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Looking beneath the Surface - Concepts and Research Avenues for Big Data Analytics Adoption in IS research

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Abstract

Big data analytics (BDA) gained importance in scholarly and practitioner literature alike. There is some disagreement, however, whether BDA is merely an evolution of established phenomena, most particularly business intelligence, or whether BDA represents a novel technology-driven innovation with potentially disruptive market impacts. Using the technology-organization-environment theory as our lens of analysis, we take a critical stance and conduct a systematic literature review to offer guidance for future research by pinpointing pivotal concepts and providing conceptually and empirically validated propositions as well as research avenues for IS research on BDA adoption. While the research avenues are intended to trigger future research, the developed propositions shall provide guidance to research endeavors that empirically analyze the adoption of BDA in organizational settings. By discussing open research issues and providing potentially fruitful theoretical perspectives for enriching our knowledge in this domain, this shall ultimately contribute to advancing BDA research.

Keywords: big data analytics, systematic literature review, adoption, technology-organization-environment theory

Introduction

Today's organizations face an exponential growth of data from diverse sources, including user-generated content, mobile transactions, social media, sensor networks, or business transactions (Constantiou and Kallinikos 2015). This phenomenon of global data proliferation exhibits the potential for organizations to seize the greater volume of data, which is generated in a more accessible and fluid manner, in order to learn from analytic insights about a diverse set of phenomena (Antonacopoulou and Sheaffer 2014). The ability to handle environmental complexity, which ranges from routine events to "events that are variously unexpected, surprising, unorthodox, and rare" (Colville et al. 2013, p. 1202), posits at least a competitive advantage, at most a strategic necessity to organizations. Thus, during the last years, the term big data analytics (BDA) gained importance in both scholarly (e.g., Baesens et al. 2016; Chen et al. 2012; Dremel et al. 2020; Goes 2014; Lehrer et al. 2018) and practitioner literature (Bughin et al. 2017; Henke et al. 2016).

BDA promises to gain insights from the ubiquitous data sources. These can be leveraged to e.g. sense a customer's desires (Wamba et al. 2015), deliver tailored services (Rust and Huang 2014), improve firm performance through data-driven decision-making (Brynjolfsson et al. 2011), or react to hidden information appropriately. We argue that BDA extends the scope of data exploitation and data analysis and thus can be regarded "an evolution of previous concepts and terminology, such as 'decision support', 'online analytical processing', and 'business intelligence'" (Loebbecke and Picot 2015, p. 150; Lycett 2013) requiring to implement novel data technologies and data management methods (Jacobs 2009). Other authors who consider BDA a disruptive innovation rather than an evolution argue that BDA holds transformational opportunities that move far beyond today's organizational application of business intelligence and analytics (Davenport 2014; Kimble and Milolidakis 2015). Agarwal and Dhar (2014, p. 443) go as far as to consider BDA as "possibly the most significant "tech" disruption in business and academic ecosystems since the meteoric rise of the Internet and the digital economy". In that, implementing BDA requires a fundamental transformation of organizational capabilities as it entails a shift in traditional paradigms for data exploitation, usage, and analysis (Woerner and Wixom 2015), but builds on previous concepts and technologies.

In this paper, we view this transformation guided by the lens of the technology-organization-environment (TOE) theory according to which the adoption of a technology innovation is largely determined by an organization's technological, organizational, and environmental preconditions (i.e., the role of context of the technology innovation) (Depietro et al. 1990). Given that BDA can be regarded as a socio-technical system innovation (Boyd and Crawford 2012), the TOE theory potentially contributes to an understanding of the role of context for BDA adoption in organizations. Academic research in the last years has already accumulated a considerable knowledge base that provides valuable insights for such an analysis, regarding technological (Chen and Zhang 2014; Gandomi and Haider 2015; Hashem et al. 2015), organizational (e.g., Tallon, 2013), and societal (e.g., Loebbecke and Picot 2015) as well as ethical (Boyd and Crawford 2012) aspects of BDA. Several authors have addressed the need to consolidate big data research and developed frameworks to guide further research in areas such as advanced analytics technologies (Sagiroglu and Sinanc 2013), big data ethics (Richards and King 2014), and types of value creation (Wamba et al. 2015). There remains a gap, however, concerning establishing an integrated framework to conceptualize the role of context in BDA adoption and assimilation (Wamba et al. 2015). Our research, therefore, follows the goal to structure the available knowledge base regarding the pivotal concepts for BDA adoption and to develop a framework providing the basis for further development of theory (Pare et al. 2015; Rowe 2014). In particular, we take a critical stance and conduct a systematic literature review to offer guidance for future research by pinpointing pivotal concepts and providing conceptually and empirically validated propositions as well as research avenues for IS research on BDA adoption (Pare et al. 2015).

This paper is structured as follows. Below, we introduce the TOE theory as our guiding theoretical lens of analysis and clarify its applicability for studying BDA before we explain our research approach. Subsequently, we present pivotal concepts and the resulting propositions for BDA adoption. We conclude by discussing future research directions, limitations, and contributions.

Background

The Technology Organization Environment Perspective on Technology Innovation

From a system theory perspective, a technology innovation is characterized by three distinctive attributes (Luhmann 2015, pp. 112–119; Roth 2009). In an object dimension, the technology innovation represents a technology artifact with novel features. In a temporal dimension, the technology innovation is associated with a process of transformation, diffusion, and change. The social dimension characterizes a technology innovation through social exclusivity, i.e. the ability to create competitive advantages. The TOE framework explains the role of context in the organizational adoption of technology innovations and directly relates to these three dimensions of innovation (Depietro et al. 1990). It consists of three elements (see Figure 1). The technological context influences the novelty of a technology artifact. The organizational context influences the process of transformation. The external environment context determines the social exclusivity of an innovation. Depietro et al. (1990) argue that these three contexts largely determine the degree to which a technology innovation evolves within an organization. As a generic theory of technology diffusion, the TOE framework has been widely used to investigate factors that affect the adoption and assimilation of technology innovations such as electronic data interchange (EDI) (Kuan and Chau 2001), RFID (Lee and Shim 2007), or BDA (Bremser 2018; Chen et al. 2015).

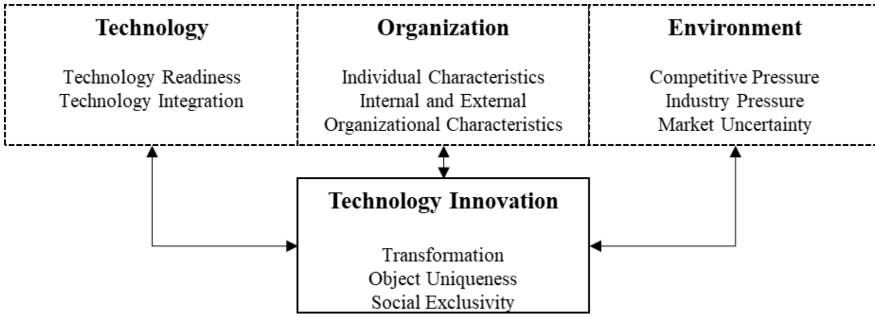

Figure 1. Technology Innovation and Theory of Context

The technological context covers internal and external technologies that are associated with the focal technology innovation (Depietro et al. 1990). Two technological factors received considerable research attention: *technology readiness and technology integration* (Zhu et al. 2006). Technology readiness is characterized by the design of the underlying information infrastructure, which is an enabler of the analyzed technological innovation, and by the knowledge and skills of IT human resources (Zhu and Kraemer 2005). Technology integration represents the inter-connectivity of internal back-office information systems and databases with information systems and databases of suppliers (Zhu et al. 2006; Zhu and Kraemer 2005). The organizational context refers to several types of firm characteristics and resources, which Rogers (1983), for example, groups into *individual characteristics* (such as attitude to change), *internal organizational characteristics* (such as centralization, complexity, formalization, interconnectedness, organizational slack, and size) and *external organizational characteristics* (such as system openness). The environmental context describes the external conditions a firm is exposed to, such as industry, competitors, accessibility of external resources, and regulation (Depietro et al. 1990). The environmental factors, which are studied the most by researchers of technology innovation, include *competitive pressure, industry pressure,* and *market uncertainty* (Kuan and Chau 2001; Lee and Shim 2007).

Big Data Analytics as a Technology Innovation

To ensure the applicability of the TOE perspective we compared several definitions for BDA based on our review sample (see Table 1). A comparison of definitions (13 in total) of the term BDA shows that many authors consider BDA as a technology innovation and reference artifact novelty, the process of transformation, and social exclusivity. Concerning artifact novelty, all authors elaborate on the characteristics of emerging data in terms of volume, velocity, variety, and veracity (e.g., Mikalef et al. 2017; Tan et al. 2015).

