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Examining the Interplay between Decision-making and Big Data Analytics in driving Decision Value: A Critical Realist Case

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Abstract

To improve organisational performance, much attention has been paid to the value that BDA can produce beyond data-driven decision-making. However, there has been less emphasis on decision value (DV) arising from BDA. To compound this, definitions of DV remain fragmented across different views from social, to technical and economic. We aim to develop an empirically grounded theoretical model characterising how BDA is used in organisations to realize DV and to provide a mechanism-based causal explanation of how DV arises from the interplay between BDA (technical subsystem) and decision-making (social subsystem) using a real-world environment. As a result, we propose using retroductive reasoning through Critical Realism (CR) as the overarching philosophy, and Grounded Theory Methodology (GTM) techniques to collect and analyse data. Potential contributions from this research will include the development of a mechanism-based theory explaining how DV arises from the interplay between BDA and decision-making.

Keywords: Big Data Analytics, Decision-making, Decision Value, Critical Realism, Grounded Theory Methodology

1 Introduction

As organisations strive to build a competitive advantage, the ability to leverage big data becomes a factor as it drives how value is created during decision-making (Günther et al. 2017; Dremel et al. 2020; Mikalef et al. 2020). Big Data Analytics (BDA) can be defined as the means to apply analytics to big data and to present the results in such a way that allows for the creation of value (Mikalef et al. 2017). BDA could have disruptive potential for decision-making processes and existing structures within an organisation. Hence, it is crucial that IS managers handle disruptions during implementation. The adoption of BDA is not the biggest challenge in organisations, but rather how to process the data, analyse it and "convert it into insights, innovation, and business value" (Davenport, 2014, p. 2). This process has become a major differentiator in organisations and has further amplified the importance of the decision-making process (Abbasi et al. 2016). As a result, the implication for organisations on a procedural (e.g., new types of decision-making), organisational (e.g., new employee knowledge) and technological (e.g., new types of data analytics tools) level brings various challenges (Mikalef et al. 2020). Against this backdrop, BDA and decision-making in organisations need to be better understood to manage how organisations can create value (Sharma et al. 2014). Much attention has been paid to the business value that BDA can produce beyond data-driven decision-making (Newell and Marabelli, 2015; Dremel et al. 2020). Less attention has been paid to the role of BDA and decision-making in realising decision value. This is particularly pertinent due to the vagueness of the 'decision value' construct. This study, therefore, aims to develop an empirically grounded mechanism-based theoretical explanation by examining BDA and decision-making and how the underlying structures and agency interplay gives rise to decision value (Günther et al. 2017; Mikalef et al. 2017; Lehrer et al. 2018; Dremel and Engel, 2020). The principal research question (RQ1) asked in the paper is: *What are the underlying causal mechanisms that yield decision value from the interaction of organisational decision-making and big data analytics (BDA)?* The complexity of the interplay corroborates a need for more research paying simultaneous attention to all aforementioned concepts. As an appropriate approach to deal with complexities and to help contribute to enhancing our understanding of this agency interplay, Critical Realism (CR) will be used as an overarching philosophy. Scholars have argued for using CR as an underpinning philosophy to study big data (Mingers and Standing, 2018; Fox and Do, 2013). CR is considered to be most beneficial in "blue ocean theorising", that is "theory that taps into truly new concepts or relationships and presents new ways of applying existing theory or theoretical concepts" (Williams and Wynn 2018, p. 320). Having this ability and deploying CR can thus help to contribute to enhancing our understanding of this agency interplay between BDA and decision-making. In the following section, an overview of the literature review is given followed by the research methodology and potential contribution to the IS discipline.

