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Clash of Stances: Catalyzing Data Innovation Through Data Labs in Established Firms

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Research-in-Progress

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Abstract

The slow speed with which established firms shift to a data-driven culture continues to be a barrier to the success of big data and analytics. Thus, established firms are looking for new ways to attract talented data scientists and instill a data-driven culture across the organization. In doing so, they increasingly create new business units focused on big data and analytics—often referred to as data labs—which are characterized by informal organizational structures, such as flat hierarchies and a start-up like work environment. However, these data labs have to interact with established corporate structures. Naturally, these interactions may not be frictionless as data labs have the data-driven mindset that may be missing in other parts of the organization. We propose a qualitative research design based on the notion of *organizational epistemic stance* to analyze the interplay between data labs and other business units in established firms.

Keywords

data lab, epistemic stance, data-driven culture, innovation.

Introduction

In recent years, big data and analytics (BDA)—defined as "the application of statistical, processing, and analytics techniques to big data for advancing business" (Grover, Chiang, Liang, & Zhang, 2018, p. 390)—emerged as the "new frontier" of technology-enabled innovations (Goes, 2014). Firms are undergoing a revolution by leveraging their data as a strategic asset to guide decision-making and optimize business processes (Gopalkrishnan, Steier, Lewis, & Guszcza, 2012; Grover et al., 2018). Yet, the slow speed with which established firms shift to a data-driven culture continues to be a barrier to the success of BDA (Davenport & Bean, 2018; McAfee & Brynjolfsson, 2012). According to a recent survey, nearly all participating executives (99%) strived to build a data-driven culture, however, only one-third (32%) claimed their success (Davenport & Bean, 2018). Thus, established firms are looking for new ways to attract talented data scientists and instill a data-driven culture across the organization. In doing so, they increasingly found new business units and subsidiaries focused on BDA—often referred to as *data labs*—which are characterized by informal organizational structures, such as flat hierarchies and a start-up like work environment (Marchand & Peppard, 2013; Schüller, 2018).

Thus, established firms seek to combine talents and know-how in data labs to create value for the entire organization. For instance, Rolls Royce has recently started a data lab to serve as "a catalyst for data innovation across the entire business" (Pickup, 2018). While this approach is very reasonable given the data-driven culture that is necessary to make BDA a success (Grover et al., 2018), these data labs do not operate in vacuum. In contrast, they have to interact with large traditional organizations and established corporate structures. Naturally, these interactions may not be frictionless as data scientists have the data-driven mindset that may be missing in other parts of the organization (Schüller, 2018). Thus, data labs can clash with an intuitive style of reasoning, which is often a core component of an existing organizational culture (Fayard, Gkeredakis, & Levina, 2016). While recent prior information systems (IS) literature has pointed to the importance of organizational culture in BDA success (Grover et al., 2018), limited research has investigated data-driven cultures in established firms and how these interact with emergent data labs

(Gabel & Tokarski, 2014). Yet, given the importance that established firms place on data innovation for long-term growth and survival, it is of importance to understand how firms can maximize the potential of BDA and keep talents within the organization.

The notion of *organizational epistemic stance* (Fayard et al., 2016) has been proposed as a theoretical device to understand the ways an organization frames and pursues opportunities to innovate. Epistemic stance refers to "an attitude that organizational actors collectively enact in pursuing knowledge" (Fayard et al., 2016, p. 302). In general, organizations frame innovations they pursue in ways that are consistent with their present and persistent epistemic stance (Fayard et al., 2016). We find the notion of epistemic stance particularly useful for investigating competing ideologies between data labs and traditional business units within an organization. While Fayard et al. (2016) consider singular stances of two different firms and their innovation capabilities, our study extends the existing notion of epistemic stance by considering different stances within the same organization and how potential conflicts between these stances resolve or sustain over time. Therefore, we propose the following research question: How do differences in epistemic stances between data labs and other business units in established firms interplay over time?

