Data as Strategic Resources

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Appendices

Chapter 2 Appendix

Table A.2.1 Details of the systematic search process.

Outlet	Search strategy	Included articles
European Journal of Information Systems (EJIS)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016 **Database:** Palgrave McMillan **Keywords:** Full Text for “big data” **Time span:** 2015 – April 2016	2
Information Systems Journal (ISJ)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016 **Database:** Wiley **Keywords:** All fields for “big data” **Time span:** 2015 – April 2016	4
Information Systems Research (ISR)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016 **Database:** Informs **Keywords:** Anywhere for “big data” **Time span:** 2015 – April 2016	0
Journal of the Association for Information Systems (JAIS)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016 **Database:** AISeL **Keywords:** All Fields for “big data” **Time span:** 2015 – April 2016	1
Journal of Information Technology (JIT)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016 **Database:** Sciencedirect **Keywords:** All Fields for “big data” **Time span:** 2015 – April 2016	8
Journal of Management Information Systems (JMIS)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016	2

	Database: JMIS website keyword index **Keywords:** “big data” **Time span:** 2015 – April 2016	
Journal of Strategic Information Systems (JSIS)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016 **Database:** Sciencedirect **Keywords:** All Fields for “big data” **Time span:** 2015 – April 2016	2
Management Information Systems Quarterly (MISQ)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016 In April 2016, we used the journal's website to search for “big data” in the title and abstract, browsed a forthcoming special issue on big data, and considered editorial statements.	0
Americas Conference on Information Systems (AMCIS)	**Database:** AISeL **Keywords:** Abstract, Title, Subject for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** January 2012 – December 2015	18
European Conference on Information Systems (ECIS)	**Database:** AISeL **Keywords:** Abstract, Title, Subject for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** January 2012 – December 2015	6
International Conference on Information Systems (ICIS)	**Database:** AISeL **Keywords:** Abstract, Title, Subject for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** January 2012 – December 2015	9
Big Data & Society (BD&S)	**Database:** Journal website (SAGE journals), archive of all content **Time span:** 2000 – March 2016	6
Communications of the Association for Computer Machinery (CACM)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016	3
Decision Support Systems (DSS)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016	2
Journal of the Association for Information Science and Technology/Journal of the American Society for Information Science and Technology (JASIST)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – February 2016	1

Academy of Management Journal (AMJ)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	0
Academy of Management Review (AMR)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	0
Information & Management (I&M)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	1
Information & Organization (I&O)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	0
Journal of Management (JOM)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	0
Journal of Management Studies	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	0
Management Science (MS)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	1
Organization Science (OrgSc)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	0
Organization Studies (OrgSt)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	0
Strategic Management Journal (SMJ)	**Database:** Web of Science **Keywords:** TOPIC for “big data”, “data driven”, “business analy*”, or “business intelligence” **Time span:** 2000 – April 2016	0
Communications of the Association for Information Systems (CAIS)	**No search. Gillon et al. (2014) started as a Panel at ICIS 2012, but was published in CAIS in 2014. We decided to include this paper.*	*1*

Table A.2.2 Summary of papers excluded from the literature review.

Excluded	Rationale	Examples of papers excluded
Inherently technical papers focusing on, for example, the design of big data algorithms, tools, frameworks, methods, systems, applications, and concepts.	Whereas they propose valuable big data artifacts, and may consider their implications for organizations, the focus is not on the process through which these artifacts deliver value.	(e.g., Brynjolfsson et al., 2016; Engel et al., 2014; Li & Kauffman, 2012; Martens et al., 2016; Sodenkamp et al., 2015)
Papers focusing on the implications of big data analytics for specific fields (e.g., research, theory, science, and education), specific practices and professions (e.g., journalism), and non-organizational entities (e.g., individuals, users, consumers, communities, and society).	Although interesting in terms of, for example, how we should educate for and study (the use of) big data, and how its use may impact professions or society, they often do not explicitly provide insight into how organizations try to realize value.	(e.g., Agarwal & Dhar, 2014; Arnott & Pervan, 2014; Chen et al., 2012; Couldry & Powell, 2014; Dal Zotto et al., 2015; George et al., 2014; Goes, 2014; Müller et al., 2016; Triche et al., 2015; Wang, 2015)
Papers focusing on the history, definition, and characterization of big data (analytics), or that identify predominant research areas and research trends around the topic.	These papers generally try to define big data, classify it, and position it within a research field. Although useful, this is not in line with our focus on big data value realization by organizations in practice.	(e.g., Dalton & Thatcher, 2015; Kitchin & McArdle, 2016; Luftman et al., 2015; Pospiech & Felden, 2012; Zafeiropoulou et al., 2015)
Papers **not** mentioning "big data" in the title, abstract, keywords, or body of the paper while studying data analytics systems within an organizational context.	We purposefully applied this criteria to unravel the hype around the term and set it apart from more "traditional" systems.	(e.g., Kowalczyk & Buxmann, 2015; Malladi & Krishnan, 2013; McCormack & Trkman, 2012; Shanks & Bekmamedova, 2013; Someh & Shanks, 2015)

Table A.2.3 Review framework.

Core idea of the paper	What is the core research question of the paper? What are the goals of the paper?
BDA conceptualization	How does the study conceptualize big data? What do the authors mean by big data? Do they provide any definition? Do they discuss any characteristics of big data? What seems unique to big data as opposed to traditional data (analytics)?
Method	Is it an empirical paper? Is it qualitative or quantitative? How did the authors go about data collection and analysis? Which empirical setting (industry/company…) do they focus on? How much data do they capture (e.g., single case, multiple cases? Sample size…) What data analysis methods have been used?
IT artifact	Which specific information technology has been considered (e.g., a database or a software or a platform, etc.) and especially, what specific characteristics of the IT artifact have been related to big data?
Business relation	What are the organizational changes, discussions, drivers, and actions that are discussed in relation to big data? What specific connection does the paper make between big data on one hand, and organizations on the other hand? For each proposed relation, how much empirical evidence is provided?
Theories	What theories have been used by the authors to substantiate their research?
Limitations & future research	What are the limitations of the article that the authors indicate? What are the limitations of the article that you can add to the above list? What suggestions for future research can be proposed?
Practical implications	What are the practical implications of the results that the authors indicate?

Table A.2.4 Reviewed papers from the "basket of eight" journals and IS conferences.

Outlet	N	Reference	Summary
EJIS	1	Lycett, M, 2013, 'Datafication': making sense of (big) data in a complex world. European Journal of Information Systems, 22(4), 381–386.	Lycett elaborates on "datafication" as a value creating logic. He uses Netflix as an illustration of a business model datafied through dematerialization, liquification, and density manifestation. He elaborates on datafication as a sensemaking process.
	2	Sharma, R., Mithas, S., & 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), 433–441.	Sharma et al. question how business analytics leads to value through three stages: from data to insight, from insight to decision, and from decision to value. They elaborate on and theorize about each of the stages, and propose a research agenda.
ISJ	3	Clarke, R, 2016. Big data, big risks. Information Systems Journal, 26(1), 77–90.	"This paper addresses the question of what risks arise from inadequate attention to quality factors in big data and big data analytics" (p. 78). Clarke presents different scenarios to explain these risks. Clarke provides story lines based on real-world experience. He himself calls them "quasi-empirical".
	4	Greenaway, K. E., Chan, Y. E., & Robert, E. C, 2015. Company information privacy orientation: A conceptual framework. Information Systems Journal, 25(6), 579–606.	Greenaway et al. look at how organizations respond to ethical, information management, and legal concerns of customers. They identify four orientations to deal with privacy: privacy ignorers, privacy minimisers, privacy balancers, and privacy differentiators.
	5	Seddon, P. B., Constantinidis, D., Tamm, T., & Dod, H, 2017. How does business analytics contribute to business value?. Information Systems Journal, 27(3), 237–269.	Seddon et al. present and preliminary assess a model (business analytics success model) on factors explaining how business analytics leads to business value. The model combines a process view and a variance model. They coded for concepts in a number of (randomly) selected success stories from business intelligence vendor websites, focused on the use of business analytics.
	6	Shollo, A., & Galliers, R, 2015. Towards an understanding of the role of business intelligence systems in organizational knowing. Information Systems Journal, 26(5), 339-367.	Shollo and Galliers focus on how business intelligence mediates knowing in organizations, in terms of new distinctions, emergence of organizational knowledge, and organizational actions. They find that business intelligence systems trigger cyclical processes of data selection and articulation. They performed a single, interpretive case study at a Scandinavian financial institution using business intelligence tools. They conducted interviews, collected background information, and made field notes.
JAIS	7	Abbasi, A., Sarker, S., & Chiang, R. H. K, 2016. Big data research in information systems: Toward an inclusive research agenda. Journal of the Association for Information Systems, 17(2), i–xxxii.	Abbasi et al. theorize on big data's uniqueness and how this disrupts the notion of the information value chain. Subsequently, they discuss challenges and provide avenues for future IS studies in behavioral IS research, design science research, and economics of IS.