2 Literature Review

A hermeneutic method (Boell and Cecez-Kecmanovic, 2014) was employed in reviewing literature on BDA, decision-making and decision value in IS. The first step involved defining the research question, problem and objective surrounding this topic. Second, an extensive database search was conducted using keywords ("big data analytics*" OR "big data" OR "data analytics" OR "business analytics" OR "decision*" OR "value realization"). Third, inclusion and exclusion criteria were applied to relevant journals and IS conference papers as identified in Web of Science and the AISeL respectively to capture only articles that relate directly to the research question. This was followed by a quality appraisal assessment and finally, an analysis of data in keeping with the hermeneutic cycle (Boell and Cecez-Kecmanovic, 2014). These steps were not performed in a rigorous, sequential fashion; but rather steps were reiterated as determined by interpretation and analysis (Boell and Cecez-Kecmanovic, 2014; Pare et al. 2016). In the following section, some of the key claims from the synthesis will be explained.

2.1 Conceptualising BDA and Decision-making as an IS Artefact Instance

To begin with, the focal phenomenon of BDA and decision-making was conceptualised for analytical purposes as being an instance of an IS artefact. The notion of an IS artefact has recently been proposed to capture the inherent socio-technical nature of an IS, and to give due recognition to information as an essential IS element, along with the social and technical elements (Lee and Baskerville, 2015). Chatterjee et al. 2021), drawing from General Systems Theory (GST), modelled an IS artefact as having social and technical sub-systems with information as a non-subsystem resulting from the interaction between the two. In the case of BDA and decision-making as an IS artefact instance, the technical sub-system includes the BDA tools, methods, processes, infrastructure and techniques (Walker and Brown, 2019). Lehrer et al. (2018) highlight the key BDA technology features as being big data sourcing, storage, analytics, and exploitation. The key characteristics of big data adopted by both practitioners and researchers are the so-called V's: Volume, Velocity, Variety and Veracity (Abbasi et al. 2016; Günther et al. 2017; Lehrer et al. 2018; Mikalef et al. 2018; Hirschlein and Dremel, 2021). The social sub-system pertains to the phenomenon of organisational decision-making, including different decision-making techniques. The affording and constraining relationships between the technical sub-system (BDA) and social sub-system (organisational decision-making) produces information (insights) (Chatterjee et al., 2021). The outcome, in the case of BDA and decision-making as IS artefact ought to be business value, and of specific interest to this study, decision value. Literature synthesis on each of the key concepts will be presented next.

2.2 Decision-making

Organisational decision-making can be broken down into technical, strategic or operational (Maitlis and Ozcelik, 2004; Rhyn and Blohm, 2019). The phases of decision-making include (1) processing of informational cues, (2) an assessment of possible courses of action, and (3) a commitment to action (Rhyn and Blohm, 2019). These phases connect sequentially, however recent literature shows that decision-making carries a multiple data-processing flow that functions in an iterative manner (Boonstra, 2003; Rhyn and Blohm, 2019). Boonstra (2003) found that decision-making is not always considered to be predetermined but rather based on patterns that can be studied. Jansen et al. (2017, p. 338) argue that "Often it is assumed that BD results in better decisions but it is unclear which factors influence the decision-making quality and how decision-making quality can be improved by organizations". This is consistent with Abbasi's et al. (2016) notion that decision-makers might find it easier to follow the "information value chains" based on data-driven decision-making procedures. Data-driven decision-making is an integral part of a systematic process as compared to intuitive decision-making (Abbasi et al. 2016). Three major decision-making types of interest are hence: Data-driven, Intuitive and Algorithmic-based. Each one will be discussed in turn below.