To address our research question, we plan to conduct interviews at a large German corporation, which has recently founded a data lab. The lab is specialized on data services and digital transformation and has currently more than 40 employees, mostly consisting of data scientists, data engineers, and business data analysts. Employees of the lab are engaged in several firm-wide BDA projects. Thus, we expect to find several interfaces to observe the interplay between the data lab and other business units. Next, we briefly review the relevant literature on data-driven culture, data labs, and epistemic stance to develop the key concepts of our study. Then, we describe our empirical context and proposed methodological approach.

Theoretical Background

Data-Driven Culture

Jim Barksdale, the former CEO of Netscape, famously stated, "If we have data, let's look at data. If all we have are opinions, let's go with mine" (Brynjolfsson & McElheran, 2016, p. 133). This quote underlines that firms are striving to establish a data-driven culture where decisions—if possible—are based on "data and rigor" instead of "gut and intuition" (McAfee & Brynjolfsson, 2012, p. 62). Although data science and big data have been called "the golden age for IS researchers" (Agarwal & Dhar, 2014, p. 444), IS literature has remained relatively silent about firms' data-driven culture enabling the discovery of value in data. Except for a recent IS research framework highlighting a firm's data-driven culture as an essential contextual enabler of BDA's value potential (Grover et al., 2018), the importance of being data-driven has mostly been emphasized by practitioner-oriented accounts (Kiron & Shockley, 2011; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; McAfee & Brynjolfsson, 2012). For instance, McAfee and Brynjolfsson (2012) interviewed executives of 330 firms about their decision-making practices and collected objective data on performance from their annual reports. The authors found that data-driven firms performed better financially and operationally. Thus, a lack of such practices may pose formidable barriers to identifying and generating value from BDA (Grover et al., 2018). Despite these findings, established firms still struggle to integrate BDA into their organizational culture (Davenport & Bean, 2018; Frizzo-Barker, Chow-White, Mozafari, & Ha, 2016). Evidence from economics literature suggests that data-driven decision making is becoming increasingly popular in the manufacturing sector, however, 70 percent of the manufacturing plants in the sample had not yet adopted this practice (Brynjolfsson & McElheran, 2016). In conclusion, "managing with analytics is now a mainstream idea, though not a mainstream practice" (Ransbotham, Kiron, & Prentice, 2016, p. 14).

Data Labs in Established Firms

To facilitate the diffusion of a data-driven culture in established firms, organizations have founded data labs as one way to bring BDA experts together and signal to staff that the organization is placing its trust on data as a core asset for strategic decision-making (Marchand & Peppard, 2013; Ransbotham et al., 2016). Practitioner-oriented accounts reveal several examples of firms who have established data labs, such as Volkswagen (Reinking, 2017), Rolls Royce (Pickup, 2018), Frankfurt Airport (Fraport) (Schüller, 2018), and Bank of England (Ransbotham et al., 2016). On one hand, data labs enable data scientists to work on specific problems in a discovery and learning environment (Marchand & Peppard, 2013). On the other hand, data labs need to cooperate with other parts of the organization to put their ideas and prototypes into practice (Pickup, 2018; Schüller, 2018). While the former point is especially important for attracting talents and generating new ideas (Ransbotham et al., 2016), it is the latter that is crucial for creating actual business value (Grover et al., 2018). However, this cooperation may also be a potential source of friction and misunderstandings within the organization (Gabel & Tokarski, 2014; Schüller, 2018). As described by Schüller (2018), Fraport has created an "experimental smart data lab" to work on different analytics-related problems, such as the effect of aircraft positioning on sales in airport shops. Yet, the author acknowledges that these initiatives were not always without internal conflicts (Schüller, 2018, p. 124):

> *"Managers who have not previously taken such analytics activities too seriously suddenly hear fragments of raw results and react anxiously or even angrily. No one has happily waited for the statisticians to uncover errors of past and perhaps even current decision-making practices. One often does not realize that changing decision processes from an experience-driven to a data-driven approach may attack hierarchical structures."*

As a result, data labs—though a promising idea—can clash with more intuitive decision-making practices (Fayard et al., 2016) and in some cases even face boycott behavior (Schüller, 2018). Therefore, Schüller (2018) argues that the importance of communication, political lobbying and sensitivity cannot be overemphasized, which means that data scientists need to spend enough time to advertise their initiatives internally.