JIT	8	Aaltonen, A., & Tempini, N, 2014. Everything counts in large amounts: a critical realist case study on data-based production. Journal of Information technology, 29(1), 97–110.	Aaltonen and Tempini provide case evidence for three nested mechanisms through which an advertising audience can be developed from network data: semantic closure, pattern-finding, and framing. The mechanisms were found through a single qualitative case study at a mobile network operator, using a critical realism lens.
	9	Bhimani, A, 2015. Exploring big data's strategic consequences. Journal of Information Technology, 30(1), 66–69.	A commentary on Constantiou & Kallinikos (2015): "considers aspects of strategy process consequences of big data deployment" (p. 66). Bhimani also briefly considers how big data redefines relations within organizations (e.g., power and authority), and between organizations and their environments.
	10	Constantiou, I. D., & Kallinikos, J, 2015. New games, new rules: Big data and the changing context of strategy. Journal of Information Technology, 30(1), 44–57.	Constantiou and Kallinikos theorize how big data may change existing strategy contexts. They argue that the big data strategic context is manifested through heterogeneous, less structured, agnostic, and trans-semiotic data, as well as inductive, short-term, and now-casting approaches.
	11	Kallinikos, J., & Constantiou, I. D, 2015. Big data revisited: A rejoinder. Journal of Information Technology 30(1), 70–74.	A commentary: "elaborate on key issues of our paper New games, new rules: big data and the changing context of strategy as a means of addressing some of the concerns raised by the paper's commentators" (p. 70).
	12	Markus, M. L, 2015. New games, new rules, new scoreboards: the potential consequences of big data. Journal of Information Technology, 30(1), 58–59.	A commentary on Constantiou & Kallinikos (2015): Markus discusses the negative consequences of big data, e.g., privacy issues and the implications of automation.
	13	Woerner, S. L., & Wixom, B. H, 2015 Big data: Extending the business strategy toolbox. Journal of Information Technology, 30(1), 60–62.	A commentary on Constantiou & Kallinikos (2015): Woerner and Wixom argue that big data optimizes organizational processes and decision making through new data, new insights and new action. They discuss two approaches to generate data-driven revenue: data monetization and digital transformation, as studied by MIT CISR.
	14	Yoo, Y, 2015. It is not about size: A further thought on big data. Journal of Information Technology, 30(1), 63–65.	A commentary on Constantiou & Kallinikos (2015): Yoo emphasizes big data's un-purposefulness and sociality. He considers the boundaries of the conceptualization by Constantiou & Kallinikos (2015) and extends big data' attributes with granularity and performativity. He proposes a new method for social inquiry.
	15	Zuboff, S, 2015. Big other: Surveillance capitalism and the prospects of an information civilization. Journal of Information Technology, 30(1), 75–89.	Zuboff uses Google as a lens to consider Varian's (2010, 2014) notions of data extraction and analysis, monitoring and contracting, personalization and communication, and continuous experimentation. She defines surveillance capitalism as a new logic of accumulation, brought about by e.g., formal indifference, privacy rights, un-contracting, lack of trust, and behavior modification.

JMIS	16	Tallon, P. P., Ramirez, R. V., & Short, J. E., 2013–14. The information artifact in IT governance: Toward a theory of information governance. Journal of Management Information Systems 30(3), 141–177.	Tallon et al. extend IT governance theories by focusing on information governance. They found empirical evidence for antecedents (enablers and inhibitors) to information governance, information governance practices (structural, procedural, and relational), and performance effects of information governance (firm performance and risk mitigation). They conducted semi-structured interviews with executives from different organizations and industries experiencing increased data growth. The interviews were coded and analyzed.
	17	Chen, D. Q., Preston, D. S., Swink, M, 2015. How the use of big data analytics affects value creation in supply chain management. Journal of Management Information Systems, 32(4), 4–39.	Motivated by the argument that not many organizations capitalize on big data, Chen et al. consider "the underlying mechanisms that lead to organizations' BDA usage, as well as the performance outcomes of such usage" (p. 5). Although success stories are provided by press, they aim to arrive at a "holistic view of BDA and associated capabilities" (p. 6). They used a cross-sectional survey (part of a collaborative effort) among supply chain executives around the world.
JSIS	18	Newell, S., & Marabelli, M, 2015. Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datafication'. Journal of Strategic Information Systems, 24(1), 3–14.	Newell and Marabelli focus on the (negative) consequences of algorithmic decision making (by businesses) for individuals and society. They elaborate on a number of tradeoffs: privacy vs. security, freedom vs. (un)informed control, and independence vs. dependence.
	19	Loebbecke, C., & Picot, A, 2015. Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. Journal of Strategic Information Systems, 24(3), 149–157.	Viewpoint paper on the impact of digitization and big data on business and society. Loebbecke and Picot focus on the question: "How do digitization and big data analytics re-shape business models and transform society?" (p. 150).
AMCIS	20	Agrawal, K. P, 2015. Investigating the determinants of big data analytics (BDA) adoption in asian emerging economies. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Agrawal provides evidence that perceived complexity and compatibility, organizational size, competition intensity, regulatory support, and environmental uncertainty impact big data adoption in developing countries. No evidence could be found for the influence of perceived advantage, technological resource competency, or absorptive capacity. A questionnaire survey with a 5-point Likert scale for all items was sent to leading firms in China and India, building on measures from existing literature
	21	Alshboul, Y., Wang, Y., & Nepali, R. K, 2015 Big data lifecycle: Threats and Security Model. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Alshboul et al. identify security threats across different stages of the big data lifecycle and provide suggestions for their mitigation. (Research-in-progress)
	22	Brinkhues, R., Da Silva Freitas, J. C., Jr., & Maçada, A. C. G, 2015. Information Management Capability as Competitive Imperfection in the	Brinkhues et al. provide evidence for the influence of information management capability on big data cost and value extraction expectations; and in turn for the influence

		Strategic Factor Market of Big Data. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	on the intent to purchase or develop big data solutions. They collect data through a quantitative survey (with a 7-point Likert scale) with managers and executives in IT or IM strategy-related areas. The study is explorative in nature. Scales are developed using literature and card sorting analysis.
	23	Cech, T. G., Spaulding, T. K., & Cazier, J. A, 2015. Applying business analytic methods to improve organizational performance in the public school system. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Cech et al. review students' success factors in secondary school. They discuss how to digitize and collect data on factors, and how schools (can) use big data.
	24	Chasalow, L. C., & Baker, E. W, 2015. Factors contributing to business Intelligence success: The impact of dynamic capabilities. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Chasalow and Baker provide preliminary evidence that organizational processes, firm IT assets, and history affect business intelligence dynamic capabilities and in turn business process performance. The results are based on preliminary data from a survey conducted with business intelligence experts. Measures were taken or modified from existing studies.
	25	Côrte-Real, N., Oliveira, T., & Ruivo, P, 2014. Understanding the hidden value of business intelligence and analytics (BI&A). In: Proceedings of the Twentieth Americas Conference on Information Systems, Savannah, Georgia, USA, August 7–9.	Côrte-Real et al. specify a path from knowledge management to dynamic capabilities (mediated by BI&A), to eventually performance. In doing so, they consider BI&A value from a knowledge based view and dynamic capabilities perspective. They will develop a questionnaire, have it validated by academics and practitioners, and do a pilot test. The questionnaire will be sent to professionals to test their hypotheses. (Research-in-progress)
	26	Dinter, B., Schieder, C., & Gluchowski, P, 2015. A stakeholder lens on metadata management in business intelligence and big data—Results of an empirical investigation. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Dinter et al. look at the benefits, needs, and challenges of metadata management (MDM) from three stakeholder perspectives (user, developer, decision maker), and investigate how this transitions to big data-MDM. They used a questionnaire including questions about respondents and their organization, business intelligence-related MDM, and big data-related MDM, which is sent to mainly business intelligence stakeholders.
	27	Gao, J., Koronios, A., & Selle, S, 2015. Towards a process view on critical success factors in big data analytics projects. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Gao et al. identify and classify several critical success factors in different phases of big data projects (business, data, analysis, implementation, measurement, overall). They performed content analysis of secondary data, including case studies, survey reports, blog entries, and industry guidelines.
	28	Ghasemaghaei, M., Hassanein, K., & Turel, O, 2015. Impacts of big data analytics on organizations: A resource fit perspective. In: Proceedings of the Twenty-first	Ghasemaghaei et al. propose that a higher fit between tasks, people, tools, and data leads to increased organizational performance, agility, and perceived resource value. Perceived value and agility then positively impact organizational performance.