"[A] cultural, technological, and scholarly phenomenon that rests on the interplay of: (1) Technology: maximizing computation power and algorithmic accuracy to gather, analyze, link, and compare large data sets **[AN][T].** *(2) Analysis: drawing on large data sets to identify patterns in order to make economic, social, technical, and legal claims* **[SE][E].** *(3) Mythology: the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy* **[PT][O]**.*"* (Boyd and Crawford 2012, p. 663)
"[...] these attributes [volume, diversity, speed] are meant to give rise to large, diffuse and shifting data structures that challenge traditional techniques (e.g., database and server technologies) **[AN][T]** *and practices (e.g., statistics, accounting, professional classifications)* **[PT][O]** *with which large data volumes have hitherto been dealt. A heated and often cross disciplinary debate has emerged over the last few years on the opportunities and challenges these developments posit for organizations, communities and individuals* **[SE][E]**.*"* (Constantiou and Kallinikos 2015, p. 44)
"We include the concept of big data analytics serving as a means to analyze and interpret any kind of digital information. Technical and analytical advancements in big data analytics, which – in large part – determine the functional scope of today's digital products and services, are crucial for the development of sophisticated artificial intelligence, cognitive computing capabilities and business intelligence **[AN][T]**. *[...] In the era of accelerating digitization and advanced big data analytics, harnessing quality data for designing and delivering state-of-the-art services will enable innovative business models* **[SE][O]** *and management approaches* **[PT][E]** *[...]."* (Loebbecke and Picot 2015, p. 150)
[AN], **[PT]**, and **[SE]** mark explicit or implicit references to artifact novelty **[AN]**, a process of transformation **[PT]**, and social exclusivity **[SE]**. **[T]**, **[O]**, and **[E]** mark references to the technological **[T]**, organizational **[O]**, and environmental context **[E]**.

Table 1. Excerpt of Three Selected Definitions of Big Data Analytics

Because big data requires "advanced and unique data storage, management, analysis, and visualization technologies" (Chen et al. 2012, p. 1166), it is not the characteristics of data, but rather the features of data processing technologies, which characterize artifact novelty. Most authors highlight the requirement for novel technologies for data management. Constantiou and Kallinikos (2015, p. 44) argue that big data "challenge traditional techniques (e.g., database and server technologies) [...] with which large data volumes have hitherto been dealt". Most authors further reference the analytical systems that are used to identify patterns and generate models from big data. Boyd and Crawford (2012) for example argue that the technological means of BDA enable a company to improve "algorithmic accuracy to gather, analyze, link, and compare large data sets" (p. 663). In summary, BDA requires novelty of all technology artifacts that are employed for big data processing in order "to analyze and interpret any kind of digital information" (Loebbecke and Picot 2015, p. 150). Concerning the process of transformation, most authors acknowledge that organizational changes are required to manage and take advantage of big data (Davenport 2014, p. 2), for example, organizational processes and capabilities for data analytics and insights generation (Chen et al. 2012; Constantiou and Kallinikos 2015; Mikalef et al. 2017). BDA implies a shift towards data-driven management (Loebbecke and Picot 2015) requiring the implementation of an organization-wide "belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy" (Boyd and Crawford 2012, p. 663). In summary, BDA implies a process of transformation that covers organizational capabilities and processes, decision making, and culture. Regarding social exclusivity, most of the authors emphasize the characteristic of BDA to create business value for its applicant. Davenport (2014), for example, states that the biggest challenge concerning the organizational adoption of BDA is not to consider the analysis of big data as an end itself but as means to an end and "to convert it into insights, innovations, and business value" (Davenport 2014, p. 2). BDA creates new opportunities for companies, e.g. by enabling novel business models or value propositions (Boyd and Crawford 2012). Loebbecke and Picot (2015) characterize the social exclusivity of BDA as follows: "In the era of [...] digitization and advanced BDA, harnessing quality data for designing and delivering state-of-the-art services will enable innovative business models" (p. 150). Summarizing the aspects from above, we define *BDA* as *a technology innovation of organizations that encompasses the usage of novel technologies to process data (which is characterized by unprecedented levels of volume, velocity, variety, and veracity), the transformation of organizational capabilities (amongst others related to the design of data analysis processes), and undertaken for the generation of competitive advantage*. Further, we refer to BDA adoption as the process of using and realizing BDA at an individual or organizational level and transforming the organization accordingly (i.e., a matter of degree) (Rogers 1983).

While our discussion of BDA definitions suggests to broadly incorporate elements of technology, organization, and environment into a study of BDA adoption, studies in the current body of knowledge focus on the technological, contextual aspect (e.g., Salleh et al. 2015). Despite some exceptions (e.g., Chen et al. 2015; Dremel, Herterich, et al. 2020; Lehrer et al. 2018), IS research is in its infancy to understanding how the promising value of BDA can be realized, and accordingly how the adoption of BDA and its technologies is affected by TOE (pre-)conditions (Günther et al. 2017; Mikalef et al. 2017; Wiener et al. 2020). To address this research gap, we conduct a systematic literature review and develop a framework structuring and critically synthesizing pivotal concepts of BDA adoption (Pare et al. 2015). Further, we propose several testable propositions as well as research avenues to guide future research. Thereby, we specifically consider the continuous nature of BDA adoption and thus position the propositions as a matter of degree, not of kind.

Research Method

The aim of this systematic literature review is to establish a clear understanding of contextual factors that influence BDA adoption in organizations. This review focuses on articles in IS literature that analyze contextual factors of BDA and has the goal to understand the "phenomenon as a whole, its meaning and its relationships" (Rowe 2014, p. 243). Based on a structured discussion of current research, we generate a set of propositions, identify research avenues, and provide future research questions. Following the guidelines for conducting literature analyses by (vom Brocke et al. 2015; Rowe 2014; Webster and Watson 2002), this review covers relevant articles published in high impact, peer-reviewed IS journals or conferences without claiming exhaustiveness. The search scope of the systematic literature review is defined along the dimensions of process, source, coverage, and applied techniques (vom Brocke et al. 2015). We adopted a sequential search process and restricted the source-scope of our analysis by searching amongst the Association for Information Systems (AIS) basket of eight top IS journals and two leading IS conferences (ICIS and ECIS) and used the scientific databases EBSCO, ProQuest and the AIS Electronic Library. We intended to reach a representative coverage of papers. Thus, we deliberately chose the broad search term 'big data' for our keyword search (technique), because not all authors use the term BDA to refer to essential aspects of generating insights from big data. As the search term is chosen to be broad and our analysis of our sample resulted in recurrent themes, we did not encounter the need to perform forward and backward search. Yet, we engaged with the extant body of knowledge to discuss future research avenues. Due to the relative novelty of the phenomenon BDA, we limited our search to articles that were published in the past fourteen years, i.e. between 2005 and 2019. Further, we restricted the search to keywords, title and abstract to limit the search to articles with big data as a focal subject of analysis. We excluded articles that mentioned big data and BDA only marginally or merely use big data as a motivational background or as a data source for data-driven use cases without explaining or relating to this concept. This process led to 66 articles that are listed in Table 2.

Outlet	**Relevant/ Hits**	**References**
Journal of Information Technology	6/16	(Bhimani 2015; Constantiou and Kallinikos 2015; Kallinikos and Constantiou 2015; Markus 2015; Woerner and Wixom 2015; Yoo 2015)
Management Information Systems Quarterly	5/12	(Baesens et al. 2016; Chen et al. 2012; Goes 2014; Rai 2016; Saboo et al. 2016)
Information Systems Research	2/5	(Agarwal and Dhar 2014; Gregory and Muntermann 2014)
Journal of Strategic Information Systems	5/6	(Ghasemaghaei et al. 2018; W. A. Günther et al. 2017; Jones 2019; Loebbecke and Picot 2015; Whittington 2014)
European Journal of Information Systems	3/4	(Chiasson et al. 2018; Lycett 2013; Müller et al. 2016)
Journal of Management Information Systems	5/6	(Chen et al. 2015; Grover et al. 2018; Kitchens et al. 2018; Lehrer et al. 2018; Müller et al. 2018)
Information Systems Journal	2/3	(Boldosova 2019; Clarke 2016)
Journal of the Association for Information Systems	1/4	(Abbasi et al. 2016)
ECIS 2005-2019	20/57	(van der Aalst 2013; Alfano et al. 2015; Bremser 2018; van den Broek and van Veenstra 2015; Cao and Duan 2014; Charoenpanich and Aaltonen 2015; Döppner et al. 2015; Duan and Cao 2015; Egger et al. 2015; Gölzer et al. 2015; Heinrich and Hristova 2014; Jensen et al. 2019; Marton et al. 2013; Mikalef et al. 2018; Olbrich 2014; Schüritz et al. 2017; Someh et al. 2016; Stange and Funk 2015; Tan et al. 2015; Tiefenbacher and Olbrich 2015)
ICIS 2005-2019	17/47	(Alexander and Lyytinen 2019; Brynjolfsson et al. 2011; Chatfield et al. 2015; Dremel, Herterich, Wulf, and Spottke 2017; Dremel, Wulf, Annegret, and Brenner 2017; Ghasemaghaei et al. 2016; Ghoshal et al. 2014; W. Günther et al. 2017; Hristova 2014; Miranda et al. 2015; Ram et al. 2015; Sodenkamp et al. 2015; Tiefenbacher and Olbrich 2017; Trieu 2013; Wang et al. 2014; Zhang et al. 2014)
Total	**66/159**	**All above**