2.2.1 Data-driven Decision-making

Data-driven decision-making (DDDM) relies on the output of data analytics to inform decision-making. It involves extracting valuable insights from decision support systems (DSS) either in a structured or unstructured form. BDA as a type of DSS has been central in the shift towards notions of "data-driven thinking" or "data-driven decision-making" in organisations (Davenport, 2014; Abbasi et al. 2016). However, many organisations lack the capability to perform data-driven decision-making due to insufficient customer data or infrastructure to convert customer data to insights. Even though BDA tools make it easy to detect patterns, trends and relationships, the critical next step of understanding the causes behind those patterns is important to undertake actions that generate decision value. Developing insights from data requires the involvement of many actors within an organisation (Lycett, 2013; Sharma et al. 2014). As Lehrer et al. (2018, p. 452) point out that "Technology is reprogrammed in some cases to automate service processes and in other cases to provide actionable spaces to human actors, leading to novel interpenetrations of human and material agencies". The managerial structure of organisations is usually built on traditional decision-making habits which can both enable and hinder the ability of data-driven teams in developing insights. Despite previous attempts to explain different data-driven approaches (i.e. 'datafication' and 'democratisation of data') (Lycett, 2013), in reconstructing this data-driven narrative, consideration is required on what is necessary to define decision value. The capability of BDA affords organisations to make data-driven decisions which enables managers to address previously unknown questions (Mikalef and Krogstie, 2020). Dremel et al. (2020, p. 11) raise the question "How is the data-to-insight process affected by the technical possibilities/affordances of BDA?". The process of sense-making becomes crucial in data-driven decisions (Mikalef and Krogstie, 2020; Dremel et al. 2020). Tan et al. (2015) argue that the development of a hypothesis is a starting point for any sense-making process, leading to debates about inductive versus deductive approaches to BDA (Gunther et al., 2017). Furthermore, to avoid the misinterpretation of data which could lead to unfitting decisions and actions ("Garbage in, garbage out"), managers are challenged by the conventional paradigms of data management (Chen et al. 2012; Sharma et al. 2014; Tan et al. 2015; Dremel et al. 2020).

2.2.2 Intuitive-based Decision-making

Decision-makers often rely on unknown processed data as a substitute for their gut feelings (Woerner and Wixom, 2015). Data-driven decision-making is used in many organisations with some exceptions from managers who prefer to use intuitive-based mechanisms. With the rise of DDDM, managers are using BDA to support many timely decision-making events. However, the nature of decision-making and proliferation of decision value is still unclear. The importance of intuition and judgement cannot be completely ignored (Davenport, 2014; Abbasi et al. 2016). Intuition is considered to be an unconscious process and in some cases based on experience (Turpin and Marais, 2004). The distinction between intuition and reasoning has been a topic of persistent interest. In particular, the differences between the two modes of thought have been invoked in attempts to organise seemingly contradictory results in studies of judgment under uncertainty (Kahneman and Frederick, 2002). There is agreement on the characteristics that distinguish the two types of cognitive processes, labelled System 1 and System 2 (Stanovich and West, 2000). The operations of System 1 are typically fast and automatic. The operations of System 2 are slower, serial, effortful, and more likely to be consciously monitored and deliberately controlled. By organisations investing in cultural transformation to improve alignment between BDA and intuition, effective and satisfactory decision value could be realised (Lycett, 2013). There is an assumption within BDA literature that worthy insights lead to better decisions (Chen et al. 2012). While many BDA case studies exist, describing the relationship between the use of data-driven and human-based intelligence decision-making (e.g., intuition or 'gut'), it is not clear under what conditions decision value is created (Mikalef et al. 2020).