Epistemic Aspects of Dealing with Technology-Enabled Innovations

While conflicts between data labs and other business units have received little attention in prior IS research, the topic can be embedded into a larger body of literature focused on the role of organizational culture in the wake of technology-enabled innovations (Dougherty & Dunne, 2012; Fayard et al., 2016; Wagner & Newell, 2004). Wagner and Newell (2004) describe the design and implementation of an enterprise resource planning (ERP) system at a university and draw on the notion of "epistemic culture" to show that no university-wide ERP best practice package exists. Epistemic culture refers to those "sets of practices, arrangements and mechanisms bound together by necessity, affinity and historical coincidence which, in a given area of professional expertise, make up how we know what we know" (Knorr Cetina, 2007, p. 363). ERP systems present a way to capture knowledge within organizations. Thus, if intra-organizational subgroups (e.g., central administration, faculty) are characterized by different epistemic cultures, conflicting underlying epistemic assumptions of ERP best practice packages may emerge between the various groups (Wagner & Newell, 2004).

Similarly, Dougherty and Dunne (2012) found that two groups of scientists with distinct epistemic cultures had difficulties to collaborate on drug development as one group focused on generating novel insights through traditional laboratory work, whereas the other relied on digital technologies. More recently, Fayard et al. (2016) advocated the use of epistemic stance to understand how non-scientific organizations deal with technology-enabled innovations. While the sociological concept of epistemic culture highlights the "stable, systemic, and material context of scientific practice," the philosophical concept of stance "places more emphasis on the active commitment to certain ways of knowing in dealing with a specific issue" (Fayard et al., 2016, p. 305). Drawing on an in-depth investigation of crowdsourcing for innovation in two consulting firms, Fayard et al. (2016) found that both firms remained committed to their epistemic stance when evaluating a new crowdsourcing platform. This enabled one firm to frame crowdsourcing as an "inspiration" and further experiment with it, whereas the other framed it as an "undisciplined" approach and rejected it.

In sum, prior literature already provides an understanding of epistemic aspects in adopting or rejecting technology-enabled innovations. However, prior work focused either on (1) "modifying the standard [of a technology]" (Wagner & Newell, 2004, p. 326) to ensure that departments with different epistemic cultures participate in technology use or on (2) technologies at an experimental stage where the implementation had not been subject to competitive or institutional pressure (Fayard et al., 2016). In contrast, leveraging BDA (1) requires established firms to fundamentally change their decision-making practices (McAfee & Brynjolfsson, 2012) and (2) is seen as "the most significant 'tech' disruption [since] the Internet and the digital economy" (Agarwal & Dhar, 2014, p. 443). Thus, we address a gap in the literature by focusing on epistemic aspects of BDA diffusion and adoption in established firms. Specifically, we draw on the notion of epistemic stance to understand and articulate the dynamic interplay between emergent data labs and traditional business units in the BDA adoption process.