Table 2. Results of Literature Search

The papers were analyzed in a concept-centric manner pursuing our goal of a critical interpretive synthesis of our review sample (Pare et al. 2015; Webster and Watson 2002). We started by extracting contextual factors of BDA mentioned in the articles in an open coding process guided by the TOE perspective (Corbin and Strauss 2014). Thereafter, we used axial coding to aggregate the codes from open coding (resulting in axial codes such as 'Leadership', 'Skills', 'Knowledge' or 'Decision-making'), and to allocate theses axial codes to nine superordinate categories (e.g., data-driven culture, institutional factors, competencies) that are unambiguously assigned to the technology, organization, or environment context and the 22 subcategories (e.g., volume, beliefs, privacy, leadership, decision-making). Next, using a concept matrix following Webster and Watson (2002), we carried out selective coding to generate a comprehensive allocation of codes to our set of articles and iteratively refined the code structure. Due to page limitations the concept matrix containing the mapping of each code category with each article is not included in the article. Following the traditional sense of the technology context, we allocated the three superordinate categories: data exposure, information technologies, and processing and analysis capabilities as well as their 9 subordinate codes. The organizational context is composed of superordinate categories data-driven culture, institutional factors, competencies, and the data-to-decision process compose as well as their 10 subordinate codes. In line with extant TOE literature, we allocated to the environmental context of BDA competitive dynamics and strategy. To validate our results, we draw on iterative discussions among two researchers according to Forman and Damschroder (2007) after each coding iteration, and seize empirical data from several published research endeavors with a total of 52 interviews from 11 companies to enrich, to substantiate, and to illustrate our results (e.g., Dremel, Herterich, et al. 2020; Dremel, Stoeckli, et al. 2020; Dremel, Wulf, Herterich, Waizmann, et al. 2017). In particular, we draw on a revelatory single case study of an organization successfully adopting big data analytics (Dremel, Herterich, et al. 2020). Though presenting our illustrations in the result section, we like to acknowledge that these statements aim at illustrating and showing the practical relevance of our findings.

Results

Figure 2 summarizes our results and propositions, which we illustrate in the following paragraphs.

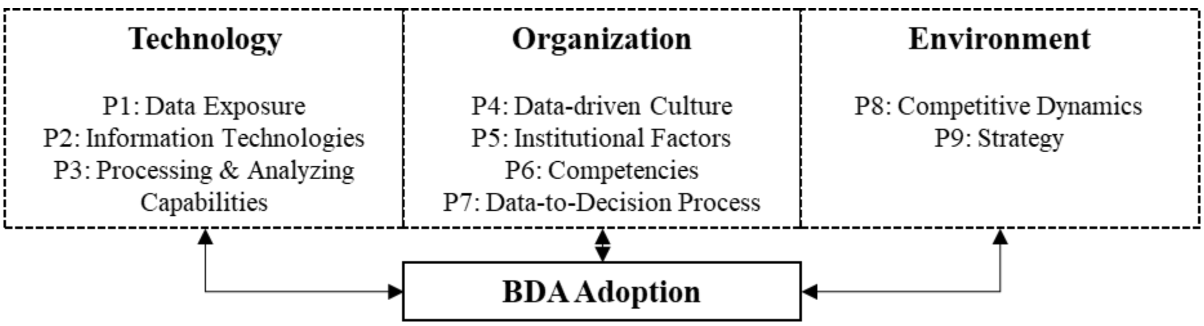

Figure 2. Adoption of Big Data Analytics from a TOE perspective and related propositions

Technology Context Concepts Affecting BDA Adoption

There are three superordinate categories that constitute the technology context: (1) *data exposure*, (2) *information technologies*, and (3) *processing and analyzing capabilities*. First, data exposure characterizes the degree to which organizations are confronted with requirements to process big data (i.e., volume, variety, velocity, and veracity). Most authors argue that organizations are confronted with an unprecedented volume of data and that key benefits arise from integration and large-scale data processing (Gölzer et al. 2015; Marton et al. 2013). Huge data volumes and the exponential growth of data are related to the diversity of data, the update frequency and its rapid pace of growing (Constantiou and Kallinikos 2015; Davenport 2014) and fostered by the evolution of storage, memory, and transmission technologies (Baesens et al. 2016). Many authors further argue that an important source of value lies in the exploitation of previously unused data sources, such as text or log data – previously mostly considered as noise (Marton et al. 2013; Yoo 2015). Processing data that are produced at high rates (i.e., velocity) represents an important technological capability for situations of organizational decision making with high dynamics, such as online marketing (Goes 2014; Stange and Funk 2015). The processing of a higher variety of data, including unstructured and inconsistent sources, enables novel analytical scenarios, such as consumer sentiment or industrial data analyses (Alfano et al. 2015; Bhimani 2015; Woerner and Wixom 2015). Therefore, data veracity as a technological challenge gains in importance, since technologies must enable a flexible handling of incomplete, inconsistent, ambiguous, heterogeneous, and agnostic data (Constantiou and Kallinikos 2015). This development leads to applications of ubiquitous computing in many business areas such as marketing (Dremel, Herterich, Wulf, Waizmann, et al. 2017), logistics (Döppner et al. 2015; Günther et al. 2017), and supply chain management (Chen et al. 2015). In summary, the business value of BDA is often rooted in handling and integrating large scale data with various levels of quality (potentially at (near) real-time) of heterogeneous and disconnected data sources. Following this argumentation, we propose ***P1***: *The higher the degree to which an organization is exposed to data that are characterized by veracity and unprecedented levels of volume, velocity, and, variety as well as disconnected data sources the higher is the level of BDA adoption.*

> ***Illustration P1:*** *"To generate a real benefit [...], we had to integrate data from cars, social media, and our internal systems in our newly created Hadoop cluster. [...] The interconnection proofed to be the most difficult aspects beyond [redesigning] our data infrastructure." Product Owner Car Data#1*

Second, BDA as a logical development requires new *information technologies*, building on advances in data storage technologies and visualization software (Olbrich 2014), new data management mechanisms such as schema-less storage to process, store and collect the vast amount of data, with different levels of variety, variability, and velocity (van den Broek and van Veenstra 2015; Constantiou and Kallinikos 2015). New technological means enable companies to discover previously unknown relationships, e.g., via machine-based data analytics techniques (Ram et al. 2015) or to conduct predictive analysis based on cross-referenced current and historical data to gain insights or to make recommendations enabling managers to foresee future trends and events (e.g., to optimize profits from advertising) (Stange and Funk 2015; Wang et al. 2014). This leads to a change in technology use that covers innovative technologies for data storage, processing, and the communication of results. For instance, Hadoop Distributed File Systems as foundational file system with MapReduce as a processing paradigm and Tableau as visualization software are often referred to as big data technologies (van der Aalst 2013; Gölzer et al. 2015; Miranda et al. 2015). More generally, to successfully handle the novel characteristics of big data, appropriate means of visualization and advanced statistical methods, e.g. machine learning are required while challenging legacy IT technologies and landscape that have primary focused on ex-post data analysis of consistent structured data (Tan et al. 2015; Woerner and Wixom 2015). Following the argumentation from above, we propose ***P2****: The lower the degree to which legacy infrastructures limit data storage, analysis, and presentation, the higher is the level of BDA adoption.*

> ***Illustration P2:*** *"The biggest challenge was the outdated system landscape [...] no one paid attention to [...] data and what has emerged over the last [...] years of operational systems [...] few individual examples with both a clean logic and a clean data model and an appropriate link [to legacy systems existed.]" Head of Data Analytics & Strategy*

Third, BDA technologies are supposed to help accelerate the data to insight process such that data is not stored for the sake of data storage but for the sake of gaining new insights (Döppner et al. 2015). The data to insight process requires the data acquisition, extracting and cleaning, and processing and analyzing supported by quality management. Due to its new technological means BDA might lead to a catch-all-you-can approach for data acquisition (Yoo 2015) while it should not be the objective to consume and analyze as much data as possible (van der Aalst 2013) but the "right" data (as a reasonable representation of the real world). Through BDA traditional processes in data management and its technologies are challenged as the traditional paradigms of data management need to be replaced by new ones (e.g., harvesting new data sources, collecting data, and integrating structured and unstructured data) (Tan et al. 2015). Before potentially storing information through traditional data management technologies, the information itself needs to be generated through processing and analyzing big data by means such as text analytics, video analytics, audio analytics, and deep learning (Chen et al. 2012; Gandomi and Haider 2015; Tan et al. 2015). In this context, quality management is a crucial accompanying process for every data analysis approach as the usage of incorrect data leads to wrong analytical results, which lead to wrong decisions and actions ("Garbage in, garbage out.") potentially affecting firm performance negatively (Hristova 2014). The objective of quality management is to achieve reliability, consistency, and dependability such that employees can use the data without further processing steps (Chatfield et al. 2015). Further, it is argued that machine learning and the ability to construct models that improve their performance with each data input should be used to leverage BDA efficiently and effectively (Yoo 2015). Summarizing the findings in the articles mentioned above, we posit **P3**: The higher the level of data processing and analyzing capabilities, the higher is the level of BDA adoption within an organization.