		Americas Conference on Information Systems, Puerto Rico, August 13–15.	They will conduct a cross-sectional survey including closed and open-ended questions among middle level managers. (Research-in-progress)
	29	Goes, P. B, 2015. Big Data—Analytics Engine for Digital Transformation: Where is IS?. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Goes elaborates on how big data is different and how IS research can play a role in this phenomenon. He provides a description of an illustrative case at the University of Arizona.
	30	Jia, L., Hall, D., & Song, J, 2015. The conceptualization of data-driven decision making capability. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Jia et al. conceptualize the data-driven decision-making process and capability based on capability literature. They identify data governance, data analytics, insight exploitation, performance management, and integration capabilities.
	31	Jiang, J., & Gallupe, R. B, 2015. Environmental scanning and business insight capability: the role of business analytics and knowledge integration. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Jiang and Gallupe argue that environmental scanning is input for business analytics tools and knowledge integration, which, when integrated, may increase business insight capability. This in turn generates business insights, which influence business goals. Business goals again trigger environmental scanning and facilitate business insight capability. They conducted interviews with part-time master's students in graduate business analytics programs who work full-time in organizations. The study is explorative in nature.
	32	Kim, H. J, 2015. Big Data: The structure & value of big data analytics. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Kim maps the 4 Vs of big data to business value (volume -> granularity, velocity -> timeliness, variety -> option choice, variability -> reliability). He also proposes steps for implementing data collection. (Research-in-progress)
	33	Knabke, T., & Olbrich, S, 2015. Exploring the future shape of business intelligence: Mapping dynamic capabilities of information systems to business intelligence agility. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, August 13–15.	Knabke and Olbrich identify dynamic capabilities relevant for business intelligence. They propose that business intelligence positively affects decision support. They consider the influence of trends, as well as the influence of environmental turbulence. In the conclusion and future research section, they do claim that preliminary interviews were held to test the proposed model. A questionnaire has been designed, but they await the results.
	34	Kulkarni, U. R., & Robles-Flores, J. A, 2013. Development and validation of a BI success model. In: Proceedings of the Nineteenth Americas Conference on Information Systems, Chicago, Illinois, USA, August 15–17.	Kulkarni and Robles-Flores provide evidence that higher levels of data and business intelligence systems capability lead to higher user satisfaction and net benefits. Analytical culture positively affects these capabilities. User involvement positively affects systems capability. However, it could not be proven that leadership commitment influences the capabilities. They conducted a survey containing questions on business intelligence systems constructs, among middle level managers familiar with business intelligence.

	35	Kung, L., Kung, H., Jones-Framer, A., & Wang, Y, 2015. Managing Big Data for Firm Performance: a Configurational Approach. In: Proceedings of the Twenty-first Americas Conference on Information Systems, Puerto Rico, 2015, August 13–15.	Kung et al. propose that different configurations of big data competences, organizational improvisational capability, information technologies, and data management strategy affect decision making quality, which in turn affects organizational performance. They intend to use a web survey containing both quantitative and qualitative questions, which they will give to executives and IT managers knowledgeable on business strategy, IT, and performance. (Research-in-progress)
	36	Malgonde, O., & Bhattacherjee, A, 2014. Innovating using big data: A social capital perspective. In: Proceedings of the Twentieth Americas Conference on Information Systems, Savannah, Georgia, USA, August 7–9.	Malgonde and Bhattacherjee propose that firms' structural, cognitive, and relational capital, and exchange capability, positively affect big data exchange with external partners. They propose that exchange of big data and combinative capability positively affect the combination of internal and external data, which in turn positively affects innovative outcomes. Big data readiness then also positively affects innovative outcomes. They aim to test propositions through a survey among top executives from US based firms. (Research-in-progress)
	37	Sidorova, A., & Torres, R. R, 2014. Business intelligence and analytics: A capabilities dynamization view. In: Proceedings of the Twentieth Americas Conference on Information Systems, Savannah, Georgia, USA, August 7–9.	Sidorova and Torres propose a new Business intelligence & analytics (BI&A) conceptualization. By doing so, they link BI&A and competitive advantage, and propose a path for strategy implementation with a focus on architecture and governance issues (strategic management).
ECIS	38	Van den Broek, T., & Van Veenstra, A. F, 2015. Modes of governance in inter-organizational data collaborations. In: Proceedings of the Twenty-Third European Conference on Information Systems, Münster, Germany, May 26–29.	Van den Broek and Van Veenstra describe four modes of data governance in inter-organizational collaborations and empirically examine ways of data sharing, coordination, and control for three of the four modes (hierarchy, bazaar, network). They performed a cross-case comparison of a retailer, municipality, healthcare insurance company, and energy platform.
	39	Cao, G., & Duan, Y, 2014. A path model linking business analytics, data-driven culture, and competitive advantage. In: Proceedings of the Twenty Second European Conference on Information Systems, Tel Aviv, Israel, June 9–11.	Cao and Duan provide evidence that: business analytics positively impacts information processing capability, directly and through the mediation of data-driven culture; information processing capabilities are valuable, rare, and inimitable; and information processing capabilities positively affect competitive advantage, both direct and through mediation of VRI. They used a questionnaire sent to managers in medium-sized and large UK enterprises from the FAME database. They did a pilot and used a 5-point Likert scale.
	40	Duan, Y., & Cao, G, 2015. An analysis of the impact of business analytics on innovation. In: Proceedings of the Twenty Third European Conference on Information Systems, Münster, Germany, May	Duan and Cao provide evidence that business analytics positively affects data-driven culture, which in turn influences product novelty. Business analytics positively affects environmental scanning, both directly and through mediation of data-driven culture. Environmental scanning positively affects product novelty and meaningfulness. Product novelty and meaningfulness correlate with

		26–29.	competitive advantage. However, although it does affect product novelty, it could not be proven that data-driven culture positively affects product meaningfulness, They used a questionnaire sent to senior managers from UK enterprises from the FAME database. They used a 7-point Likert scale.
	41	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 Twenty Second European Conference on Information Systems, Tel Aviv, Israel, June 9–11.	Olbrich wants to test whether behavioral economics theses and streams hold true for experts in statistics, decision, and risk management, who increasingly ground decisions on big data. Olbrich conducted experiments with actuaries and actuarial consultants, and presents preliminary results related to anchor bias. (Research-in-progress)
	42	Tan, C., Sun, L., & Liu, K, 2015. Big data architecture for pervasive healthcare: A literature review. In: Proceedings of the Twenty-Third European Conference on Information Systems, Münster, Germany, May 26–29.	Tan et al. performed a systematic literature review. They identify themes in the literature related to pervasive healthcare implementation and big data solutions in healthcare. They propose a big data architecture for pervasive healthcare.
	43	Tiefenbacher, K., & Olbrich, S, 2015. Increasing the level of customer orientation - A big data case study from insurance industry. In: Proceedings of the Twenty Third European Conference on Information Systems, Münster, Germany, May 26–29.	Tiefenbacher and Olbrich emphasize the importance of process alignment and data integration when applying big data techniques. Consequently, they define different stages of a big data maturity model. They performed a case study at a German cross-segment insurance group with a cross-selling aim. **(**Research-in-progress)
ICIS	44	Chatfield, A., Reddick, C., & Al-Zubaidi, W, 2015. Capability challenges in transforming government through open and big data: Tales of two cities. In: Proceedings of the Thirty Sixth International Conference on Information Systems, Fort Worth, Texas, USA, December 13–16.	Motivated by the lack of empirical case studies, Chatfield et al. aim to answer the following research question: "What are socio-political, strategic change, analytical, and technical capability challenges in transforming the government through the use of open and big data?" (p. 3). They performed a systematic literature review and studied two cases: city governments in Houston and San Antonio, where they had interviews with the city's COO (Houston), CIO (both) and CTO (San Antonio).
	45	Ghoshal, A., Larson, E. C., Subramanyam, R., Shaw, M. J, 2014. The impact of business analytics strategy on social, mobile, and cloud computing adoption. In: Proceedings of the Thirty Fifth International International Conference on Information Systems, Auckland, New Zealand, December 14–17.	Ghoshal et al. present 5 clusters of business analytics use by organizations: analytics leader, market responder, organization optimizer, efficiency seeker, and analytics laggard. They expect these types to score differently on social-mobile-cloud antecedents. They use data from 2012 IBM Business Analytics Survey (IBM, 2012). (Research-in-progress)
	46	Krishnamoorthi, S., & Mathew, S. K, 2015. Business analytics and business value: A case study. In: Proceedings of the Thirty Sixth International Conference on	Motivated by the lack of research on how BA creates business value, Krishnamoorthi and Mathew ask: "How does business analytics contribute to business value of firms?" (p. 2). They identify concepts along dimensions of analytics technology assets, analytics capability, control