Epistemic Stance and Data Analytics

The notion of stance has first been developed by van Fraassen (2002) and has recently been debated by other philosophers of science (Baumann, 2011; Boucher, 2014, 2015; Chakravartty, 2011; Rowbottom & Bueno, 2011a, 2011b). In particular, Boucher (2015) offers four distinct characteristics of stances, arguing that stances are (1) not reducible to beliefs and therefore adopted rather than believed (like an approach or policy); (2) non-propositional (i.e., not thought of as true or false); (3) value-driven (i.e., one adopts a stance which is coherent with one's values); (4) pragmatically justified in terms of their fruits (i.e., one adopts a stance on the basis of the consequences of doing so). These descriptions offer a broad account of the characteristics a stance may entail and why one may adopt a specific stance. It is important to note that stances may both be related to epistemic and non-epistemic values (Boucher, 2014). While non-epistemic values include social, political, ethical or aesthetic issues, epistemic values are concerned with the generation of knowledge (Boucher, 2014; Chakravartty, 2011). Given that our work is situated in the context of leveraging BDA in established firms, our focus is on epistemic stances as these can explain whether and how organizational actors generate and evaluate knowledge from data. Epistemic stances include "whether one values explanations, the sorts of explanations one values, the kinds of methods of inquiry, epistemic strategies and approaches one values" (Boucher, 2014, pp. 2319–2320), which closely resemble different modes of working and decision-making in firms.

By focusing our investigation on epistemic stances, we tap in to recent prior work by Fayard et al. (2016) who adapted the concept to the organizational context. O*rganizational epistemic stance* is defined as "an attitude that organizational actors collectively enact in pursuing knowledge" (Fayard et al., 2016, p. 302) and its dimensions are summarized in Table 1. To better illustrate the dimensions of epistemic stance, we develop an exemplary stance for data labs. First, as an epistemic stance is concerned with generating knowledge, this guides the selection of domains. Thus, domains need to be worth investigating and capable of providing new insights. Data labs are focused on evidence-based analyses, which means that they are restricted to domains where data is currently available or can be made available. Second, an epistemic stance involves a mode of investigation, such as being closer to or more detached from phenomena (Rowbottom & Bueno, 2011a). Though data labs need context-specific knowledge, they may be more detached from phenomena—e.g., optimizing aircraft positioning at an airport—than those being responsible for the task on a daily basis. In general, data labs are able to apply similar statistical tools and techniques across a range of phenomena. Third, generating knowledge also requires a style of reasoning, for instance, deductive or inductive reasoning. Data labs generally use inductive and deductive reasoning by either exploring patterns in data or finding answers to predefined hypothesis. For instance, Fraport's smart data lab may have used deductive reasoning to find an answer to the investigation of aircraft positioning on sales in airport shops (Schüller, 2018). They may have had specific hypotheses in mind—e.g., Asian customers are more inclined to buy German products—and were able to show that flights to and from Asia located closer to the airport shopping mall generated more sales. Fourth, the mode of evaluating knowledge encompasses being more or less skeptical or critical toward propositions. For data labs, solutions or insights generated through high-quality data and statistical models are better than those generated through intuition and experience.

Lastly, we discuss the role of commitment in epistemic stances. According to philosophers of science (Fayard et al., 2016; van Fraassen, 2002), we are committed to a certain stance, mainly expressed through our reactions and emotions. Commitment to a stance happens often "pre-reflective" which means that commitment occurs implicitly and that we do not necessarily think about what we should be committed to (Fayard et al., 2016). However, when prompted to critically question our commitment, we are able to offer justifications about why adopting a particular stance is beneficial (see point 4 on this page related to adopting stances based on the consequences). Thus, different firms may be committed to different epistemic stances, however, commitment to stances may also differ within firms, such as between different business units. In general, epistemic stances offer an interesting lens on the competing values for pursuing novel insights within established firms. We find the notion of stance especially interesting to unpack the conflict between emergent business units focused on BDA (i.e., data labs) and traditional business units focused on intuitive or experience-based decision-making. Therefore, "using data science may clash with an intuitive style of reasoning, which might be a core component of an existing organizational stance" (Fayard et al., 2016, p. 321)—especially as each actor remains committed to their stance.

Table 1. Dimension of Epistemic Stance (Fayard et al., 2016, p. 305)	
Dimensions	**Explanation**
Domains of investigation	The domain(s) of reality that is (are) judged as candidate(s) for generating new knowledge.
Mode of investigation	The way of approaching epistemic issues, including how closely an investigator explores and observes an empirical phenomenon to generate understanding of it.
Style of reasoning	How one thinks and reasons about an epistemic issue (e.g., inductively, deductively) and uses inference devices such as models, tools, etc.
Mode of evaluation	How one goes about judging an epistemic proposition or evidence and expresses such judgment in action. For example, one might be skeptical towards certain kinds of propositions.

