phase-specific usage of mechanisms in the investigated cases for the decision types Q1–Q4.

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

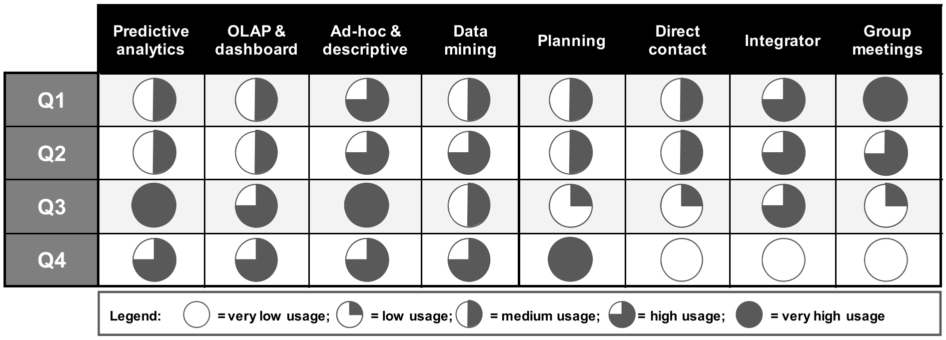

Fig. 3 Extent of mechanism usage by decision type

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 utilized.

In summary, we have discovered that planning plays an important 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/her 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 located together 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*).

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 4**, **5**, and **6** show results at a

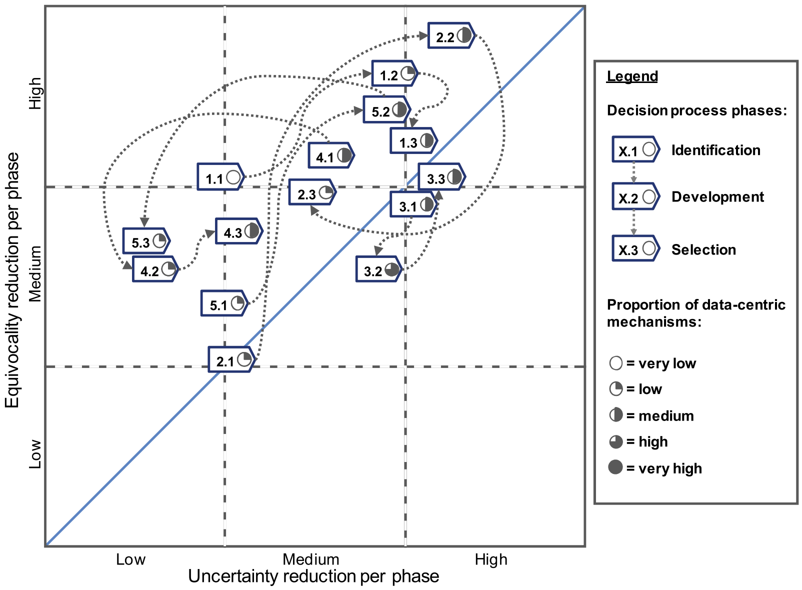

Fig. 4 Mechanism composition and dynamics (Q1)