		Information Systems, Fort Worth, Texas, USA, December 13–16.	variables, and business performance. They use a single site multiple case study approach with replication at a computer technology company. They adopt a retroductive reasoning approach, performed semi-structured interviews with (key) informants, and looked at relevant documents. The data were coded and inter-coder reliability was assessed.
	47	Miranda, M., Kim, I., & Wand, 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 Thirty-Sixth International Conference on Information Systems, Fort Worth, Texas, USA, December 13–16.	Looking at social media and big data as two technological innovations, Miranda et al. pose the following questions:"To what extent do contributions by adopters and vendors to discourse about IT innovations differ between less decentralizable IT innovations and more decentralizable IT innovations?" and "How does the decentralizability of an IT innovation influence the effects of discourse contributions by adopters and vendors on subsequent diffusion of the IT innovations?" (p. 2). They performed a "*Factiva search"* to identify relevant organizations for operationalizing discourse and assessed diffusion by looking at the top 50 Fortune firms. They collected firms' press releases and coded for adopters and vendors. The panel dataset then allowed them to "model the effects of community discourse (by adopters and vendors) in a given quarter on diffusion of the IT innovations within a firm in subsequent quarters" (p. 11).
	48	Namvar, M., & Cybulski, J, 2014. BI-based organizations: A sensemaking perspective. In: Proceedings of the Thirty Fifth International Conference on Information Systems, Auckland, New Zealand, December 14–17.	Namvar and Cybulski look into the requirements of BI-based organizations and BI use for both operational decision-making and sensemaking. They find that, in order to become business intelligence-based, organizations need to promote business intelligence identity at both organizational and individual levels. They conducted interviews with primarily business intelligence users, mostly from large enterprises. They adopt a hermeneutic phenomenology perspective.
	49	Stein, M., Newell, S., Galliers, R. D., & Wagner, E. L, 2013. Classification systems, their digitization and consequences for data-driven decision making: Understanding representational quality. In: Proceedings of the Thirty-Fourth International Conference on Information Systems, Milan, Italy, December 15–18.	Stein et al. set out to find “how representational quality of digitized classification systems is/is not achieved in practice” (p. 7), assuming that representational quality is not static. They performed a multi-site case study across two North-American universities. They collected interview data, observational data, documentation, and other additional data. They looked at the FP Software Package.
	50	Tamm, T., Seddon, P., & Shanks, G, 2013. Pathways to value from business analytics. In: Proceedings of the Thirty Fourth International Conference on Information Systems, Milan, Italy, December 15–18.	Tamm et al. focus on different business analytics user types, i.e., analytics professionals and analytics end-users, and the roles they play. They find 3 pathways to value, i.e., advisory services, tool creation, and end-user analytics, and describe factors influencing each. They conducted interviews with business analytics-affiliated practitioners. The methodology is framed as a preliminary assessment.
	51	Van Hau Trieu, T, 2013. Extending the theory of effective use: The	Van Hau Trieu proposes relations between learning actions, effective business intelligence use, and decision-

		impact of enterprise architecture maturity stages on the effective use of business intelligence systems. In: Proceedings of the Thirty Fourth International Conference on Information Systems, Milan, Italy, December 15–18.	making performance. Moreover, she argues that enterprise architecture level 3 or higher in terms of data integration influences effective BI use. More detailed propositions are given. She will use a two-phased, mixed-method approach: an exploratory qualitative phase followed by a quantitative survey phase. She will approach managers with BI experience in Australia. (Research-in-progress)
	52	Wang, Y., Kung, L., Wang, W. Y. C., & Cegielski, C. G, 2014. Developing a big data-enabled transformation model in Healthcare: A practice based view. In: Proceedings of the Thirty Fifth International Conference on Information Systems, Auckland, New Zealand, December 14–17.	Wang et al. identify big data capabilities (traceability, analytical, decision support, and predictive), health-care specific transformations enabled by big data, and subsequent benefits and performance indications. Specifically, they find two chains leading to performance They performed content analysis: they collected cases from practical journals, print publications, case collections, and reports, that present big data implementations and provide clear descriptions of software and benefits. (Research-in-progress).

Table A.2.5 Reviewed papers from other outlets.

Outlet	N	Reference	Summary
BD&S	53	Bholat, D, 2015. Big data and central banks. Big Data & Society, 2(1), 1–6.	Bholat describes big data initiatives of the Bank of England, as well as general themes regarding big data for banking (granularity of big data; data collection and legal considerations; inductive approaches).
	54	Kennedy, H., & Moss, G, 2015. Known or knowing publics? Social media data mining and the question of public agency. Big Data & Sociey, 2(2), 1–11.	Kennedy and Moss consider how the "democratization of data mining" (specifically social media) can be established, i.e., through supervision and control, availability and accessibility to the public, and using it to enable a reflexive and active public. Thus, they consider the move from “known publics” to more active “knowing publics”. Although it stays largely on societal level, some interesting examples of implications for and practices by organizations are discussed.
	55	Kshetri, N, 2014. The emerging role of big data in key development issues: Opportunities, challenges, and concerns. Big Data & Society, 1(2), 1–20.	Kshetri looks at the diffusion of big data in developing countries and how it is affected by social, political, and economic contexts. He specifically looks at agriculture firms in developing countries. Kshetri adopts a positivistic epistemology approach: building on existing empirical research, practice and experience. He looked at academic literature, policy documents, and industry and media reports.
	56	Madsen, A. K, 2015. Between technical features	Madsen identified two environmental data features influencing digital social analytics (DSA) projects: character of the data structures, and need for

		and analytic capabilities: Charting a relational affordance space for digital social analytics. Big Data & Society, 2(1), 1–15.	automatization. He describes two ends of a continuum for each, and maps projects on the suggested affordance space. Madsen adopts a most different multiple case studies approach with DSA project leaders. He conducted semi-structured interviews and looked at documentation.
	57	Struijs, P., Braaksma, B., & Daas, P. J. H, 2014 Official statistics and big data. Big Data & Society, 1(1), 1–6.	Struijs et al. address big data changes, opportunities, challenges, and collaborations for National Statistical Institutes.
	58	Van der Vlist, F. N, 2016. Accounting for the social: Investigating commensuration and Big Data practices at Facebook. Big Data & Society, 3(1), 1–16.	Van der Vlist onsiders the role of commensuration while looking at Facebook's big data infrastructure, its applications and challenges. He discusses issues around data mining, algorithms, and analytics. He used an "empirical inquiry" and read published materials and available documentation such as reports, periodicals, proceedings, slides, blogs, and technical documents.
CACM	59	Davis, C. K, 2014 Beyond data and analysis. Communications of the ACM, 57(6), 39–41.	Davis discusses how business analytics (or big data) may be different and how this impacts organizations.
	60	Jagadish, H. V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J. M., Ramakrishnan, R., & Shahabi, C. (2014). Big data and its technical challenges. Communications of the ACM, 57(7), 86–94.	Jagadish et al. mention challenges inherent to the different stages of the big data lifecycle. Although a "technical paper", it also includes the interpretation phase, which has an individual/organizational focus.
	61	Kim, G., Trimi, S., & Chung, J, 2014 Big-data applications in the government sector. Communications of the ACM, 57(3), 78–85.	Kim et al. consider how big data for governments differs from big data for businesses. They look into big data applications in different countries and suggest ways for implementing big data in government settings.
DSS	62	Chae, B, 2014. A complexity theory approach to IT-enabled services (IESs) and service innovation: Business analytics as an illustration of IES. Decision Support Systems, 57, 1–10.	Chae focuses on business analytics as an example of an IT-enabled service (IES). He focuses on these IES and IES innovation, and develops a number of propositions accordingly.
	63	Holsapple, C., Lee-Post, A., & Pakath, R, 2014. A unified foundation for business analytics. Decision Support Systems, 64, 130–141.	Holsapple et al. provide a foundation for business analytics through: an exploration of its 3 dimensions, 6 perspectives, and the design of a framework. They provide a brief illustration/ framework application near the end.

JASIST	64	Ekbia et al, 2015. Big data, bigger dilemmas: A critical review. Journal of the association for information science and technology, 66(8), 1523–1545.	Ekbia et al. synthesize literature to arrive at “conceptual and practical dilemmas surrounding Big Data” (Abstract). They discuss drivers and challenges, and provide avenues for future research to move beyond the dilemmas.
I&M	65	Işik, Ö., Jones, M. C., Sidorova, A, 2013. Business intelligence success: The roles of BI capabilities and decision environments. Information & Management 50(1), 13–23.	Işik et al. focus on the relation between business intelligence capabilities (technological and organizational) and business intelligence (BI) success, as well as the influence of the decision environment on this relationship. They used a survey to test the hypotheses, consisting of four measurement parts: demographic information, BI success, BI capabilities, and decision environment. The survey was reviewed by academic experts, went through a pilot study with BI professionals, and was spread among randomly sampled business managers using BI for strategic and operational decision making.
MS	66	Tambe, P, 2014. Big data investment, skills, and firm value. Management Science, 60(6), 1452–1469.	Tambe suspects that differences in worker supply, in terms of people with BDA skills, impact value realization in different labor markets and propose: “(a) that investment in emerging data technologies should be concentrated in select labor markets, (b) that investments in these technologies should yield higher returns in these labor markets, and (c) that the advantages of labor market concentration should decline as technologies mature” (p. 1453). They collected data from Linkedin, focusing on workers who report having or using Hadoop skills, where Hadoop sets big data apart from more traditional investments. The method is actually one of the main contributions.
CAIS*	67	Gillon, K., Aral, S., Lin, C., Mithas, S., & Zozulia, M, 2014. Business analytics: Radical shift or incremental change? Communications of the Association for Information Systems, 24(13), 287–296.	Based on a panel discussion: The session on which Gillon et al. report was focused on two questions, i.e., “To what extent do increasingly advanced analytics systems represent a qualitative change in opportunities to generate value and competitive advantage?” and "To what extent do organizations need to develop new resources, capabilities and skills to maximize the impact of analytics systems?" (p. 289).

Table A.2.6 Grounding for each of the debates based on example quotes.