Planned Research Design

Research Setting

In 2015, a large German corporation with more than 120,000 employees worldwide ("Alpha") founded a new subsidiary focused on data services and digital transformation ("Beta"). As of mid-2018, Beta had more than 40 employees. Beta was established with the goal to support BDA initiatives at Alpha. Beta's employees are currently involved in approximately 10 projects—mainly BDA-related—at Alpha and its subsidiaries. By founding Beta, Alpha's managers hope to attract more talents with a curious and data-driven mindset, such as data scientists, data engineers, and business data analysts, which are lacking in Alpha's more traditional organization. In fact, Beta's managing director argued that these people "don't approach things from a traditional perspective but are constantly looking to develop their knowledge in new directions. People like that do not fit into traditional structures and hierarchies." Thus, Beta also moved to separate offices and created a start-up like environment for its talented staff, including a dartboard, writable desks, cube seats, and movie nights. Beta's slogan is "we are fearlessly curious truth seekers" and each Friday the firm hosts a "data science talk" with internal and external speakers to discuss topics related to BDA. Beta has gradually developed into an acknowledged hub for data innovation. One recent success for Beta was the award of Alpha's firm-wide innovator award for a reinforcement learning software.

Beta is very different from Alpha. The latter is characterized by more traditional values and hierarchical structures. Alpha's managers are on average 52 years old and not as experienced with BDA as the "digital natives" working for Beta. Therefore, we expect that Alpha and Beta have distinct epistemic stances that interplay in BDA-related projects. We selected Alpha and Beta for being "polar types in which the process of interest is 'transparently observable'" (Eisenhardt, 1989, p. 537). Through our investigation of Alpha and Beta, we hope to gain an empirically grounded understanding of how different organizational actors encounter BDA and which cultural aspects matter in these encounters.

Method

We use a qualitative and exploratory research strategy to address our research question. To identify different ways of staying committed to epistemic stances while encountering BDA and to explore how different BDA-related activities are linked to conflicts between different epistemic stances, we plan to adopt a multiple-case study approach (Yin, 2009). Case studies are especially suitable to understand the dynamics of a phenomenon (Yin, 2009). We plan to collect data on both (1) general work and decision-making practices of Alpha and Beta and (2) the actions and responses regarding BDA-enabled innovations. In particular, we will choose different BDA projects where Alpha and Beta cooperate in order to find patterns of how Alpha and Beta stay committed to their epistemic stances, whether stances between Alpha and Beta differ, how they interplay over time and whether a party adapts their stance. Therefore, we plan to conduct interviews with employees of Alpha and Beta—who work together on BDA-related projects—at multiple points in time. Each project will constitute a separate case, which allows us to observe how Alpha and Beta frame BDA-related innovations. In addition, we plan to collect published documents (articles, books, blogs, and videos) on Alpha and Beta.

We plan to follow an iterative approach to data analysis and theory building that involves moving back and forth between data and theory using open, axial, and selective coding (Corbin & Strauss, 1990). First, we plan to code documents and interviews to understand the epistemic stances of Alpha and Beta. For our empirical analysis, we plan to adopt Fayard et al.'s (2016) definition of epistemic stance to identify the unique stances of Alpha and Beta. As outlined in the previous section, we plan to find differences between Alpha's and Beta's epistemic stance. However, we expect that epistemic stances within Alpha and Beta do not vary greatly between the different cases as they should be relatively stable. To ensure that we will be able to observe differences between Alpha and Beta but little variation within Alpha and Beta, case selection will be crucial. We will therefore try to find cases that are comparable, for instance, with respect to the size of the project, experience of project members, and timeline of the project.

