BUSINESS INTELLIGENCE & ANALYTICS AND DECISION QUALITY – INSIGHTS ON ANALYTICS SPECIALIZATION AND INFORMATION PROCESSING MODES

Complete Research

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Abstract

Leveraging the benefits of business intelligence and analytics (BI&A) and improving decision quality does not only depend on establishing BI&A technology, but also on the organization and characteristics of decision processes. This research investigates new perspectives on these decision processes and establishes a link between characteristics of BI&A support and decision makers' modes of information processing behavior, and how these ultimately contribute to the quality of decision outcomes. We build on the heuristic–systematic model (HSM) of information processing, as a central explanatory mechanism for linking BI&A support and decision quality. This allows us examining the effects of decision makers' systematic and heuristic modes of information processing behavior in decision making processes. We further elucidate the role of analytics experts in influencing decision makers' utilization of analytic advice. The analysis of data from 136 BI&A-supported decisions reveals how high levels of analytics elaboration can have a negative effect on decision makers' information processing behavior. We further show how decision makers' systematic processing contributes to decision quality and how heuristic processing restrains it. In this context we also find that trustworthiness in the analytics expert plays an important role for the adoption of analytic advice.

Keywords: Business analytics, business intelligence, heuristic–systematic model, information processing, decision quality.

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 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 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, which 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.

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.

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).

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 these 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 solely 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 research gap in IS, 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.

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 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, individual 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 this theory 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.

3 Research Model and Hypotheses

The heuristic–systematic model (HSM) of information processing provides the theoretical foundation for the research model proposed in Figure 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.

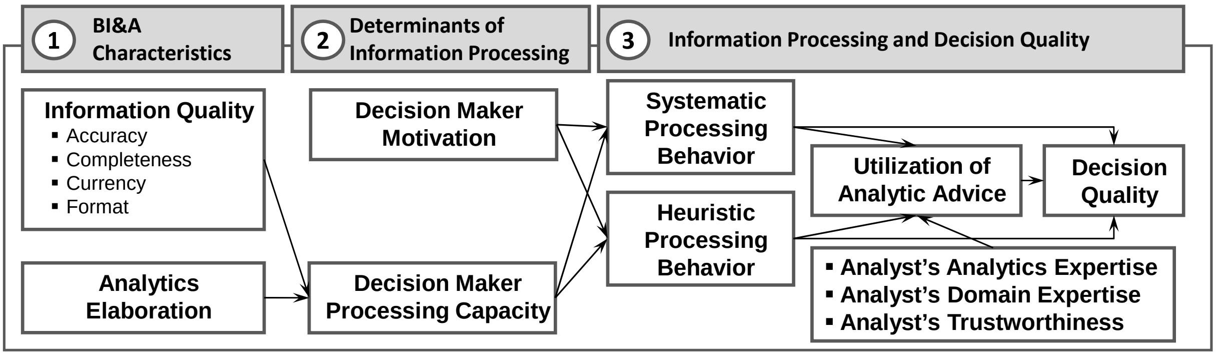

Figure 1. Conceptual model

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 utilization 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 their benefits, 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.

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 for 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 involvement will decrease the extent of heuristic processing behavior.

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 analysts, 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 dimensions expertise and trustworthiness and 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 maker 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 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.

4 Methodology

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 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), non-routineness (mean = 4.07; SD = 1.52; 7-point scale), and time pressure (mean = 4.46; SD = 1.63; 7-point scale).

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				

Table 1. Sample structure by industry, number of employees, and annual revenue

4.2 Operationalization and Measurement Properties

Where possible, we used established scales from IS, 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 second-order formative construct, which includes the dimensions of information accuracy, completeness, currency, and format that are 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, 2013; 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, non-routineness, 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, 1993), uncertainty and non-routineness were based on reflective three-item scales (Dean and Sharfman, 1993; 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, 1981), which states that the square root of AVEs must surpass all bivariate correlations between the construct and another variable. All variable pairs fulfilled this condition. These quality statistics as well as latent variable correlations are shown in Table 2. Further details and on new or modified constructs and items can be found in the Appendix.

						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	SysPorc	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; SysPorc = 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.

Table 2. Latent variable statistics and correlations

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 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.

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 3 provides an overview of all study hypotheses and their levels of significance. Figure 2 displays the model results, path coefficients as well as R^2 of our dependent variables. 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 role of the characteristics of analysts' credibility vary in their influence.