Debates	Codes	Illustrative quotes
Inductive and deductive approaches to big data analytics	Inductive approaches can lead to new insights	“The boundaries of pattern-finding are therefore a priori undefined, for it is not known in advance what can be done with the data” (Aaltonen & Tempini, 2014, p. 104)
		“It should make a rather stark difference whether data is gathered on the basis of a well-trodden cognitive architecture that serves preconceived organizational purposes and objectives or whether it is the data itself that is used to distil a posteriori an organizational plan, a purpose, a human intention, a service or a set of services” (Constantiou & Kallinikos, 2015, p. 7) “First, the top-down, deductive approach to data gathering and utilization, a cornerstone of standard and predominantly prescriptive ways of depicting sensible strategy making, is challenged. Many of the methods and techniques of data crunching are strongly associated with bottom-up procedures of data processing that are supposed to (re)discover patterns in huge data masses. The overall scheme, which these methods epitomize, can roughly be summarized as follows: first data then search for any possible uses of what is already available as data (Anderson, 2008; Lee et al., 2014). An ad hoc, inductivist way of strategy making seems to be emerging as the outcome of the trends we are describing. This seems to undermine the foundations of predictive models of strategy making based on the purposeful, deductive and ex-ante character of organizational intelligence and information collection and use” (Constantiou & Kallinikos, 2015, p. 8).
		“Kelly explicates the following approach when he explains how his way of visualizing political communities is different from his competitors: Some people would go in and color the nodes on the basis of some pre-existing typology. They got the categories that they think are relevant in their minds and they go in and they assign everything to a category. I sort of wanted the data to tell me what kind of categories that were in it. I did not want to go in with presuppostitions [. . .]. (MA1)” (Madsen, 2015, p. 11).
		“Consequently, the challenge in such a data-driven process is the ex-post articulation of a sound hypothesis to explain the data (Hey et al., 2009). If the search logic is reversed – as it is by Big Data Analytics - the limits of induction have to to be considered” (Olbrich, 2014, p. 4).
		“When this pre-defined goal is achieved, the same legislation requires organisations to delete their data. The explorative nature of big data, however, implies a lack of pre-defined goals or applications and stimulates organisations to expand rather than delete datasets. Whereas European data protection legislation requires data minimisation, big data is based on the notion of data maximisation” (Van den Broek & Van Veenstra, 2015, p. 10)
	Deductive approaches provide valuable focus	“Having a clear vision on how successful projects contribute to the business is vital. Otherwise the projects run into the risk of discovering hidden knowledge within the organizations data that does not contribute to the business success. Therefore, Big Data projects need to focus on delivering a return on investment (ROI). Projects won’t be successful, if they are just started for the sake of being innovative” (Gao et al., 2015, p. 9).

		"Justifying action is one of the reasons why some decision-makers use BI reports (LaValle et al. 2011). In such situations, extensive reports are not effective, as decision-makers are looking for specific numbers or patterns that they already have in mind [Chandler, ID43], and BI systems simply provide decision-makers with tools to support what they already know are the possible options" (Namvar & Cybulski, 2014, p. 10).
		"Second, APs are sometimes asked to answer very open-ended questions (e.g., What is the best approach for segmenting our customers?). Our interviewees were skeptical about the value potential of such questions. Rather, they suggested that clearly defined questions and a business case are usually essential for maximizing the likelihood of value realization" (Tamm et al., 2013, p. 12).
		"Making sense of the health data is imperative for delivering the value of pervasive healthcare such as to increase patient safety and to reduce the operational costs. Forming a hypothesis is a departure point for any sense-making process and it articulates the process of how data is collected, processed, analysed and disseminated in the pervasive healthcare setting. In hindsight, sense-making of health data is hypothesis-driven. Despite of the existing technological platforms that enable the features such as finding patterns, trends and relationship through the collected health data, it is still short of literature in postulating the methodology of making sense of these data" (Tan et al., 2015, p. 8).
	Balancing inductive and deductive approaches to data collection and analysis	"Among these themes are the benefits for central banks in having standardised granular data, the importance of legal considerations in enabling and constraining the scope of granular data collections, and the development of inductive analytical approaches to complement deductive approaches that traditionally have held sway in central banks" (Bholat, 2015, p. 1). "Of course, deduction and induction are ideal types. In reality, explanatory approaches are always mixed" (Bholat, 2015, p. 4).
		"Due to the innovative character of Big Data projects, members of the analysis team need to be engaged to think in innovative ways and come up with creative ideas. Nevertheless, it is necessary to set some boundaries for the analysis team to ensure the project does not lose its focus. Within these boundaries, however, team members should be granted total freedom (Sicular, 2012: 29)" (Gao et al., 2015, p. 3).
Algorithmic and human-based intelligence	Algorithms provide sophisticated and fast ways of processing data	"Big data analytics has recently risen to potential prominence due to greater ability to both capture vast amounts of data and employ more powerful analytical techniques to vast data sets. This recent ability of firms to be able to both collect big (and varied) data and also apply powerful analytical techniques to such data enables the organization to automate highly complex decisions that have traditionally been dependent (primarily or solely) on human judgment and intuition [6, 29]" (Chen et al., 2015, p. 7).
		"This powerful combination of data and analytical techniques enables increasingly complex decisions to be automated. As a result, the possibility of automation is moving far beyond traditional transaction processing tasks into territory which has historically been seen as reliant on human judgment [Brynjolfsson and McAfee, 2011b]. In other words, the combination of data and analytical techniques can potentially enable firms to move beyond description to prediction, and eventually to prescription in their analytics maturity" (Gillon et al., 2014, p. 288).

		“Increasingly, sophisticated software fosters machine-based interpretation of data. It thus enables (almost) autonomous decision-making and a deeper integration of big data applications in traditional value creation activities” (Loebbecke & Picot, 2015, p. 150).
		“Netflix provides a salient example of algorithmic shaping effects – according to their figures, 75% of content choice is now influenced by recommendation. Although algorithms are ‘doers and not informed sceptics’, the shaping power inherent in their design should clearly not be under- estimated” (Lycett, 2013, p. 383)
		“Automatization is used to avoid the drawbacks involved in relying too heavily on a priori human intuition. This is a kind of use that is also promoted by Guilhem Fouetillou in his mapping of products (L1). Similarly, Ana Andjelic supports this inductive form of analysis because it enables analysts to see ‘‘[. . .] something that [they] have previously missed’’ (D2)” (Madsen, 2015, p. 12).
		“Together with today’s growing ‘ data lakes,’ algorithms increasingly afford organizations the ability to automate the operational, and possibly even the strategic, decision making that is the core of managers’ and knowledge workers’ jobs” (Markus, 2015, p. 58)
		“In addition, machine learning also enables the ‘discovery’ – typically through inference – of additional attributes currently absent from such feature spaces, thereby introducing entirely new dimensions and categories” (Van der Vlist, 2016, p. 10).
		“Big data does not just represent the world. It actively shapes the world. And it does it through algorithms. While algorithms might be ‘ a last step in a complex chain of data operation, data structures and operations,’ it certainly is an important last step from a user experience standpoint” (Yoo, 2015, p. 64)
	Humans possess relevant personal knowledge, interpret information, and act on insights	“The pattern-finding mechanism is characterized by the role played by human operators, who need to devise strategies that could reveal more information from the data” (Aaltonen & Tempini, 2014, p. 104). “In the context of such practices, employees selectively associate metrics and patterns found in the data with other sources of information, trends and objectives” (Aaltonen & Tempini, 2014, p. 105).
		“While earlier technologies may have been designed with the explicit purpose of replacing human labor or minimizing human involvement in sociotechnical systems, Big Data technologies heavily rely on human labor and expertise in order to function” (Ekbia et al., 2015, p. 1535).
		"Ideally, analytics for Big Data will not be all computational—rather it will be designed explicitly to have a human in the loop. The new subfield of visual analytics is attempting to do this, at least with respect to the modeling and analysis phase in the pipeline. There is similar value to human input at all stages of the analysis pipeline" (Jagadish et al., 2014, p. 93).
		“Human experts may need to perform tasks involving decision problems and processes for which no algorithm exists or the algorithm has not yet been developed. In some cases, due to unknowns no algorithm can solve all instances of the problem. In agriculture, some examples of situations include tasks involving unknown soil types, and extreme weather