> ***Illustration P3:*** *"Faced by car data of each car we [...] had to build a Hadoop cluster enabling us to store and analyze each necessary data point. [...] [A crucial] step as we slowly understood in detail our [technology and analytics] challenges and matured with our capabilities for car data analysis." Product Owner Car Data #1*

Organization Context Concepts Affecting BDA Adoption

These four superordinate categories constitute the technology context*: (1) data-driven culture, (2) institutional factors, (3) competencies,* and *(4) data-to-decision process*. First, the data-driven culture within an organization successfully adopting BDA can be characterized by the beliefs of the company's workers, privacy, data collaboration/cooperation, decision-making, and leadership. A data-driven culture positively affects information processing capabilities (Cao and Duan 2014) as well as a company's ability to innovate products (Duan and Cao 2015). To receive benefits from the data-driven innovation BDA, managers and employees must approach this task with the appropriate mindset and beliefs (Constantiou and Kallinikos 2015). This appropriate mindset is that employees should use data as "fuel" for analysis and a critical success factor for firm performance (van der Aalst 2013; Boyd and Crawford 2012). Data sharing within the company and between other companies gains more and more relevance, as the recombination of diverse sets of data may provide useful insights into any organizational ecosystem (Chatfield et al. 2015). To have the ability to process, access and glean the insight from this data of various data owners (Miranda et al. 2015), internal collaboration across department boundaries and cooperation across organizations increase in importance. Particularly, the collaboration of IT and business departments plays an important role for BDA adoption as organizations ought to combine technology and domain knowledge (Miranda et al. 2015). Yet, the sharing of data including data collected from social media and the use of BDA itself has several ethical and privacy implications depending on the content of the data (Chatfield et al. 2015; Someh et al. 2016). Articles mentioning privacy focus on the combination of multiple data sets (Chatfield et al. 2015), leading to re-identification of individuals (van den Broek and van Veenstra 2015), the importance of protecting it (Chatfield et al. 2015) and the effects of theft, inappropriate use of data and consequently infringement of data privacy (van den Broek and van Veenstra 2015; Markus 2015; Tan et al. 2015). On an organizational level, BDA, as a strategic change initiative (Chatfield et al. 2015), provides the possibility to form big data-drawn insights into convincing arguments for managers and, thus, ultimately changes the dynamics of managerial decision-making (Bhimani 2015). The way in which information becomes available to decision-makers changes and, consequently, totally new insights can be leveraged (Woerner and Wixom 2015). Further, a data-driven culture will lead to new ideas and approaches that challenge and transform work routines and practices through the use of information (Duan and Cao 2015). The respective changes, initiated by these developments, need to be accommodated by organizational means such as change management (Chatfield et al. 2015). As leadership can support these changes and fosters the importance of the required changes in organizational mindset and practices, leadership is a necessary precondition for BDA adoption (Davenport 2014). Summarizing the above argumentations, we posit: ***P4**: The higher the degree of data-driven culture the higher is the level of BDA adoption.*

> ***Illustration P4:*** *"[To] achieve anything with big data analytics you need to consider the human aspect in your organizations. It requires a mindset of support for [this] technology-driven topic. [...] This is a journey we current are in and slowly learn on a daily basis [...] [also] in regard to collaborating intensively with our IT unit" Product Manager Analytics-as-a-Service*

Second, in consideration of the specific challenges that BDA imposes (e.g., analytical knowledge), new structures (e.g., analytical competence center, Chief Data Officer, or analytics subsidiaries) (Dremel, Herterich, Wulf, and Spottke 2017; Miranda et al. 2015; Schüritz et al. 2017), respective organizational governance (e.g., data governance) are implemented in organizations (Tan et al. 2015). At this juncture, data governance establishes a set of rules, such as the person who has the rights to define data standards and management indicators for data quality (Tan et al. 2015). Most importantly, data governance is about closing the gap between the current level of confidence in data and the necessary level of confidence for specific big data settings (Chatfield et al. 2015). A data governance model should be comprehensive, which means taking into consideration the following issues: privacy, data reuse, data accuracy, archiving and preservation, and development of data standards (Chatfield et al. 2015). Accordingly, organizational governance mechanisms such as structures and roles (e.g. Chief Data Officer, Data Scientist) have to be instantiated, ensuring the proper usage of big data and its potential (Miranda et al. 2015). Data scientists in collaboration with data engineers should be able to handle unstructured big data and to derive answers to an organization's key questions (Chatfield et al. 2015). Especially, when trying to monetize big data, a dedicated unit is supposed to be required to build up the necessary competencies (Woerner and Wixom 2015). Consequently, we posit: ***P5**: The higher the level of effective organizational governance (including data governance and the definition and allocation of structures and roles) the higher is the level of BDA adoption.*

> ***Illustration P5:*** *"In such a [competence center] everyone has specific responsibilities, [roles], and powers. [...] [Only if] everyone knows his role and is aligned with others IT, [our subsidiary], and our [analytics] unit we succeed." Product Owner Car Data #2*

Third, the literature suggests, that the development of specific BDA competencies (i.e., required skills and knowledge specific to big data analytics) is a major challenge for companies (Ghasemaghaei et al. 2016), especially those, who digitize their business models (McAfee and Brynjolfsson 2012). Skills in the area and intersections of technology, analytics and business have to be developed (Miranda et al. 2015) while a general knowledge of big data analytics is necessary for leadership and employees to implement successful big data initiatives (Chatfield et al. 2015). Due to the pervasive nature of BDA on decision-making organizations need be able to know how to act when decision-making processes become more and more automated, and the ability to intervene with those processes needs to be developed (Markus 2015). An organization needs to acquire or develop analytical capabilities and organization-specific technical capabilities e.g., concerning the effective deployment of big data within the current IT landscape (Chatfield et al. 2015; Miranda et al. 2015; Woerner and Wixom 2015). One approach is to invest in the training or recruiting of experts in data analysis, IT experts, and employees translating and mediating between business, IT and analytics departments (Dremel, Wulf, Annegret, and Brenner 2017; Ghoshal et al. 2014). Big data related knowledge helps organizations to understand the scenario of how big data analytics and its technologies as well as methods work while respective decision-makers in the organization need to have an understanding of the implications resulting from these new technologies to foster a positive effect for big data analytics while nurturing the previously discussed data-driven culture (Chatfield et al. 2015; Duan and Cao 2015). In summary, we posit: ***P6**: The higher the level of analytical competency the higher is the effect on the level of BDA adoption.*

> ***Illustration P6:*** *"It was clear that we must internalize knowledge. In the past, the IT department did not answer the questions of the […] sales division, [yet] the consultancies did […] We had to change in regards to experience and expertise both from the business side [but also beyond that] in regards to our analytical capabilities." Product Owner Analytical Services#3*

Fourth, BDA recursively shapes data-to-decision practices by enabling companies to answer questions that hitherto could not be answered (Bhimani 2015) and as, for instance, large data sets from social media give "a myriad of opportunities for monitoring and modeling people's intentions, preferences, and opinions" (Brynjolfsson et al. 2014, p. 1). Sense-making of data and subsequent decision-making is vital to make evidence-based decisions, otherwise data itself is useless (Chatfield et al. 2015; Ghasemaghaei et al. 2016; Trieu 2013). The formulation of a hypothesis is a possible starting point for every sense-making process and paves the way for how data needs to be collected, processed, analyzed (Tan et al. 2015), and most importantly be used for decision-making. BDA and the respective tied connection to machine learning (Kallinikos and Constantiou 2015) leads as a consequence to the automation of decision-making processes (Baesens et al. 2016; Markus 2015) of the investigation of markets (e.g. market manipulation) (Gregory and Muntermann 2014), of operational or strategic processes (Markus 2015), and, at last, to a deeper integration in value-creating decision-making processes (Loebbecke and Picot 2015; Saboo et al. 2016). At this juncture, an automated decision-making is characterized by a computerized knowledge-based process that is performed on its own without (Markus 2015) or at least with minimum human intervention to resolve inferences stemming from poor data quality (Clarke 2016). This automation not only has positive effects as it can also lead to labor substitution (Loebbecke and Picot 2015). However, there are other estimations that – through the new technology-driven business opportunities – more jobs will be augmented and/or created than replaced (Markus 2015). This increases the relevance of managing the risks in decision making and being sure that the decision made will have the positive effects predicted (Ghoshal et al. 2014). The replacement mostly results from the automation of the decision-making process itself as machines will in the future outpace human brains (Loebbecke and Picot 2015). Of course, this implies on the one hand cost reduction but on the other hand, ethical issues arise. In summary, we posit*: **P7**: Effective data-to-decision practices increase the level of BDA adoption.*

> ***Illustration P7:*** *"[By bringing] analytics step-by-step to your customers it is easier to achieve commitment […] in the organizations. [We] had to prove that it makes sense […] regarding its business value. […] our top management enforced reporting and informing leveraging our trusted data pool." Head of Data Analytics & Strategy*

Environment Context Concepts Affecting BDA Adoption

These two superordinate categories constitute the environment context: (1) *competitive advantage* and *(2) strategy making*. First, big data is supposed to have a significant impact on the way organizations nowadays react to trends in their fast-moving environment because of analytical analyses (Constantiou and Kallinikos 2015). As a result, the strategic toolbox is extended by BDA (Woerner and Wixom 2015). In markets with high competitive dynamics (e.g., Netflix with its video-on-demand service or Spotify with its music-on-demand service), BDA increased in importance, as it is a possible source of competitive advantage having an impact on firm performance e.g., through customization of products and new service offerings (Sodenkamp et al. 2015), and the entrance into new markets (Constantiou and Kallinikos 2015). Organization nowadays realize that they have to analyze big data to stay competitive (Olbrich 2014; Tiefenbacher and Olbrich 2015) in terms of profits and efficiency (Ghoshal et al. 2014), speed and service (van der Aalst 2013), and products