2.2.3 Algorithmic-based Decision-making

Algorithmic decision-making is the collection, processing and analysis of large amounts of data to make decisions (Sharma et al. 2014; Newell and Marabelli, 2015). Algorithms analyse the collected data without necessarily understanding the causes of specific data patterns (Sharma et al. 2014; Newell and Marabelli, 2015). Lehrer et al. (2018) demonstrate how algorithmic decision-making using BDA, adds value to organisations in implementing service automation. BDA captured through algorithms, however, is likely to introduce concerns due to the lack of decision-making structures that hinder the understanding of why some decisions are made (Lycett, 2013; Tan et al. 2015). Decisions are typically made following a specific algorithm which limits the possibility to learn from any data errors that might exist (Mikalef et al. 2017; Dremel et al. 2020). As a result, managers are no longer in a position to make any decisions in their own capacity which could lead to further tensions (Günther et al. 2017). Günther et al. (2017, p. 196) point out "that too much reliance on algorithms by decision makers may lead to a loss or replacement of such relevant knowledge, particularly when it is not clear how algorithms arrive at certain results, patterns, and decisions". One indirect assumption is that organisational managers have accepted algorithmic decision support systems while others "again express concerns about the 'unknown' and 'out of context' nature of what might be termed the 'blind' dependence on the algorithmic approach" (Galliers et al. 2017, p. 186). However, this has not been fully investigated in IS research. Markus (2015, p. 58) considers that "some businesses may benefit from using Big Data and algorithms, others may suffer". The use of algorithms might raise negative effects on customers but benefit managers who may lack BDA related knowledge (Markus, 2015; Dremel et al. 2020). With BDA and the influence of automation using machine learning, artificial intelligence, data management and decision modelling becomes an immediate challenge for organisations (Baesens et al. 2016; Dremel et al. 2020) as human intervention will be kept at a minimum which might impact decision value as a result of poor data governance. In this regard, to achieve decision value, managers need to consider developing a certain level of trust and acceptance for the generated insights extracted from data in algorithmic-based decision-making (Lycett, 2013; Sharma et al. 2014).

3 'Information' in a BDA and Decision-making Artefact View

Information conceptually encompasses the notion of the information value chain (i.e. data, information, knowledge), which leads to decision, and actions in BDA (Abbasi et al. 2016). It also captures the notion of insight, which is often cited as an outcome of BDA implementation (Davenport, 2014). Information has been viewed from different stances in IS research (physical, objective, subject-oriented and sociocultural) (Boell, 2017). Consideration of these different stances with respect to BDA and decision-making would offer additional contributions to knowledge about the phenomenon. Hence, one of the objectives of this paper is to develop a BDA artefact which includes the social, technical and information elements (Boell, 2017; Lee et al. 2015; Mingers and Standing, 2018; Chatterjee et al. 2021).

4 Decision Value

While prior literature has focused on the ability of BDA to generate better insights and decisions, the focus on the role of BDA in realising decision value has been limited (Sharma et al. 2014). BDA studies suggest that the quality of organisational decisions are improved through BDA (Günther et al. 2017; Mikalef et al. 2020; Sharma et al. 2014), however the question of how organisational decision-making and BDA interact to create decision value is not fully addressed. Three common measures used to characterise decision value are: (1) *Quality of the decision*, particularly whether the decision is able to achieve its goal; (2) *Satisfaction with the decision*, particularly its acceptance amongst managers and stakeholders and; (3) *Effectiveness of the decision* relating to the reliability of the proposed decision (Sharma et al. 2014b). The acceptance of decisions depends in large part on the decision-making process (Lycett, 2013; Sharma et al, 2014). Fiorini et al. (2018) identify that the relationship between managers, stakeholders and subordinates have a direct influence on decisions, BDA adoption and acceptability of BDA implementations. Further, in some instances, stakeholders are not always involved in the decision-making cycle. Synthesising the arguments above suggests that decision value can be seen as an outcome of the interacting decision-making process (social sub-system) and BDA technical sub-system as depicted in Figure 1. The interplay between BDA and decision-making for decision value is not fully addressed in IS literature. Many IS scholars and practitioners have focused on the technical functionalities of BDA and not enough on the institutional and social surroundings which has raised concerns regarding the lack of coordination of these socio-technical elements in BDA studies (Sarker et al. 2013; Dremel et al. 2017). To tackle this, it is necessary to identify underlying causal mechanisms that give rise to decision value. These mechanisms are triggered from the multitude of interactions between BDA tools, decision-making techniques, decision-makers, and information (Schryen, 2013). These interrelationships are illustrated in the initial conceptual framework below (Figure 1). Investigating the reciprocal influences between BDA and decision-making brings additional complexity to the analysis (Chatterjee et al. 2021). To address the presented shortcomings, we propose using CR as a philosophical framework (Wynn and Williams, 2012) to help explain the generative mechanisms leading to decision value, as described next.