		conditions, which often need to be performed by humans rather than algorithms" (Kshetri, 2014, p. 10).
		"The analytic ideal type at the opposite end of the continuum is conceptualized as training because it builds on the idea that "it is imperative that the analyst 'train the algorithm' (UN2). It is an alternative to following because it suggests guiding the automated algorithm to reflect categories that are recognizable in the context in which they are going to have an impact" (Madsen, 2015, p. 12).
		"One also has to ask about the consequences for organizational knowledge and learning as algorithms encroach ever further into content domains. Can people learn the knowledge and skills of underwriting, trading, or medical diagnosis when these tasks are deeply automated? (People may learn a lot about how to use or maintain automation while knowing very little about the underlying knowledge domain.)" (Markus, 2015, p. 59)
		"illustrating that algorithmic decision-making incorporates advantages (in this context, for users) but at the same time precludes a full understanding of why some decisions are being made. This limits learning through practice (Brown and Duguid, 1991) that in the long term might modify an individual's ability to learn new tasks and, more generally, adapt to the workplace or to society more generally (Dall'Alba and Sandberg, 2010; Nicolini et al., 2003)" (Newell & Marabelli, 2015, p. 9).
		"Our reason for including this example (Figures 3 and 4 and the paragraph in the preceding text) in this paper is to make three very simple points: (1) Despite all the computing power available to the analyst, the creative work (e.g. sense-making, framing, understanding and deciding) in using business analytics tools is done by people, not computers, (2) the work these people do is called 'human problem solving', a much-studied topic of huge complexity, and (3) the model in Figure 3 provides a useful depiction of this intensely human problem-solving activity. In other words, it is people who look at the data, assign meaning to it, search for patterns, sense opportunities and so on. Further, it is people – with all their different knowledge and cognitive capabilities and limitations – who derive insights, through a process like that depicted in Figure 3" (Seddon et al., 2017, p. 12).
		"However, human insights are still involved in 'accepting' the insights generated via machine learning as being valid and useful, in 'deciding' to deploy them to run operations in an unguided manner, and in 'accepting' the refinements to the algorithms generated via machine learning as being valid" (Sharma et al., 2014, p. 436).
		"Almost all the interviewees agreed that supplementing the data with personal knowledge is key. Personal knowledge incorporates previous experience and expertise, common sense and contextual knowledge. The following quote is representative: 'I think we'll always use our common sense because you have to see figures over a very long period.' (Business Analyst, 2010) Up to this point, the articulation practice takes place between the BI system and the user's personal knowledge, thereby giving voice to new distinctions" (Shollo & Galliers, 2015, p. 353).
	Interactions between human and	"The new audience product is defined and maintained by the operation of semantic closure, pattern-finding and framing mechanisms that operate on the raw CDR data. The three mechanisms are nested so that an output

	algorithmic intelligence	from one feeds the other (see Appendix). This allows information about the audience to cascade through metrics, reporting applications and practices, becoming richer and more relevant for audiencemaking practices at every step" (Aaltonen & Tempini, 2014, p. 105).
		"As an extreme example of automation, the use of big data analytics to replace human involvement from certain business processes has already begun to take shape (Davenport & Kirby, 2015); in Section 4, we mention real-time analytics pipelines that are replacing traditional business processes. However, in many contexts, big data analytics provides complementary "augmentation" to human-driven processes (Davenport & Kirby, 2015). Augmentation and automation signify a departure from the traditional human-centered computing paradigm toward autonomous computing albeit with varying degrees of separation depending on the level of human involvement" (Abbasi et al., 2016, p. xvi)
		"Rather than describing the use of machines in Big Data in terms of automation, perhaps we should acknowledge the continuing creative role of humans in knowledge infrastructure and call it "heteromation" (Ekbia & Nardi, 2014). Heteromation and the rise of social machines also highlights the distinction between data generated by people versus data generated about people." (Ekbia et al., 2015, p. 1535) "The right approach, in response to this unbridled enthusiasm, is not to deny the light side of Big Data, but rather to devise techniques that bring human judgment and technological prowess to bear in a meaningfully balanced manner." (Ekbia et al., 2015, p. 1539).
		"However, all of the project leaders translate this condition into a need for finding a balance between the strengths of machines and humans" (Madsen, 2015, p. 7). "In their practical work with web-based data, they all experience the need for human classification at some point in the process" (Madsen, 2015, p. 7).
		"Individuals using a BI system or analysis (the product of the system) 'take' sense from the data; they add meaning, in other words. The meaning that emerges from the interaction of the individual with the BI analysis, originates from the data through practices of selection and articulation" (Shollo & Galliers, 2015, p. 357)
		"representational quality is continuously achieved in practice through information consumers and producers negotiating the materiality of classification systems embedded into the surface and deep structures of the software. (Stein et al., 2013, p. 13).
Centralized and decentralized big data capability Structures	Centralizing capabilities can help overcome issues of resource shortage and data handling	"The ''New Approach to Data and Analysis'' initiative created an Advanced Analytics Division with the objective of establishing a centre of excellence for the analysis of Big Data" (Bholat, 2015, p.2)
		"In order to manage these evolutions, organizational structures like BI competence centers (BICC) have been introduced. Such trends will sustainably affect BI and impact the future shape of BI" (Knabke & Olbrich, 2015, p. 3)
		"We characterize the big data innovation as minimally decentralizable. While users may have the know why, some know-what and know-how, and even the financial resources to implement big data, the absence of complementary resources limits decentralized adoption of big data innovations. Specifically, absent access to complementary resources such

		as data, processes, and related applications, users will lack the architecture and infrastructure decision rights necessary for implementing big data initiatives" (Miranda et al., 2015, p. 9).
		"Centralization was seen as enabling information governance, whereas decentralization was seen as allowing disparate approaches to information management that then made it difficult to govern information in a holistic fashion" (Tallon et al., 2013-14, p. 158).
	Decentralizing capabilities connects analytics and business	"A crucial point for any organization is to locate data scientists close to the products and services inside the organization, reducing the gap between decision makers and data scientists. Organizations working with big data are struggling to close this gap by building their own platforms, because acquiring in-depth knowledge from data scientists in the domain of big data typically takes years (Marx, 2013)" (Chatfield et al., 2015, p. 7).
		"Dale, an enterprise intelligence data analyst, also cautioned on the use of self-service analytics by unskilled managers acting on BI reports without the presence of an analyst capable of explaining the results and their meanings, as well as, how such results should be used in action [Dale, ID49]. Daniel added to this view by noting that the main issue for understanding an organization through BI is clarifying what decision-makers want to see in business terms, rather than in terms of BI functionality. He said "we have to sit down with them and take them through that process" [Daniel, ID67]" (Namvar & Cybulski, 2014, p. 12).
		"Anecdotal evidence, as well as our own research (Shanks et al, 2010, 2011; Shanks and Sharma, 2011) suggests that such central units do not connect very well to business units and that they find it difficult to convert their insights into value through competitive actions by business units. More importantly, it is not clear how such a structural innovation can address the limitations to insight generation discussed here" (Sharma et al., 2014, p. 436).
		"However, in addition to these factors, a number of other important issues emerged during our discussions with BA thought leaders in Australia. These included [...], and (e) concerns about the concept of BA Centers of Excellence (also called Competency Centers), which promise much, but often do not deliver" (Tamm et al., 2013, p. 14).
	Hybrids between centralized and decentralized capability structures	"Centralization of internal and external data collection management, as well of identification of discontinuities in the internal and external environments offers synergistic benefits. However, identification of maladjustments and corresponding requests for change require capability specific expertise and focus (Sidorova & Torres, 2014, p. 6)
		"The analytics division has teams or departments (also known as 'Analytics Organizations') catering to analytics needs of all key business functions of CompuCorp [..]. It is a centralized analytics entity having a global view of the entire organization, catering to most of the analytics needs of the computer technology company working closely with all global business functions. [..] The analytics division has its own employees as well as partners to provide resources for the analytics needs. While the business divisions are free to outsource their analytics services requirements from the recognized vendors, the captive analytics division seems to be well patronized by the business divisions. [...] In the initial years, the business functions were not clear about the

		contribution of Analytics division - 'are they building only models and acting as consultants or are they part of the extended team?' From the point of view of senior management, the analytics division was a strategic partner. From the point of view of operational teams at ground level, there were problems for Analytics division as a whole. However, over the years, business divisions have started feeling that Analytics division is part of their extended team. Over the last ten years, the analytics division has transformed itself completely in terms contributions made to the business, from a reporting arm to a completely decision science based data driven analytics division, driving business" (Krishnamoorthi & Mathew, 2015, p.6)
		"Khatri and Brown [18] explain that structural practices can be positioned on a decentralized-centralized continuum. For example, data custodians or stewards (whose responsibilities can be defined at the function, user group, or application level) can decide on overarching IT principles such as strategies on how to use information for competitive advantage or how to comply with new legal requirements. In contrast, decentralized users can act as data owners since they have an ability to use local knowledge to assign a value to their information. users can also work with IT managers on ways to protect and enable that value through retention policies" (Tallon et al., 2013–14, p. 149). "There is also a willingness to allow storage decisions to be made by users, even if the policies that pertain to information retention and disposal are set at a central level. This was particularly prevalent in research-intensive medical facilities. For example, in Johns hopkins Medicine, MD Anderson Cancer Center, Memorial Sloan Kettering Cancer Center, Tufts Medical Center, and university of Washington Medical Center, researchers are able to self-administer their data files and develop policies rather than centralizing that information within an institution-wide data center" (Tallon et al., 2013–14, p. 162).
Big data-driven business model improvement and innovation	Business model improvement through incremental enhancements	"Efficiency Seekers who are internal operations dominant analyzers seeking to use business analytics primarily for improving internal operational efficiencies (Ghoshal et al., 2014, p. 4).
		"Lin also gave an example of how advanced analytics can bring value to an organization by improving internal processes. IBM's Small Blue system links together IBM employees from around the world into a single network, and includes information about expertise, publications, blogs and other connections. It has been used to improve knowledge sharing and efficiency around the organization" (Gillon et al., 2014, p. 291).
		"This insight allowed them to adjust their stocks accordingly in advance of a hurricane and thereby better cater for their customers' 'needs' (Hays, 2004). Thus, incremental enhancements to established business models through increased digitization and big data analytics may replace less efficient business models (and thereby companies) in the long run" (Loebbecke & Picot, 2015, p. 151).
		"Improve the business model Companies are using big data to resolve previously unanswerable burning questions in order to refine and optimize business processes and decision making. In these cases, big data supports the measurement and monitoring of strategy in novel ways by offering new data, insight, and action" (Woerner & Wixom, 2015, p. 60).
	Business model innovation and	"The existence of such records is thus a structural pre-condition related to the functioning of the network infrastructure, rather than a decision by the company that harnesses the data to enable business model innovation. Therefore, while the records make the new kind of media business