(Constantiou and Kallinikos 2015; Duan and Cao 2015; Markus 2015) through timely (Trieu 2013) and more wise decisions (Woerner and Wixom 2015). In conclusion, data-based decisions lead to better performing firms (Döppner et al. 2015). BDA can be seen as a solution for gaining better insights from different and diverse data sources (e.g., social media, wearables, RFID, and IoT) and uncovering patterns, unknown correlations or other information unknown hitherto within this data (Duan and Cao 2015). The economic potential of big data led to organizations in high competitive dynamics silently listening to user-generated content to optimize market research activities, and product and brand management (Egger et al. 2015; Stange and Funk 2015). In summary, we posit: ***P8**: The higher the level of competitive dynamics the higher is the level of BDA adoption.*

***Illustration P8:** "Companies like Tesla, Faraday Future, or new possible entrants like Google require us to respond to the trend of digitization and big data analytics. I think soon our car on its own will not suffice." Product Owner Car Data #1*

Second, BDA, as a strategic change initiative (Chatfield et al. 2015), provides the possibility of forming big data-drawn insights into convincing arguments for managers and thus ultimately changes the dynamics of managerial decision-making (Bhimani 2015). These better insights generated from the combination of data techniques and information across sources and applications contribute to the competitive *strategy* and can be used to develop new innovative products and services or enrich existing ones (Constantiou and Kallinikos 2015; Duan and Cao 2015). This relevance for competitive strategy resulted in the importance of BDA for C-level management (Olbrich 2014). They can enhance (Bhimani 2015) and renew strategies (Yoo 2015) used by companies and government. It is even possible to enable ad-hoc strategy making as the time horizon for analyses reduces dramatically (Constantiou and Kallinikos 2015), expand the strategic toolbox (Woerner and Wixom 2015), and enhance the flexibility of decision-making through technical advancements altering strategic core processes (Bhimani 2015). Following this argumentation, we posit: ***P9**: The higher the level of awareness of BDA potentials in an organization's competitive strategy, the higher is the level of BDA adoption."*

***Illustration P9:** "Digital transformation and data analytics have to be on top of our strategy and looked at as an invest topic instead of a cost-driven topic." Team Lead Strategy*

Discussion and Future Research Avenues

For some, the value of BDA appears to be unquestionable (Kimble and Milolidakis 2015). For others, it is unclear whether more data and faster, more intelligent analytics implies better products and decisions (Buhl et al. 2013). The results of our research suggest that value creation through BDA is not just rooted in technological capabilities, but equally in capabilities related to organizational design and environmental positioning. From a *technology* perspective, data inherently holds a self-contained value and the proper analysis of these data points determines the realizable value (Schermann et al. 2014). The extension of traditional data sources through big data sources may, for example, ensure the agility of a company regarding potential market disruption or change (Constantiou and Kallinikos 2015). There is evidence that it not only provides unprecedented insights into customers' buying behavior but also makes internal processes visible, enables better decision-making and leads to a partial replacement of human sense-making through machine learning (Kimble and Milolidakis 2015). Organizations that gain the ability to collect, store and analyze more accurate and detailed customer data may achieve superior mass customization of services and personalized marketing communications (Loebbecke and Picot 2015; Rust and Huang 2014). From an *environmental* perspective, BDA may profoundly transform business landscapes (Agrawal and Dhar 2014, Dhar et al. 2014). As a consequence, companies must adapt to their competitive environment and readily innovate business models with data-driven approaches (Agarwal and Dhar 2014; Loebbecke and Picot 2015). Though anecdotal evidence has been given for BDA benefits, their realization is by no means assured and the complex nature of organizational designs challenges the effective use of BDA (Chen et al. 2015). Despite first empirical insights (e.g., Dremel et al. 2020; Lehrer et al. 2018), it is largely unexplored how BDA can be used to generate business value in our complex world (Conboy et al. 2020) and through which routes value is realized (Constantiou and Kallinikos 2015; George et al. 2014; Günther et al. 2017; Kimble and Milolidakis 2015). Future research should, therefore, focus more closely on the mechanisms and complexities of industry transformation, value creation and realization related to BDA adoption: *How does BDA allow for digital innovation and business model innovation? How does BDA lead to a transformation of industries or emergence of new ecosystems? How does BDA affect value creation and realization?* Procedural perspectives, which acknowledge the nature of the BDA as a technology innovation as well as their potential recursive relationship with digital innovation, business model innovation, and the emergence and transformation of ecosystems, potentially help to unfold and unravel underlying mechanisms (e.g., Ancona 2001; Van De Ven and Poole 1995).

The vast amount of data requires a data-to-insight process to give decision-makers the possibility to use these insights to transform them into decisions (Sharma et al. 2014; Wamba et al. 2015). This process of value creation might be seen as an active and collaborative sense-making process of organizational participants (e.g. analyst and business manager) (Gandomi and Haider 2015; Hashem et al. 2015; Lycett 2013; Sharma et al. 2014; Woerner and Wixom 2015). The data-to-insight process comprises several steps. The steps include data acquisition, information extraction and cleaning, data integration, modeling and analysis and, at last, interpretation and deployment based on the respective information technologies, processes, and personnel (Abbasi et al. 2016; Jagadish et al. 2014; Wamba et al. 2015). The introduction of big data technologies poses novel and largely unanswered challenges in these steps (Chen and Zhang 2014; Hashem et al. 2015; McAfee and Brynjolfsson 2012). In this regard, creating value from big data requires more than just the application of analytical techniques (Sharma et al. 2014). However, many discussions of big data focus on only one or two steps, ignoring the rest (Jagadish et al. 2014). Data is not anymore collected, stored, and processed with a specific analytical goal but for the sake of the inherent value of data itself requiring effort to unravel the specifics of the required changes in data acquisition and collection (Constantiou and Kallinikos 2015; Yoo 2015). Through integration with other sources or new analytical methods, data may be variously used a posteriori (Constantiou and Kallinikos 2015). Besides that, organizations face the challenge of how to integrate the large amounts of unstructured and semi-structured data (e.g., user-generated content, tagging and other social media outputs) (Constantiou and Kallinikos 2015; Whelan et al. 2016). Machine learning algorithms offer the possibility to automate and improve the data-to-insight process (Sharma et al. 2014). While such technical approaches are certainly helpful, organizations still rely on individuals to determine which information is relevant (Whelan et al. 2016). We suggest that a process-theoretical perspective is required and formulate the following research question: *How is the data-to-insight process affected by the technical possibilities/affordances of BDA? How does BDA lead to a recursive change or imbrication of decision-making routines and practices?* The perspectives of Leonardi (2011, 2012) will allow researchers to consider how the material properties and material agency of BDA in the specific socio-technical context and the social/human agency of a decision-maker affects and alters underlying routines and practices.

After performing the data-to-insight process, the analytical models have to be deployed in a digestible manner and, subsequently, need to be transformed into decisions by managerial decision-makers (Sharma et al. 2014). The new amounts of data from social media, radio frequency identification tags, web clickstreams, consumer sentiments, and mobile provide further insights for managerial decision-making (Schermann et al. 2014). Instead of acting on reported data, decision-makers can now use automated suggestions (prescriptive analytics) or base their decisions on insights into the future, which are generated by the exploration of data (predictive analytics) (George et al. 2014). Consequently, human judgment is more and more replaced through automated processes and may, in the long run, lead to labor substitution, of which its consequences remain largely unclear (Constantiou and Kallinikos 2015; Kallinikos and Constantiou 2015; Kimble and Milolidakis 2015; Loebbecke and Picot 2015; Markus 2015). Already today, decision-makers have the possibility to use previously unknown information instead of their gut feeling (Woerner and Wixom 2015). As a result, decision-making processes need to change to harvest the ability to have a better picture of the future (Sharma et al. 2014). However, in order to achieve this, decision-makers need to develop trust and acceptance for the insights generated via algorithms such as machine learning to benefit from the potentially positive effects of analytics on managerial decision-making (Schermann et al. 2014; Sharma et al. 2014). This draws attention to the need for further research on the following research questions: *How does BDA influence decision-making behavior? Which factors influence managers' adoption of BDA at the individual level? How do trust factors of a BDA solution affect the decision-making behavior?* We suggest focusing on established streams in IS research such as trust while putting the individual at the focal point of analysis e.g., by integrating the 4Es of cognitive science.

Finally, Table 3 summarizes prospective research avenues including exemplary research questions as well as fruitful non-exclusive theoretical lenses and theories while delineating our propositions towards the focal and important context for future research. Following our argumentation throughout the article, every context will have a recursive effect and needs to acknowledge this while exploring these research avenues. As we argue, BDA affects and is affected by the organization as the organization shapes the material agency of technology and technology shapes the organizations' "social" agency (Orlikowski 2000).