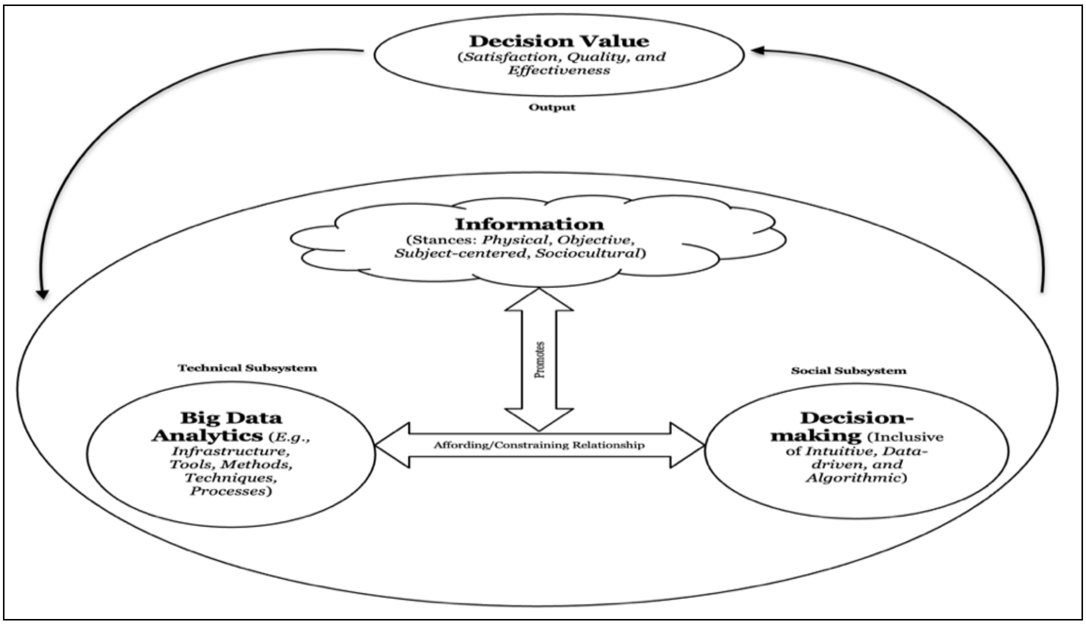

Figure 1: A GST-informed Conception of a BDA and Decision-making Artefact (adapted from Chatterjee, Sarker, Lee, Xiao, and Elbanna, 2021)

5 Research Methodology

5.1 Research Philosophy

CR has emerged as a viable philosophical paradigm for IS research in particular its sophisticated stance on agency and its stratified ontology (Wynn and Williams, 2012). An important element in CR research is generative (or causal) mechanisms which have been defined as "causal forces that would have to exist in order to explain a given phenomenon" (Williams and Wynn 2018, p. 318). These generative mechanisms provide causal explanations and contribute to the development of mid-range theories (Mingers and Standing 2017). Though recent papers (Bygstad et al. 2016) have proposed an approach in identifying generative mechanisms, Wynn and Williams (2020) highlighted that "bringing greater conceptual and practical clarity to what mechanisms really are and how they should be described has become a fundamental challenge to the advancement of Critical Realism-based research in IS" (p. 56). The concept of generative mechanisms can add value to our theoretical understanding of the agency interplay between BDA and decision-making. This will yield a coherent understanding of the types of generative mechanisms necessary for DV to arise from the interplay. At an ontological level CR advocates for a stratified ontology which is nested into three domains: the empirical ("which refers to our perceptions and experiences of these events") - e.g. decision value, the actual ("comprised of events, that is, what happens when mechanisms are activated"), and the real ("made up of these natural and social objects, structures and their mechanisms") - e.g., BDA, organisational decision-making etc.) (Archer, 1995; Hoddy, 2019, p. 112). At the epistemological level CR advocates for explanation via mechanisms, i.e. to "explain the phenomenon by identifying and justifying the existence and activity of the set of structures (technological, material and social etc.)" (Wynn and Williams, 2020, p. 52). At the methodological level, CR advocates for abduction, which involves theoretically redescribing a phenomenon of interest (e.g., BDA and decision value) and ascertaining new generative mechanisms (retroduction) that arise from the interactions between the different underlying structures (e.g., BDA tools and technology, organisational decision-making, information artefacts etc.), that explain the empirical phenomenon (e.g. decision value) (Easton, 2010; Hoddy, 2019).