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 Involvement (+) → Systematic Processing	0.29**	0.002	Supported
H4b	DM Involvement (-) → 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: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$				

Table 3. Summary of tested hypotheses and results

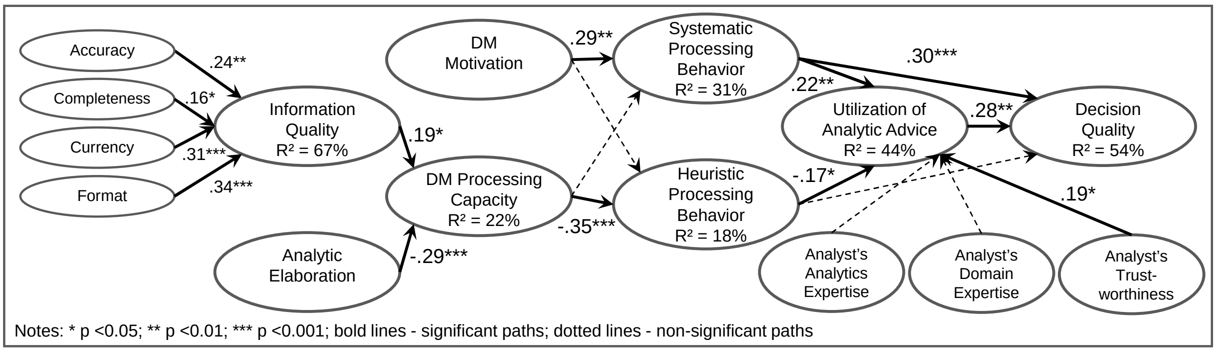

Figure 2. Model results

6 Discussion

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 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.

6.2 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 their 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 analyst 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.

6.3 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.

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Appendix A – Scales and Items

*** Item loading, significant at <0.001 level (two-tailed test)**

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 [0.79*] - Data mining (e.g. neural nets, classification and regression trees, support vector machines)

AE2 [0.80*] - Advanced statistical analysis (e.g. regression modeling, time-series analysis, factor analysis, discriminant analysis, forecasting, sensitivity analysis)

AE3 [0.71*] - 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 [0.90*] - Predictive statistical modeling, optimization and simulation techniques

AE5 [0.79*] - Very advanced analytic approaches

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 [0.87*] - The delivered analytic result/information was difficult to understand for the decision maker(s).

DM_PC2 [0.93*] - The decision maker(s) had difficulties seeing how the analytic results/information fit together into an overall picture that made sense.

DM_PC3 [0.89*] - 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 [0.87*] - The decision maker(s) didn't feel capable of understanding and using the analytic results/information that were needed in order to decide.

Systematic processing behavior (SysPorc) (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:

SysPorc1 [0.82*] - The decision maker(s) made a strong effort to carefully examine the information presented on the question of the decision.

SysPorc2 [0.85*] - In order to be completely informed about the decision topic, the decision maker(s) asked for multiple viewpoints on the issue.

SysPorc3 [0.81*] - After thinking about the information on the decision topic, the decision maker(s) gained a broader understanding.

SysPorc4 [0.80*] - The decision maker(s) read or listened to most of the provided information, even though they may not have agreed with its perspective.

SysPorc5 [0.80*] - Receiving more viewpoints on this matter was perceived as better by the decision maker(s).

Heuristic processing behavior (HeuPorc)) (1 = not at all; 7 = extensively)

[Elbanna and Younies, 2008; Khatri and Ng, 2000]

Please rate the following aspects regarding the decision process:

HeuPorc1 [0.86*] - To what extent did decision maker(s) rely basically on personal judgment?

HeuPorc2 [0.65*] - To what extent did past experience play the main role in making this decision?

HeuPorc3 [0.91*] - 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, 2013; 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 [0.91*] - The decision maker(s) closely followed the suggestions and decided in line with the recommendation.

UAA2 [0.94*] - The decision maker(s) agreed with the opinion suggested in the recommendation.

UAA3 [0.94*] - The decision maker(s) agreed with the action suggested in the recommendation.

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

[Amason, 1996; Nutt, 2008]

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

DQ1 [0.90*] - Overall, the decision value was …

DQ2 [0.89*] - The quality of the decision relative to its original intent was …

DQ3 [0.86*] - The quality of the decision given its effect on organizational performance was …

DQ4 [0.88*] - The overall quality of the decision was …