Research Avenues and Exemplary Research Questions	**Promising Theoretic Lenses and Theories**	**Focal TOE Context and Propositions**
Digital innovation, business model innovation and industry transformation – How does BDA allow for digital innovation and business model innovation? – How does BDA lead to a transformation of industries and emergence of new ecosystems? – How does BDA affect value creation and realization?	– General System/Socio-Technical System Theory – Temporal (Complexity) Perspective – Sociomateriality and affordance theory – Cognitive Perspectives: Social Cognitive Theory Boundary Objects	*Technology Context:* P1: Data Exposure P3: Processing & Analyzing Capabilities *Organization Context:* P7: Data-to-Decision Process *Environment Context:* P8: Competitive Dynamics P9: Strategy
Change of decision-making process within work-practices and routines – How is the data-to-insight process affected by the technical possibilities of BDA? – How does BDA lead to a recursive change or imbrication of decision-making routines and practices?	– Organizational ambidexterity – Socio-materiality and affordance theory – Temporal (Complexity) Perspective – Cognitive Perspectives: Social Cognitive Theory Boundary Objects	*Technology Context:* P3: Processing & Analyzing Capabilities *Organization Context:* P4: Data-Driven Culture P5: Institutional Factors P6: Competencies P7: Data-to-Decision Process
Change of decision-making behavior and data-driven culture on individual level – How does BDA influence decision-making behavior? – Which factors influence managers' adoption of BDA at the individual level? – How do trust factors of a BDA solution affect the decision-making behavior?	– Administrative Behavior Theory – Behavioral Decision Theory – Attention-based View – Absorptive Capacity Theory Information Processing Theory – Cognitive Perspectives: 4Es	*Technology Context:* P3: Processing & Analyzing Capabilities *Organization Context:* P4: Data-Driven Culture P7: Data-to-Decision Process

Table 3. Research Topics, Fruitful Theoretic Lenses and Theories, and Focal TOE Context

The datafication of both our social and work life gives rise to several ethical issues of societal impact potentially accumulating into a 'surveillance capitalism' (Loebbecke and Picot 2015; Lycett 2013; Zuboff 2015). BDA provides new opportunities for collecting, integrating, and analyzing data of our increasing digital lives for companies while at some point in time requiring the purposeful consideration of inappropriate use of data or the infringement of data privacy and ethical standards (van den Broek and van Veenstra 2015; Markus 2015). In light of the generative nature of BDA, data themselves, and the digitized world BDA may even reinforce ethical and societal issues and thus enable unethical behavior (Loebbecke and Picot 2015; Yoo et al. 2012; Zuboff 2015). To allow for addressing these imminent issues the IS discipline will have to take a leading role in extending our current body of knowledge regarding BDA-related ethical intricacies.

Contribution and Limitation

By conducting a systematic literature review synthesizing past and current research on BDA adoption, we intend to contribute to both research and practice. Our contribution to research is threefold. First, there is no shared understanding of the term BDA in prior literature. We theoretically ground BDA in the technology innovation literature and synthesize prior definitions of the term BDA. Second, we use the TOE theory to identify and structure the antecedents of BDA adoption discussed in prior literature. Our proposition framework can guide further research that empirically analyzes the adoption of BDA in organizational settings. Third, we discuss open research issues and provide suggestions for future research that would enrich our knowledge in this domain. With the introduced TOE framework of contextual antecedents of BDA adoption, we also contribute to practice. Practitioners such as consultants, vendors, and organizations can use this framework to structure contextual factors that need to be considered to successfully manage the introduction of BDA in organizational settings. We believe that the key limitations are as follows. First, we limited our review on articles in the AIS Senior Scholars' basket and the two top-ranked conferences ECIS and

ICIS. While this strategy guarantees the retrieval of a representative set of high-quality articles, we cannot claim to generate an exhaustive view on the current state-of-the-art in BDA research. Second, we based our review and proposition development on the TOE framework and explained why this theoretical perspective enriches our understanding of BDA adoption. Alternative theoretical perspectives may further enrich these results. Third, in our review, we put the focus on the organizational level. An analysis of the adoption of BDA at other levels, such as the employee-level, requires further research efforts.

References

van der Aalst, W. 2013. "Mine Your Own Business": Using Process Mining to Turn Big Data into Real Value," in *Proceedings of the 21st European Conference on Information Systems*, Utrecht, The Netherlands.

Abbasi, A., Sarker, S., and Chiang, R. H. 2016. "Big Data Research in Information Systems: Toward an Inclusive Research Agenda," *Journal of the Association for Information Systems* (17:2).

Agarwal, R., and Dhar, V. 2014. "Editorial —Big Data, Data Science, and Analytics," *Information Systems Research* (25:3), pp. 443–448.

Alexander, D. T., and Lyytinen, K. 2019. "Organizing Around Big Data: Organizational Analytic Capabilities for Improved Performance," in *Proceedings of the 40th International Conference on Information Systems*, Munich, Germany.

Alfano, S., Feuerriegel, S., and Neumann, D. 2015. "Is News Sentiment More Than Just Noise?," in *Proceedings of the 23rd European Conference on Information Systems*, Münster, Germany.

Ancona, D. G. 2001. "Time: A New Research Lens," *Academy of Management Review* (26:4).

Antonacopoulou, E. P., and Sheaffer, Z. 2014. "Learning in Crisis: Rethinking the Relationship Between Organizational Learning and Crisis Management," *Journal of Management Inquiry* (23:1).

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., and Zhao, J. L. 2016. "Transformational Issues of Big Data and Analytics in Networked Business," *MIS Quarterly* (40:4).

Bhimani, A. 2015. "Exploring Big Data's Strategic Consequences," *Journal of Information Technology* (30:1), pp. 66–69.

Boldosova, V. 2019. "Deliberate Storytelling in Big Data Analytics Adoption.," *Information Systems Journal* (29:6), pp. 1126–1152.

Boyd, D., and Crawford, K. 2012. "Critical Questions for Big Data," *Information, Communication & Society* (15:5), pp. 662–679.

Bremser, C. 2018. "STARTING POINTS FOR BIG DATA ADOPTION," in *Proceedings of the 26th European Conference on Information Systems*, Portsmouth, UK.

vom Brocke, J., Simons, A., Riemer, K., Niehaves, B., Plattfaut, R., and Cleven, A. 2015. "Standing on the Shoulders of Giants: Challenges and Recommendations of Literature Search in Information Systems Research," *Communications of the Association for Information Systems* (37:1).

van den Broek, T., and van Veenstra, A. F. 2015. "Modes of Governance in Inter-Organizational Data Collaborations," in *Proceedings of the 24th European Conference of Information Systems*, Münster, Germany.

Brynjolfsson, E., Geva, T., and Reichman, S. 2014. "Using Crowd-Based Data Selection to Improve the Predictive Power of Search Trend Data," in *Proceedings of the 35th International Conference on Information Systems,* Auckland, New Zealand.

Brynjolfsson, E., Hitt, L., and Kim, H. 2011. "Strength in Numbers: How Does Data-Driven Decision-Making Affect Firm Performance?," in *Proceedings of the 32nd International Conference on Information Systems*, Shanghai, China.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N., and Trench, M. 2017. "Artificial Intelligence: The next Digital Frontier," *McKinsey Global Institute*, pp. 1–80.

Buhl, H. U., Röglinger, M., Moser, F., and Heidemann, J. 2013. "Big Data: A Fashionable Topic with(out) Sustainable Relevance for Research and Practice?," *Business & Information Systems Engineering* (5:2).

Cao, G., and Duan, Y. 2014. "A Path Model Linking Business Analytics, Data-Driven Culture, and Competitive Advantage," in *Proceedings of the 22nd European Conference on Information Systems*, Tel Aviv, Israel.

Charoenpanich, A. L. S. of E. and P. S., and Aaltonen, A. B. S. 2015. "(How) Does Data-Based Music Discovery Work?," in *Proceedings of the 24th European Conference of Information Systems*, Münster, Germany.

Chatfield, A., Reddick, C., and Al-Zubaidi, W. 2015. "Capability Challenges in Transforming Government through Open and Big Data: Tales of Two Cities," in *Proceedings of the 36th International Conference on Information Systems*, Fort Worth, USA.

Chen, C. P., and Zhang, C.-Y. 2014. "Data-Intensive Applications, Challenges, Techniques and Technologies: A Survey on Big Data," *Information Sciences* (275), pp. 314–347.

Chen, D. Q., Preston, D. S., and Swink, M. 2015. "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management," *Journal of Management Information Systems* (32:4), pp. 4–39.

Chen, H., Chiang, R. H. L., and Storey, V. C. 2012. "Business Intelligence and Analytics: From Big Data to Big Impact," *MIS Quarterly* (36:4), pp. 1165–1188.

Chiasson, M., Davidson, E., and Winter, J. 2018. "Philosophical Foundations for Informing the Future(S) through IS Research.," *European Journal of Information Systems* (27:3), pp. 367–379.

Clarke, R. 2016. "Big Data, Big Risks," *Information Systems Journal* (26:1), pp. 77–90.

Colville, I., Pye, A., and Carter, M. 2013. "Organizing to Counter Terrorism: Sensemaking amidst Dynamic Complexity," *Human Relations* (66:9), pp. 1201–1223.