5.2 Research Strategy

A CR-based case-study strategy will be employed (Easton, 2010). As part of theory building, this research will make use of a single-case study (Easton, 2010). The goal of using a single case-study is to develop a theory that can best describe the case. The single case-study can be used to identify the key causal mechanisms that explain decision value from BDA in organisations, and which emerge as the effects of the organisational context, structures, and individual influences (Easton, 2010; Wynn and Williams, 2020).

5.3 Data Collection

This research will use a purposefully selected method to choose the case organisation. The expectation of the organisation is that of considerable experience and knowledge in the collection of big data and use of data visualization tools to present data. The organisation should be one that considers BDA as an innovative tool and should use BDA extensively throughout the organisation for decision-making. BDA should be strategically placed within the organisation as part of value-creation (Lehrer et al. 2018). Specifically, it will be conducted in a single financial services organisation. The case is purposefully selected with regards to its relevance in using BDA and with the considerable experience and expertise in the management and analysis of large amounts of customer data. The case organisation considers BDA to be strategically part of its decision-making process. The aforementioned insights from literature will be gathered and an initial set of interview questions will be compiled (Hoddy, 2019). Insights related to coordinating participatory interviews suggest that the selection of interviewees will be made on the basis of respondent BDA knowledge (Lehrer et al. 2018) and the role in organisational decision-making. For the case site, we will sample eight to twelve participants, who will be selected through purposeful sampling. These will represent diverse functions as the use of BDA for decision-making involves multiple business units, e.g., digital business, strategic marketing, customer management, sales etc.

5.4 Data Analysis

Techniques from Grounded Theory Methodology (GTM) will be used to analyse data, within a CR framework. GTM provides procedures which will be used to code and analyse data through stages of the CR research project (Hoddy, 2019). The formal stages of CR-informed research include "Description", "Analytical resolution", "Abduction and retroduction", and "Concretisation and contextualization" (Hoddy, 2019, p. 115). These stages will incorporate GT techniques and analysis guided by the recommendations from Corbin and Strauss (2008) with a specific focus on the use of the coding procedures (i.e. open, axial and selective coding) (Hoddy, 2019). As per Hoddy (2019) in the Description stage, we will identify literature and concepts that are directly related to BDA and decision-making using open coding. In the analytic resolution stage, we will perform axial coding ("diagramming") to identify the BDA, decision-making and information elements as it relates to the strategic organisational goals. During the Abduction and retroduction stage we will use axial coding along with the continuous review of literature as we compare data with theory. Retroduction will be used to identify causal mechanisms. In the concretisation and contextualisation stage, using selective coding, the research aims to identify the relationship between the aforementioned elements. NVivo will be used as the preferred data analytic tool to analyse and manage the collected data. The analysis process will be conducted in accordance with the key CR principles (Wynn and Williams, 2012).

6 Potential Contributions

The core objective of the current research seeks to make a potential contribution to IS in theoretical, methodological, and practical perspectives as follows: Theoretically, a mechanism-based theory explaining how decision value arises from the interplay between BDA technologies and organisational decision-making. CR has had limited use in BDA studies, so methodologically this will be a contribution along with insights into how grounded theory techniques can be incorporated in CR. In practice, this research will assist organisations in deriving decision value from their BDA implementations.

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