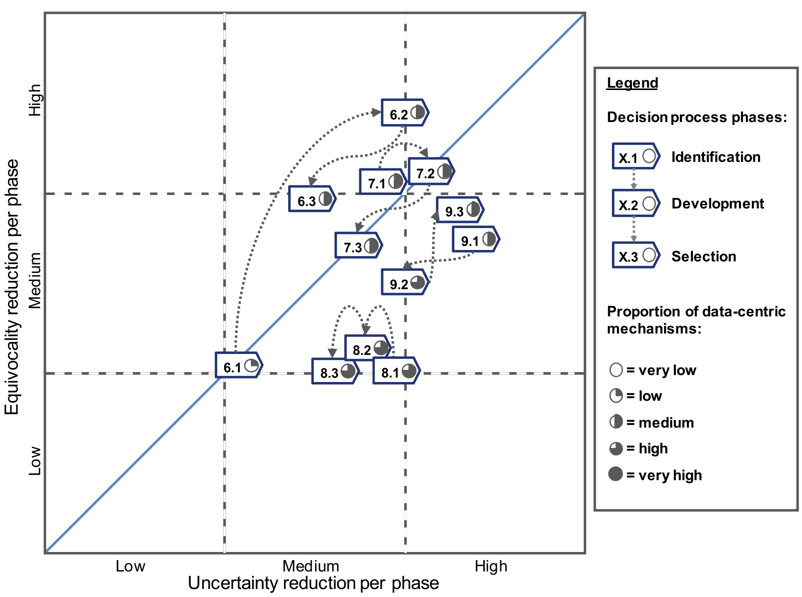

Fig. 5 Mechanism composition and dynamics (Q2 & Q3)

decision-process level, which allows making inferences about dynamics between phases.

Figures 4, 5, and 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 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 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 **Fig.** 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 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

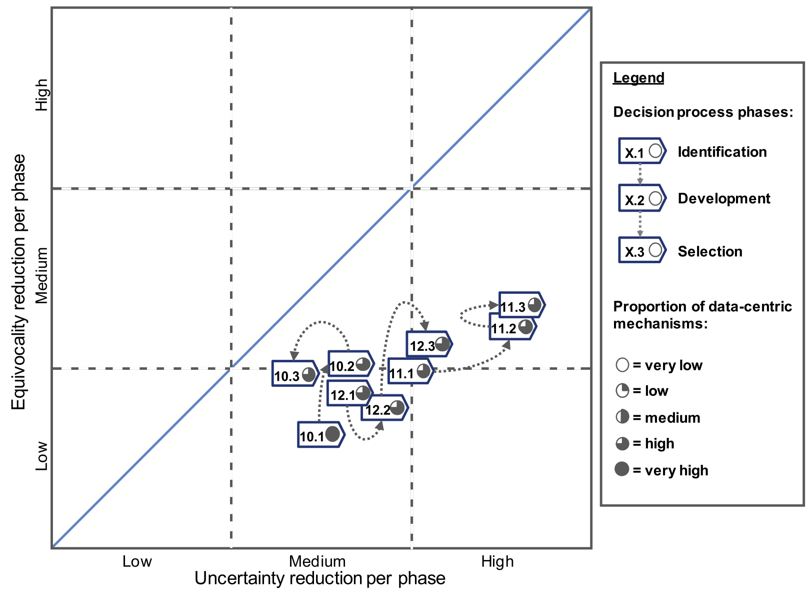

Fig. 6 Mechanism composition and dynamics (Q4)

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.

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.

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.

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 wishing to utilize big data for their decision processes should first focus on reducing equivocality. Focusing initially 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.

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

Abstract

Martin Kowalczyk, Peter Buxmann

Big Data and Information Processing in Organizational Decision Processes

A Multiple Case Study

Data-centric approaches such as big data and related approaches from business intelligence and analytics (BI&A) have recently attracted major attention due to their promises of huge improvements in organizational performance based on new business insights and improved decision making. Incorporating data-centric approaches into organizational decision processes is challenging, even more so with big data, and it is not self-evident that the expected benefits will be realized. Previous studies have identified the lack of a research focus on the context of decision processes in data-centric approaches. By using a multiple case study approach, the paper investigates different types of BI&A-supported decision processes, and makes three major contributions. First, it shows how different facets of big data and information processing mechanism compositions are utilized in different types of BI&A-supported decision processes. Second, the paper contributes to information processing theory by providing new insights about organizational information processing mechanisms and their complementary relationship to data-centric mechanisms. Third, it demonstrates how information processing theory can be applied to assess the dynamics of mechanism composition across different types of decisions. Finally, the study's implications for theory and practice are discussed.

Keywords: Big data, Business intelligence and analytics, Information processing theory, Decision processes

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's support of decision processes in big data scenarios, and we hope that it will encourage further research in this direction.

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