Conboy, K., D. Dennehy and M. O'Connor 2020. "'Big time': An examination of temporal complexity and business value in analytics." *Information & Management* (57:1).

Constantiou, I. D., and Kallinikos, J. 2015. "New Games, New Rules: Big Data and the Changing Context of Strategy," *Journal of Information Technology* (30:1), pp. 44–57.

Corbin, J., and Strauss, A. 2014. Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory, Sage publications.

Davenport, T. 2014. Big Data @ Work: Dispelling the Myths, Uncovering the Opportunities, Harvard Business Review Press.

Depietro, R., Wiarda, E., and Fleischer, M. 1990. "The Context for Change: Organization, Technology and Environment," in *Processes of Technological Innovation* (Vol. 199), Lexington Books.

Döppner, D. A., Schoder, D., and Siejka, H. 2015. „Big Data and the Data Value Chain: Translating Insights from Business Analytics into Actionable Results-The Case of Unit Load Device (ULD) Management in the Air Cargo Industry", in *Proceedings of the 23rd European Conference on Information Systems*, Münster, Germany.

Dremel, C., Herterich, M. M., Wulf, J., and vom Brocke, J. 2020. "Actualizing Big Data Analytics Affordances: A Revelatory Case Study," *Information & Management* (57:1).

Dremel, C., Herterich, M., Wulf, J., and Spottke, B. 2017. "Actualizing Affordances: A Socio-Technical Perspective on Big Data Analytics in the Automotive Sector," in *Proceedings of the 37th International Conference on Information Systems*, Seoul, South Korea.

Dremel, C., Herterich, M., Wulf, J., Waizmann, J.-C., and Brenner, W. 2017. "How AUDI AG Established Big Data Analytics in Its Digital Transformation*," MIS Quarterly Executive* (16:2), pp. 81–100.

Dremel, C., Stoeckli, E., and Wulf, J. 2020. "Management of Analytics-as-a-Service - Results from an Action Design Research Project," *Journal of Business Analytics*, pp. 1–16.

Dremel, C., Wulf, J., Annegret, M., and Brenner, W. 2017. "Understanding the Value and Organizational Implications of Big Data Analytics? The Case of AUDI AG," in *Proceedings of the 37th International Conference on Information Systems*, Seoul, South Korea.

Duan, Y., and Cao, G. 2015. "Understanding the Impact of Business Analytics on Innovation," in *Proceedings of the 23rd European Conference on Information Systems*, Münster, Germany.

Egger, M., Lang, A., and Schoder, D. 2015. "Who Are We Listening to? Detecting User-Generated Content (UGC) on the Web," in *Proceedings of the 24th European Conference of Information Systems*, Münster, Germany.

Forman, J., and Damschroder, L. 2007. "Qualitative Content Analysis," in Empirical Methods for Bioethics: A Primer (Vol. 11), Advances in Bioethics, L. Jacoby and L. A. Siminoff (eds.), Emerald Group Publishing Limited, pp. 39–62.

Gandomi, A., and Haider, M. 2015. "Beyond the Hype: Big Data Concepts, Methods, and Analytics," *International Journal of Information Management* (35:2), pp. 137–144.

George, G., Haas, M. R., and Pentland, A. 2014. "Big Data and Management," *Academy of Management Journal* (57:2), pp. 321–326.

Ghasemaghaei, M., Ebrahimi, S., and Hassanein, K. 2016. "Generating Valuable Insights through Data Analytics: A Moderating Effects Model," in *Proceedings of the 36th International Conference on Information Systems*, Fort Worth, USA.

Ghasemaghaei, M., Ebrahimi, S., and Hassanein, K. 2018. "Data Analytics Competency for Improving Firm Decision Making Performance," *The Journal of Strategic Information Systems* (27:1), pp. 101–113.

Ghoshal, A., Larson, E., Subramanyam, R., and Shaw, M. 2014. “The Impact of Business Analytics Strategy on Social, Mobile, and Cloud Computing Adoption,” in *Proceedings of the 35th International Conference on Information Systems*, Auckland, USA.
Goes, P. 2014. “Editor’s Comments: Big Data and IS Research,” *Management Information Systems Quarterly* (38:3), pp. iii–viii.
Gölzer, P., Cato, P., and Amberg, M. 2015. “Data Processing Requirements of Industry 4.0 - Use Cases for Big Data Applications,” in *Proceedings of the 23rd European Conference on Information Systems*, Münster, Germany.
Gregory, R. W., and Muntermann, J. 2014. “Research Note —Heuristic Theorizing,” *Information Systems Research* (25:3), pp. 639–653.
Grover, V., Chiang, R. H. L., Liang, T.-P., and Zhang, D. 2018. “Creating Strategic Business Value from Big Data Analytics: A Research Framework,” *Journal of Management Information Systems* (35:2).
Günther, W. A., Mehrizi, M. H., Huysman, M., and Feldberg, F. 2017. “Debating Big Data: A Literature Review on Realizing Value from Big Data,” *The Journal of Strategic Information Systems* (26:3).
Günther, W., Mehrizi, M. H. R., Huysman, M., and Feldberg, F. 2017. “Rushing for Gold: Tensions in Creating and Appropriating Value from Big Data,” in *Proceedings of the 37th International Conference on Information Systems*, Seoul, South Korea.
Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., and Ullah Khan, S. 2015. “The Rise of ‘Big Data’ on Cloud Computing,” *Information Systems* (47), pp. 98–115.
Heinrich, B., and Hristova, D. 2014. “A Fuzzy Metric for Currency in the Context of Big Data,” in *Proceedings of the 22nd European Conference on Information Systems*, Tel Aviv, Israel.
Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., and Sethupathy, G. 2016. “The Age of Analytics: Competing in a Data-Driven World,” http://www.mckinsey.Com/business-functions/Mckinsey-Analytics/Our-Insights/the-Age-of-Analytics-Competing-in-a-Data-Driven-World. (accessed December 8, 2019).
Hristova, D. 2014. “Considering Currency in Decision Trees in the Context of Big Data,” in *Proceedings of the 35th International Conference on Information Systems*, Auckland, USA.
Jacobs, A. 2009. “The Pathologies of Big Data,” *Communications of the ACM* (52:8), pp. 36–44.
Jagadish, H. V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J. M., Ramakrishnan, R., and Shahabi, C. 2014. “Big Data and Its Technical Challenges,” *Communications of the ACM* (57:7), pp. 86–94.
Jensen, M. H., Nielsen, P. A., and Persson, J. S. 2019. “MANAGING BIG DATA ANALYTICS PROJECTS: THE CHALLENGES OF REALIZING VALUE,” in *Proceedings of the 27th European Conference on Information Systems*, in *Proceedings of the 27th European Conference on Information Systems,* Stockholm-Uppsala, Sweden.
Jones, M. 2019. “What We Talk about When We Talk about (Big) Data,” *The Journal of Strategic Information Systems* (28:1), pp. 3–16.
Kallinikos, J., and Constantiou, I. D. 2015. “Big Data Revisited: A Rejoinder,” *Journal of Information Technology* (30:1), pp. 70–74.
Kimble, C., and Milolidakis, G. 2015. “Big Data and Business Intelligence: Debunking the Myths,” *Global Business and Organizational Excellence* (35:1), pp. 23–34.
Kitchens, B., Dobolyi, D., Li, J., and Abbasi, A. 2018. “Advanced Customer Analytics: Strategic Value Through Integration of Relationship-Oriented Big Data.,” *Journal of Management Information Systems* (35:2), pp. 540–574.
Kuan, K. K. Y., and Chau, P. Y. K. 2001. “A Perception-Based Model for EDI Adoption in Small Businesses Using a Technology–Organization–Environment Framework,” *Information & Management* (38:8), pp. 507–521
Lee, C.-P., and Shim, J. P. 2007. “An Exploratory Study of Radio Frequency Identification (RFID) Adoption in the Healthcare Industry,” *European Journal of Information Systems* (16:6), pp. 712–724.
Lehrer, C., Wieneke, A., Vom Brocke, J., Jung, R., and Seidel, S. 2018. “How Big Data Analytics Enables Service Innovation,” *Journal of Strategic Information Systems* (35:2).
Loebbecke, C., and Picot, A. 2015. “Reflections on Societal and Business Model Transformation Arising from Digitization and Big Data Analytics: A Research Agenda,” *The Journal of Strategic Information Systems* (24:3), pp. 149–157.
Luhmann, N. 2015. Soziale Systeme: Grundriß einer allgemeinen Theorie, (16. Auflage.), Suhrkamp-Taschenbuch Wissenschaft, Frankfurt am Main: Suhrkamp.
Lycett, M. 2013. “‘Datafication’: Making Sense of (Big) Data in a Complex World,” *European Journal of Information Systems* (22:4), pp. 381–386.

Markus, M. L. 2015. “New Games, New Rules, New Scoreboards,” *Journal of Information Technology* (30:1), pp. 58–59.

Marton, A., Avital, M., and Jensen, T. B. 2013. “Reframing Open Big Data,” in *Proceedings of the 21st European Conference on Information Systems*, Utrecht, The Netherlands.

McAfee, A., and Brynjolfsson, E. 2012. “Big Data. The Management Revolution,” *Harvard Business Review* (90:10), pp. 61–67.