	radical change	practicable, the genesis of CDR production falls outside the scope of the current investigation" (Aaltonen & Tempini, 2014, p. 102). "In several ways, the research site represents many of those organizations that execute novel business models around what is vaguely termed Big Data (Boyd and Crawford, 2012)" (Aaltonen & Tempini, 2014, p. 108).
		"More widely sourced information content and form point to the capacity for enterprises to utilize data that alters corporate strategy rather than simply supporting it, and to mobilize effective restructuring instead of alignment with current organizational priorities and arrangements" (Bhimani, 2015, p. 67).
		"A company such as Google sits at the leading edge of big data and analytics and therefore is likely to be at the forefront of radical changes. In other industries, companies may have to make radical changes to compete more effectively in the marketplace. Aral outlined two examples of businesses using analytics to shift their business models radically: Nike historically based its business success on brand and sourcing. Now, by gathering data from many new sources, it has built a digital platform offering innovative fitness services, leading to a radically different business model and new competitors. The New York Times is a traditional print newspaper struggling to survive in a digital environment. As a result, it has established a research and development lab to experiment with data and learn new ways of engaging with readers and making money in this radically different environment" (Gillon et al, 2014, p. 291).
		"In daily terms, the Netflix dematerialisation has some 30 million daily plays and 3 million odd searches to inform the dynamics of recommendation. What that offers via dematerialisation and liquidity combined has allowed an interesting manifestation of density, via Netflix's recent move from streaming content to producing it" (Lycett, 2013, p. 383).
		"Innovate the business model Companies are using big data to find different ways to generate revenues. Two contemporary approaches that MIT CISR has studied in depth include data monetization and digital transformation. Digital transformation occurs when companies leverage digitization to move into completely new industries or to create new ones." (Woerner & Wixom, 2015 p. 61).
	Ongoing business model improvement and innovation	"These solutions, in brief, have given rise to a spectrum of alternative solutions to the continuity–innovation dilemma. Placed on this spectrum, Hadoop can be considered a compromise solution: it is designed to work on commodity servers and yet it stores and indexes both structured and unstructured data (Turner, 2011)" (Ekbia et al., 2015, p. 1534).
		"It proposes to move stepwise from one stage to another, i.e. from less mature selective use cases (stage A) through functional excellence (stage B) and value proposition (stage C) towards a fully integrated analytical IS infrastructure (stage D)" (Tiefenbacher & Olbrich, 2015, p. 7).
Controlled and open access to big data	Organizations may aim for control over who has access to their	"In sharing large volumes of data sets, such as social media data sets, there are ethical and privacy implications around what these data sets contain, including the posts and associated metadata of thousands or millions of users. This presents a barrier to an open sharing of data sets, causing difficulties in the sharing process (Bruns, 2013; Choudhury et al., 2014). In some organizations, the most challenging issue is how to protect

	data resources	the privacy and how to transfer information securely" (Chatfield et al., 2015, p. 6).
		"While these firms are likely to acquire in-formation about customers from various sources (to round out profiles of existing customers and to identify potential new customers), they are less likely to sell customer information be- cause it is of competitive value to them. From a data analytics perspective, firms in this category utilise the information they collect to advance the goals of their firm, but are unlikely to sell this information to others for the sake of making a profit" (Greenaway et al., 2015, p. 590).
		"Privacy is but one aspect of data ownership. In general, as the value of data is increasingly recognized, the value of the data owned by an organization becomes a central strategic consideration. Organizations are concerned with how to leverage this data, while retaining their unique data advantage, and questions such as how to share or sell data without losing control are becoming important" (Jagadish et al., 2014, p. 93).
		"At present, elite commercial companies like Google, Facebook and Amazon have the best access to data, as well as the best tools and methods to make sense of it (Williamson, 2014). Some companies restrict access to data entirely, others sell access for a high fee, some offer small data sets to university-based researchers. Thus those with money or inside a company have differential access to social media data from those without financial resources or operating outside the major companies. These data inequalities relate not only to data and analytics tools, but also to the expertise needed to use and make sense of them" (Kennedy & Moss, 2015, p. 4).
		"One ideal type is conceptualized structured channeling . It represents a suggestion to give high priority to deriving structure from communication channels that are deemed valid and reliable. The identification of a relevant channel to repurpose data from is a core methodological act and what counts as a relevant channel naturally varies from project to project. However, the approach of structured channeling prioritizes channels that have specialized competencies in organizing data from specific groups that communicate about specific issues through specific genres" (Madsen, 2015, p. 8).
		"we found that two important reasons for wanting to keep tight control over data were the commercial sensitivity of data and the privacy risks involved. The clearest case in which commercial sensitivity is involved, is in the case of personal marketing. All data remain clearly within control of the retailer that does not want their competitors to get the same insight into their customers' behaviour. But also in the case of the energy data platform this was mentioned as a barrier to establishing inter-organisational data collaboration. While this is a barrier to data collaborations, it may be overcome by installing appropriate governance mechanisms" (Van den Broek & Van Veenstra, 2015, p. 10) "In case data are shared for a generic purpose, for instance for a societal goal, this needs to be controlled tightly. This was the reason for installing a review board in the case of the healthcare database" (Van den Broek & Van Veenstra, 2015, p. 10). "The reason for this is the existence of data protection legislation, which requires organisations to retain control over any personal data they process. As data minimisation is an important principle of personal data legislation, this means that organisations need to have a clear ground for processing or sharing personal data" (Van den Broek & Van Veenstra,

		2015, p. 10).
	By openly approaching access to big data, organizations may benefit from collaboration	“The ‘‘One Bank research agenda’’ initiative commits the Bank to opening up to the public previously proprietary data sets in order to crowd-source solutions to challenging policy questions” (Bholat, 2015, p. 2).
		"Open government reform practices have now spread to other developed and developing nations. Globally, as of 2015, Open Government Partnership (OGP), which was launched in 2011, has 65 nations which are committed to collaborate towards promoting open government policies among its member nations to realize the potential benefits of open data implementation (Open Government Partnership, 2015). In consequence, a number of large local governments in New York, Chicago, Los Angeles, and Houston, which all generate and capture big data, have implemented open data portals to share its big data with citizens and businesses" (Chatfield et al., 2015, p. 2)
		“It is diffuse and distributed lay actors en masse rather than experts or other kind of dedicated personnel that lie at the heart of big data generation. These different arrangements and mechanisms lend big data many of its distinctive and also fascinating qualities. The circumstances of big data production are, in most cases, not controlled by organizations, nor are they subject to the widespread principles of expert rule on which data and expert knowledge have commonly relied” (Constantiou & Kallinikos, 2015, p. 8).
		“Open data groups lobby for access to and the ability to re-use datasets, often focusing on those produced by public institutions. They insist on access and re-use for everyone, ‘free of charge, and without discrimination’ (Bates, 2013: np). Such groups see the opening up of public datasets as a form of democratisation of data, allowing the access to data that Boyd and Crawford argue is ominously absent from the data delirium (van Zoonen, 2014)” (Kennedy & Moss, 2015, p. 6)
		“The goals for the municipality in relation to open data are to increase efficiency of the organisation, stimulate innovation within the municipality and allow for re-use and innovation within other organisations, such as app developers, and to increase transparency and accountability” (Van den Broek & Van Veenstra, 2015, p. 6).
	Mixing controlled and open modes of access	“The Network mode of governance is a hybrid, with member(s) laterally exchanging data while retaining control over this exchange. Trust relations are formed, which form the basis of the data exchange” (Van den Broek & Van Veenstra, 2015, p. 5) “In the Network mode of governance, all types of coordination co-exist, based on the specific data and the organisations involved. The only coordination taking place is that all data are shared via the platform” (Van den Broek & Van Veenstra, 2015, p. 9).
Minimizing and neglecting the social risks of big data value realization	Organizations are careful to respond to regulation and concerns	“Another challenge arises from the huge security and ethical issues, which come along with Big Data projects. Therefore, risk management and legal experts should be involved in very early project stages,as well as compliance representatives (Sicular, 2012: 27)” (Gao et al., 2015, p. 3).
		“Firms oriented as Privacy Differentiators are most likely to offer significantly enhanced privacy protection as part of their business strategy in order to set themselves apart from their peer group (Greenaway & Chan, 2005). [..] In today’s highly connected environment, many of these