Second, we plan to analyze how Alpha and Beta are influenced by their epistemic stance when developing and implementing BDA-enabled innovations. We expect to find that Alpha has a more intuitive style of reasoning, which may render them more skeptical toward BDA-enabled innovations. Thus, we expect to see some hesitations in the data , for instance, arguments that certain projects cannot be realized due to privacy issues. In contrast, Beta may be more enthusiastically with respect to new BDA initiatives, embracing it as a chance rather than a problem. Third, we plan to observe how the interplay between different stances unfolds over time. On one hand, as BDA-enabled innovations become more mature, the benefits may become visible so that Alpha may look for ways to embrace BDA as an opportunity while remaining committed to their stance. On the other hand, as BDA-related innovations do not produce the expected output, Beta may evolve their epistemic stance as Alpha remains committed to its stance. These are just two very broad examples; however, they illustrate the number of interesting patterns that could emerge from our observations.

Potential Challenges

It may be difficult to observe the different dimensions of epistemic stance (Table 1) in our actual case. However, these dimensions serve as a guiding framework for our investigation and can subsequently be refined. In Fayard et al.'s (2016) case, it quickly emerged from the data that the two consulting firms under investigation differed in every dimension of their epistemic stances due to their opposing views on many issues. As we investigate "a firm within a firm," there may be overlapping aspects of the stances between Alpha and Beta. Additionally, Fayard et al. (2016) analyzed a crowdsourcing platform at a time where firms were still unsure whether the innovation delivered actual value. As we plan to analyze BDA-related innovations, there may be greater consensus on the innovations' usefulness among Alpha and Beta and thus less potential to observe conflicting stances. Lastly, philosophers of science still debate on the different conceptualizations of epistemic stance. Consequently, this can become problematic in building a coherent stream of research on the phenomenon. As a potential remedy, we start with the conceptualization of Fayard et al. (2016) and subsequently enrich it with current literature (e.g., Boucher, 2018) as we move forward with this project and get to know the actual stances of Alpha and Beta.

Conclusions

Established firms still struggle to leverage the potential of BDA because many of them lack the data-driven culture to act on the insights generated through data. Thus, newly founded data labs may be a promising avenue for established firms to catalyze data innovation across the organization. However, recent IS research suggests that an organization's epistemic stance may determine how an organization frames a technology-enabled innovation opportunity (Fayard et al., 2016). Based on prior research (Davenport & Bean, 2018; Schüller, 2018), we expect that data labs and other business units may have very different epistemic stances and thus struggle to cooperate successfully on BDA-enabled innovations. Our qualitative research proposal highlights a research design to uncover different epistemic stances between data labs and traditional business units. Furthermore, we aim to give an account of the interplay between different stances and how they can evolve to embrace BDA as a chance rather than a threat. By focusing on competing stances within an organization and focusing on a technology that has the potential to fundamentally alter organizational practices, we extend prior research on the role of culture in the wake of technology-enabled innovations. Additionally, we hope to provide an in-depth understanding of how established firms can make use of BDA despite competing ideologies.

References

Agarwal, R., & Dhar, V. (2014). Editorial—Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research. *Information System Research*, *25*(3), 443–448.

Baumann, P. (2011). Empiricism, stances, and the problem of voluntarism. *Synthese*, *178*(1), 27–36.

Boucher, S. C. (2014). What is a philosophical stance? Paradigms, policies and perspectives. *Synthese*, *191*(10), 2315–2332.

Boucher, S. C. (2015). Functionalism and structuralism as philosophical stances: van Fraassen meets the philosophy of biology. *Biology & Philosophy*, *30*(3), 383–403.

Boucher, S. C. (2018). Stances and Epistemology: Values, Pragmatics, and Rationality. *Metaphilosophy*, *49*(4), 521–547.

Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review*, *106*(5), 133–139.

Chakravartty, A. (2011). A puzzle about voluntarism about rational epistemic stances. *Synthese*, *178*(1), 37–48.