Mikalef, P., Boura, M., Lekakos, G., and Krogstie, J. 2018. “COMPLEMENTARITIES BETWEEN INFORMATION GOVERNANCE AND BIG DATA ANALYTICS CAPABILITIES,” in *Proceedings of the 26th European Conference on Information Systems*, Portsmouth, UK.

Mikalef, P., Pappas, I. O., Krogstie, J., and Giannakos, M. 2017. “Big Data Analytics Capabilities: A Systematic Literature Review and Research Agenda,” *Information Systems and E-Business Management*.

Miranda, S., Kim, I., and Wang, D. D. 2015. “Whose Talk Is Walked? IT Decentralizability, Vendor versus Adopter Discourse, and the Diffusion of Social Media versus Big Data,” in *Proceedings of the 36th International Conference on Information Systems*, Fort Worth, USA.

Müller, O., Fay, M., and vom Brocke, J. 2018. “The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics,” *Journal of Management Information Systems* (35:2), pp. 488–509.

Müller, O., Junglas, I., Brocke, vom J., and Debortoli, S. 2016. “Utilizing Big Data Analytics for Information Systems Research: Challenges, Promises and Guidelines,” *European Journal of Information Systems* (25:4), pp. 289–302.

Olbrich, S. 2014. “Madness of the Crowd - How Big Data Creates Emotional Markets and What Can Be Done to Control Behavioural Risk,” in *Proceedings of the 21st European Conference on Information Systems*, Tel Aviv, Israel.

Orlikowski, W. J. 2000. “Using Technology and Constituting Structures: A Practice Lens for Studying Technology in Organizations,” *Organization Science* (11:4), pp. 404–428.

Pare, G., Trudel, M.-C., Jaana, M., and Kitsiou, S. 2015. “Synthesizing Information Systems Knowledge: A Typology of Literature Reviews,” *Information & Management* (52:2), pp. 183–199.

Panicker, R. 2013. “Adoption of Big Data Technology for the Development of Developing Countries,” in Proceedings of the National Conference on New Horizons in IT-NCNHIT, (http://www.conference.bonfring.org/papers/met_ncnhit2013/ncnhit49.pdf).

Rai, A. 2016. “Editor’s Comments,” *MIS Quarterly*, pp. iii–xi.

Ram, S., Wang, Y., Currim, F., and Currim, S. 2015. “Using Big Data for Predicting Freshmen Retention,” in *Proceedings of the 36th International Conference on Information Systems*, Fort Worth, USA.

Richards, N. M., and King, J. H. 2014. “Big Data Ethics,” *Wake Forest Law Review* (49), pp. 393–432.

Rogers, E. M. 1983. Diffusion of Innovations, 3rd Ed., Free Press of Glencoe.

Roth, S. 2009. “New for Whom? Initial Images from the Social Dimension of Innovation,” International *Journal of Innovation and Sustainable Development* (4:4).

Rowe, F. 2014. “What Literature Review Is Not,” *European Journal of Information Systems* (23:3).

Rust, R. T., and Huang, M.-H. 2014. “The Service Revolution and the Transformation of Marketing Science,” *Marketing Science* (33:2), pp. 206–221.

Saboo, A. R., Kumar, V., and Park, I. 2016. “Using Big Data to Model Time-Varying Effects for Marketing Resource (Re)Allocation,” *MIS Quarterly* (40:4), pp. 911–940.

Sagiroglu, S., and Sinanc, D. 2013. “Big Data: A Review,” in *2013 International Conference on Collaboration Technologies and Systems (CTS)*, San Diego, USA.

Salleh, A. K., Janczewski, L., and Beltran, F. 2015. “SEC-TOE Framework: Exploring Security Determinants in Big Data Solutions Adoption,” in *Proceedings of the 19th Pacific Asia Conference on Information Systems*, Singapore.

Schermann, M., Hemsen, H., Buchmüller, C., Bitter, T., Krcmar, H., Markl, V., and Hoeren, T. 2014. “Big Data: An Interdisciplinary Opportunity for Information Systems Research,” *Business & Information Systems Engineering (*6:5), pp. 261–266.

Schüritz, R., Brand, E., Satzger, G., and Bischhoffshausen, J. 2017. “HOW TO CULTIVATE ANALYTICS CAPABILITIES WITHIN AN ORGANIZATION? – DESIGN AND TYPES OF ANALYTICS COMPETENCY CENTERS,” in *Proceedings of the 25th European Conference on Information Systems*, Guimarães, Portugal.

Sharma, R., Mithas, S., and Kankanhalli, A. 2014. “Transforming Decision-Making Processes: A Research Agenda for Understanding the Impact of Business Analytics on Organisations,” *European Journal of Information Systems* (23:4), pp. 433–441.

Sodenkamp, M., Kozlovskiy, I., and Staake, T. 2015. "Gaining IS Business Value through Big Data Analytics: A Case Study of the Energy Sector," in *Proceedings of the 36th International Conference on Information Systems*, Fort Worth, USA.

Someh, I. A., Breidbach, C., and Davern, M. 2016. "ETHICAL IMPLICATIONS OF BIG DATA ANALYTICS," in *Proceedings of the 24th European Conference of Information Systems*, Istanbul, Turkey.

Stange, M. U. L., and Funk, B. U. L. 2015. "How Much Tracking Is Necessary? - The Learning Curve in Bayesian User Journey Analysis," in *Proceedings of the 23rd European Conference on Information Systems*, Münster, Germany.

Tallon, P. P. 2013. "Corporate Governance of Big Data: Perspectives on Value, Risk, and Cost," *Computer* (46:6), pp. 32–38.

Tan, C., Sun, L., and Liu, K. 2015. "Big Data Architecture for Pervasive Healthcare: A Literature Review," in *Proceedings of the 23rd European Conference on Information Systems*, Münster, Germany.

Tiefenbacher, K., and Olbrich, S. 2015. "Increasing the Level of Customer Orientation-A Big Data Case Study from Insurance Industry," in *Proceedings of the 23rd European Conference on Information Systems*, Münster, Germany.

Tiefenbacher, K., and Olbrich, S. 2017. "Applying Big Data-Driven Business Work Schemes to Increase Customer Intimacy," in *Proceedings of the 37th International Conference on Information Systems*, Seoul, South Korea.

Trieu, T. 2013. "Extending the Theory of Effective Use: The Impact of Enterprise Architecture Maturity Stages on the Effective Use of Business Intelligence Systems," in *Proceedings of the 34th International Conference on Information Systems*, Milan, Italy.

Van De Ven, A. H., and Poole, M. S. 1995. "Explaining Development and Change in Organizations," *Academy of Management Review* (20:3), pp. 510–540.

Wamba, S. F., Akter, S., Edwards, A., Chopin, G., and Gnanzou, D. 2015. "How 'Big Data' Can Make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study," *International Journal of Production Economics* (165), pp. 234–246.

Wang, Y., Kung, L., Wang, C., Yu, W., and Cegielski, C. 2014. "Developing a Big Data-Enabled Transformation Model in Healthcare: A Practice Based View," in *Proceedings of the 35th International Conference on Information Systems*, Auckland, USA.

Webster, J., and Watson, R. T. 2002. "Analyzing the Past to Prepare for the Future: Writing a Literature Review," *MIS Quarterly* (26:2), pp. xiii–xxiii.

Westerman, G., Tannou, M., Bonnet, D., Ferraris, P., and McAfee, A. 2012. "The Digital Advantage: How Digital Leaders Outperform Their Peers in Every Industry," *MIT Sloan Management and Capgemini Consulting*, MA, pp. 2–23.

Whelan, E., Teigland, R., Vaast, E., and Butler, B. 2016. "Expanding the Horizons of Digital Social Networks: Mixing Big Trace Datasets with Qualitative Approaches," *Information and Organization* (26:1–2).

Whittington, R. 2014. "Information Systems Strategy and Strategy-as-Practice: A Joint Agenda," *The Journal of Strategic Information Systems* (23:1), pp. 87–91.

Wiener, M., Saunders, C., and Marabelli, M. 2020. "Big-Data Business Models: A Critical Literature Review and Multiperspective Research Framework," *Journal of Information Technology* (35:1), pp. 66–91.

Woerner, S., and Wixom, B. H. 2015. "Big Data: Extending the Business Strategy Toolbox," *Journal of Information Technology* (30:1), pp. 60–62.

Yoo, Y. 2015. "It Is Not about Size," *Journal of Information Technology* (30:1), pp. 63–65.

Yoo, Y., Richard J. Boland, J., Lyytinen, K., and Majchrzak, A. 2012. "Organizing for Innovation in the Digitized World," *Organization Science* (23:5), pp. 1398–1408.

Zhang, W., Lau, R., and Li, C. 2014. "Adaptive Big Data Analytics for Deceptive Review Detection in Online Social Media," in *Proceedings of the 35th International Conference on Information Systems*, Auckland, USA.

Zhu, K., and Kraemer, K. L. 2005. "Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry," *Information Systems Research* (16:1), pp. 61–84.

Zuboff, S. 2015. "Big Other: Surveillance Capitalism and the Prospects of an Information Civilization," *Journal of Information Technology* (30:1), SAGE Publications Ltd, pp. 75–89.