		strategies likely include staying at the leading edge of providing security protections for customers' data, acting as a proxy for controlling customers' information as they desire by providing customers with enhanced control and justice. [..] These firms purposefully aim to stay ahead of the curve to protect their customers' privacy. Privacy Differentiators proactively seek competitive advantage not through exploitation but by offering their customers significantly enhanced control and justice. Apple is increasingly operating as a privacy differentiator" (Greenaway et al., 2015, p. 596-7).
		"The other is the extensive privacy model adopted by Facebook. Data needs to be accessed using authorizations from likes and games" (Kim, 2015, p. 4).
		"Compliance in highly regulated industries (such as financial services and health care) is yet another obstacle for gathering data for big-data government projects; for example, U.S. health-care regulations must be addressed when extracting knowledge from health-related big data" (Kim et al., 2014, p. 81)
		"Regulation was mentioned as a significant driver of data growth and one of the key forces behind information governance. Industry mandates can be unique, but there was consistency in how organizations reacted to these rules by enacting information governance policies to accelerate compliance and to reduce the risk of financial or reputational penalties in cases of noncompliance" (Tallon et al., 2013–14, p. 159).
		"As data minimisation is an important principle of personal data legislation, this means that organisations need to have a clear ground for processing or sharing personal data. This ground for data processing can be a specific purpose alone (but this means that data cannot be shared), based on a strong generic purpose (such as a scientific purpose), or based on (informed) consent by the data subject. The cases do not show that specific purpose binding is considered a problem by organisations. In all use cases organisations are very careful to process data, which means that they are also careful in determining the purposes for data processing before asking consent" (Van den Broek & Van Veenstra, 2015, p. 10). "To minimise privacy risks, the insurance company emphasises the importance of transparency and widely communicates its data policies to its clients" (Van den Broek & Van Veenstra, 2015, p. 7).
	Organizations may ignore regulations and concerns, or limit compliance	"Because such processes lack transparency and foster children are young and largely without a voice, the new policy remains 'under the radar' for some time. Massive resistance then builds from social welfare non-governmental organizations, as it becomes apparent that children are being forced to stay with foster parents who they are fundamentally incompatible with, and that accusations of abuse are being downplayed because of the forcefulness of the policy directives based on mysterious 'big data analytics'" (Clarke, 2016, p. 81)
		"Fuchs (2010), coming to the debate from a Marxist perspective, has argued that users of social media sites such as Facebook are exploited in the same fashion that TV spectators are exploited.8 The source of exploitation, according to Fuchs, is the "free labor" that users put into the creation of user-generated content (Terranova, 2000). Furthermore, the fact that users are not financially compensated throws a very diverse group of people into an exploited class that Fuchs, following Hardt and Negri (2000), calls the "multitude." (Ekbia et al., 2015, p. 1537).

		“Accordingly, a commissioner from the FTC recently indicated that some companies are willingly violating the law and ignoring privacy rights in order to collect large amounts of personal data. These data are then being used to capitalise on the growing market for big data analytics (Brill, 2013)” (Greenaway et al., 2015, p.592). “Firms oriented as Privacy Ignorers provide little to no control or procedural justice for their customers regarding the control of information collected by the firm, and they rely on individuals taking personal control of their information by choosing when to provide it. For example, they may not display a privacy policy on a website, may not provide detailed information to customers about the organisation’s use of personal information when requested or may misrepresent whether and how they gather and use customer information. In these cases, the firms are more likely to seize control of customer information, not provide customers with opportunities to express their preferences regarding its use and not provide avenues for recourse (i.e. for procedural justice). [..] Uber is an example of a firm that can be classified as a Privacy Ignorer. Ultimately, they offer very little control or procedural justice to their consumers” (Greenaway et al., 2015, p. 594-5). “Firms oriented as Privacy Minimisers engage in only as many privacy behaviours as necessary to avoid legal action. Responding to the minimum requirements of government regulation is considered to be a key driver of an organisation’s privacy approach (Milberg et al., 2000; Milne, 2000). They tend to provide the minimal amount of control of information to customers that is required and little to no mechanisms of justice for the expression of customer preferences or for recourse. These firms can be characterised as being interested in the strict letter of privacy laws rather than in the spirit of offering customers privacy protection. The orientation of Privacy Minimisers is distinguished by their characterisation of privacy as a problem to be minimised rather than as an opportunity to serve customers and, potentially, to distinguish the organisation. Google represents a company that appears to have a Privacy Minimiser orientation” (Greenaway et al., 2015, p. 595).
		"To minimise privacy risks, the insurance company emphasises the importance of transparency and widely communicates its data policies to its clients. When signing the health insurance contract, clients automatically accept that their data could be shared for scientific purposes. This procedure, however, is not an informed and explicit consent as formulated in regulation, as that would be too time-consuming. While the right on privacy of clients is important, it is carefully considered and compared with scientific and societal goals" (Van den Broek & Van Veenstra, 2015, p. 7). “The healthcare database case also explained that that the costs of obtaining proper (informed) consent from the data subjects are expected to be higher than the revenues. Therefore, consent is usually obtained by having people accept general terms, which is not very elegant, nor does it have a strong legal basis. All cases hold that there are still many uncertainties involved in sharing data within a network of organisations” (Van den Broek & Van Veenstra, 2015, p. 10).
		“In the case of Google, Facebook, and other exemplars of surveillance capitalism, many of their rights appear to come from taking others’ without asking – in conformance with the Street View model. Surveillance capitalists have skillfully exploited a lag in social evolution as the rapid development of their abilities to surveil for profit outrun public understanding and the eventual development of law and regulation that it produces” (Zuboff, 2015, p. 83).

	Bridging the trade-off between value and societal implications	“Often times, organizations tout “informed consent” and upfront notice as an answer to critics; yet, as Barocas and Nissenbaum (2014: 32) note, “upfront notice is not possible because new classes of goods and services reside in future and unanticipated uses”. Identifying acceptable levels of intrusion, and finding the right balance (and the principles of balancing) between insights obtained due to access to big data and the infringement such access results in is an important area of inquiry for IS scholars” (Abbasi et al., 2016, p. x).
		“Firms oriented as Privacy Balancers adhere to industry or professionally based privacy codes, including those codes that exceed legal requirements. In this manner, they embrace both the letter and the spirit of privacy laws. In so doing, they provide customers with limited control as well as the ability to express preferences and avenues for recourse related to the handling of information. The orientation of Privacy Balancers is demonstrated by providing customers with a salient means of specifying their information-related preferences and interacting with the company in the use of the information. Walmart is an example of a company that demonstrates a Privacy Balancer orientation” (Greenaway et al., 2015, p. 596). For example, Walmart balances their needs to gather and analyse customer information with the customers’ desire to protect their privacy by giving them the opportunity to opt out of contests and customised marketing (Walmart, 2015). In this way, Walmart is demonstrating an ethical approach in their information management strategy by respecting their customers’ information privacy requests” (Greenaway et al., 2015, p. 583).
		“Privacy and legal issues form another challenge. The prevention of the disclosure of the identity of individuals is an imperative, but this is difficult to guarantee when dealing with Big Data. Since legislation typically lags behind the emergence of new social phenomena, the legal situation for cases involving Big Data is not always clear. In such cases, one may have to fall back on ethical standards to decide on whether and how to use Big Data” (Struijs et al., 2014, p. 3).

Table A.2.7 Socio-technical features of big data.

Levels	Debates	Portability	Interconnectivity
Work-practice level	**Inductive and deductive approaches to big data analytics**	Portability enables data collectors to access data for which they have no pre-defined purpose (e.g., Constantiou & Kallinikos, 2015).	Interconnectivity enables analysts and decision makers to arrive at more insights by exploring synthesized data (e.g., Bholat, 2015; Shollo & Galliers, 2015).
	Algorithmic and human-based intelligence	Portability enables humans to select readily available data (e.g., Shollo & Galliers, 2015).	Interconnectivity enables finding connections in data through the interplay between algorithmic and human intelligence (e.g., Aaltonen & Tempini, 2014; Madsen, 2015; Seddon et al., 2017; Van der Vlist, 2016).
Organi-zational level	**Centralized and decentralized big data capability structures**	Portability allows decision makers and analysts across the organization to perform their own analytics (e.g., Tamm et al., 2013).	Interconnectivity enables centralizing of capabilities to ease the synthesis of different data sets (e.g., Miranda et al., 2015; Tallon et al., 2013–14).
	Big data-driven business model improvement and innovation	Portability enables access to new data sources that can be sold and traded as a form of innovation (e.g., Woerner & Wixom, 2015).	Interconnectivity enables arriving at whole new value propositions from combined data (e.g., Lycett, 2013).
Supra-Organi-zational level	**Controlled and open access to big data**	Portability enables data exchange and sharing among different parties for different strategic reasons (e.g., Malgonde & Bhattacherjee, 2014; Van den Broek & Van Veenstra, 2015).	Interconnectivity enables organizations to connect with different parties in the ecosystem (e.g., Van den Broek & Van Veenstra, 2015).
	Minimizing and neglecting the social risks of big data value realization	Portability enables potentially harmful practices such as sharing personal data (e.g., Greenaway et al., 2015).	Interconnectivity enables public concerns due to the (re)identification of individuals (e.g., Ekbia et al., 2015; Van den Broek & Van Veenstra, 2015).

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