Corbin, J. M., & Strauss, A. (1990). Grounded theory research: Procedures, canons, and evaluative criteria. *Qualitative Sociology*, *13*(1), 3–21.

Davenport, T. H., & Bean, R. (2018). Big Companies Are Embracing Analytics, But Most Still Don't Have a Data-Driven Culture. *Harvard Business Review Digital Articles*, 2–4.

Dougherty, D., & Dunne, D. D. (2012). Digital science and knowledge boundaries in complex innovation. *Organization Science*, *23*(5), 1467–1484.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, *14*(4), 532–550.

Fayard, A.-L., Gkeredakis, E., & Levina, N. (2016). Framing innovation opportunities while staying committed to an organizational epistemic stance. *Information Systems Research*, *27*(2), 302–323.

Frizzo-Barker, J., Chow-White, P. A., Mozafari, M., & Ha, D. (2016). An empirical study of the rise of big data in business scholarship. *International Journal of Information Management*, *36*(3), 403–413.

Gabel, T. J., & Tokarski, C. (2014). Big Data and Organizational Design: Key Challenges Await the Survey Research Firm. *Journal of Organization Design*, *3*(1), 37–45.

Goes, P. B. (2014). Editor's comments: big data and IS research. *MIS Quarterly*, *38*(3), iii–viii.

Gopalkrishnan, V., Steier, D., Lewis, H., & Guszcza, J. (2012). Big data, big business: bridging the gap. In *Proceedings of the 1st International Workshop on Big Data, Streams and Heterogeneous Source Mining: Algorithms, Systems, Programming Models and Applications* (pp. 7–11). ACM.

Grover, V., Chiang, R. H. L., Liang, T.-P., & Zhang, D. (2018). Creating Strategic Business Value from Big Data Analytics: A Research Framework. *Journal of Management Information Systems*, *35*(2), 388–423.

Kiron, D., & Shockley, R. (2011). Creating business value with analytics. *MIT Sloan Management Review*, *53*(1), 57.

Knorr Cetina, K. (2007). Culture in global knowledge societies: Knowledge cultures and epistemic cultures. *Interdisciplinary Science Reviews*, *32*(4), 361–375.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, *52*(2), 21.

Marchand, D. A., & Peppard, J. (2013). Why IT Fumbles Analytics. *Harvard Business Review*, *91*(1/2), 104–112.

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

Pickup, O. (2018). Be inspired by Rolls-Royce's 'catalyst' for data innovation. Retrieved July 27, 2018, from https://www.telegraph.co.uk/education/stem-awards/digital/rolls-royces-catalyst-for-data-innovation/

Ransbotham, S., Kiron, D., & Prentice, P. K. (2016). Beyond the hype: the hard work behind analytics success. *MIT Sloan Management Review*, *57*(3).

Reinking, G. (2017). The Cloud in the Driver's Seat. In F. Abolhassan (Ed.), *The Drivers of Digital Transformation: Why There's No Way Around the Cloud* (pp. 45–55). Cham: Springer International Publishing.

Rowbottom, D. P., & Bueno, O. (2011a). How to change it: modes of engagement, rationality, and stance voluntarism. *Synthese*, *178*(1), 7–17.

Rowbottom, D. P., & Bueno, O. (2011b). Stance and rationality: a perspective. *Synthese*, *178*(1), 1–5.

Schüller, K. (2018). Big Data in der statistischen Methodenberatung. In C. König, J. Schröder, & E. Wiegand (Eds.), *Big Data: Chancen, Risiken, Entwicklungstendenzen* (pp. 111–127). Wiesbaden: Springer Fachmedien Wiesbaden.

van Fraassen, B. C. (2002). *The Empirical Stance*. New Haven, CT: Yale University Press.

Wagner, E. L., & Newell, S. (2004). "Best" for whom?: the tension between "best practice" ERP packages and diverse epistemic cultures in a university context. *The Journal of Strategic Information Systems*, *13*(4), 305–328.

Yin, R. K. (2009). *Case study research: design and methods*. London: Sage.