

Approaching a Data-Dominant Logic

Petra Kugler

“The goal is to turn data into information, and information into insight.”

Carly Fiorina

Former CEO, Hewlett-Packard

This paper introduces the construct of “data-dominant logic”. The findings of a multi-step exploratory study indicate that SME have an established mindset (dominant logic) that often hinders these firms from turning data in innovative products, services, and business models. The availability of large amounts of data and the use of this data through data science-driven practices has reached a stage when it now enables new and promising possibilities for firms to innovate. However, the actual use of data and data science insights has proven to be difficult for many companies. The firms under consideration in this paper recognize that the availability of data fundamentally changes their businesses. But also, they lack the appropriate culture, mindset, and business repertoire that would enable them to act by turning data into innovation. The paper concludes that firms first need to establish a new mindset in which data plays a central role. Here I term this mindset “data-dominant logic” (DDL). Future research is required to further concretize the construct beyond this introduction.

Introduction

This paper introduces the construct of “data-dominant logic” (DDL). SMEs that aim to use data and adopt data science insights within their company currently lack this way of thinking. DDL is a hurdle for (established) companies that use data in their value creation process.

Researchers agree that organizations and the prevailing rules of competition alike are fundamentally changing in the digital age (Brynjolfsson & McAfee, 2014; Iansiti & Lakhani, 2017; Parker et al., 2018; McAfee & Brynjolfsson, 2018). The recent spread of digital technology is enabling new and promising possibilities for many firms, such as efficiency increases (Kugler, 2019), new products and services, or innovative business models (Parker et al., 2018). Especially the use of insights from data and data science seems to be a key success factor in the digital economy. The fact that at least seven out of the ten most valuable companies today ground their business in data, platforms, and networks, demonstrates this.

However, generating new business and new value that is linked to data science, still proves to be difficult (Chin et al., 2017), especially for established companies. Little is

known concretely about which organizational and managerial requirements (established) companies need to consider as ways of facilitating the efficient adoption of data science-driven approaches and practices. When compared to large firms, the situation seems to be even more difficult for SMEs. Small and young firms face specific challenges, such as the liability of smallness and market entry barriers (Gruber & Henkel, 2004). In comparison with large firms, SMEs lack resources, giving them a competitive disadvantage.

Against this background, the growing availability of data and data science seem to offer valuable opportunities for SMEs to build up competitive advantages, and thus to stay in business. At the same time, exploiting data-oriented opportunities can be a challenging task for these firms. This paper therefore asks about the organizational and managerial requirements that facilitate data- and data science-driven value creation, focusing especially on SMEs.

The findings of this manuscript emerged out of a literature review and an exploratory field study that aimed at gaining deeper knowledge of the current state of data and data science-related practices in SMEs. Empirical data was gathered through a series of

Approaching a Data-Dominant Logic

Petra Kugler

interviews with 16 SMEs in Austria, Germany, and Switzerland that were condensed into a list of working hypotheses, as well as a survey with more than 100 fully completed replies.

The study's findings suggest that established organizational and managerial structures are the most critical factors that hinder firms from adopting data and data science-driven approaches for new business value creation. A firm's established business mindset or, "dominant logic", came out as being most critical for the companies studied. This is defined as "the dominant way in which managers think and act" (Bettis et al., 2003). Firms that wish to adopt data science-driven approaches, therefore first need to transfer their established dominant logic into a new DDL. At least, that is the main argument presented in this paper.

The remainder of the paper is structured as follows: The next section discusses the relevance of SMEs adapting data-science driven practices and the construct of a dominant logic in the realm of business. The section after gives a brief overview of the paper's research design. The section following discusses key findings of the study and introduces the concept of a data-dominant logic and the final section concludes the paper, setting the new construct up for further elaboration, exploration and testing.

Current Understanding

SMEs are adopting data science-driven practices

"Data science" refers to large data sets that require deep analysis for generating insights from these data (Gupta & George, 2016). Data science practices can be described by up to five characteristics: volume, variety, velocity, veracity, and value (Remane et al., 2011; Fosso Wamba et al., 2015, 2017). Researchers and practitioners alike agree that data science has the potential to fundamentally change the rules of competition and to enable immense possibilities for generating value, profit, innovation, and competitive advantages. Consequently, a firm's performance can be enhanced by using data analytics (Henke et al., 2016; Fosso Wamba et al., 2017). Data science, then, is responsible for the "new gold rush" (Tabesh et al., 2019), "the next frontier for innovation, competition, and productivity" (Manyika et al., 2011), a "new paradigm of knowledge assets" (Hagstrom, 2012), that which requires an "analytics revolution" (Chin et al., 2017).

timreview.ca

One complaint has been that firms struggle to turn data into value and that the potential inherent to data science to a large degree cannot be exhausted (Henke et al., 2016; Chin et al., 2017). Large amounts of information by themselves do not make the ability to sense change and respond effectively to it easier. However, "What is seen instead, are information-rich, but interpretation-poor systems. In other words, systems that seem to confuse raw information or data with appropriate actionable knowledge" (Bettis & Prahalad, 1995), when it comes to changing a firm's dominant logic in situations of fundamental structural change.

Researchers have identified a variety of challenges that organizations face if they wish to adopt data science-driven practices. To date many studies have focused on large firms, without illustrating the situation of SMEs. Other work has identified a lack of data competence on all hierarchical levels of companies. This lack of competence has led to difficulties in identifying data science use cases involving organizational and technical issues (Bange et al., 2015; Wamba et al., 2015). Firms, thus, find it hard to identify and use value that is generated by data science-driven approaches and insights. These studies concluded that employees and management alike lack the appropriate competences and knowledge that could help them to understand how new insights can be generated through data science-driven practices (Barton & Court, 2012; Wamba et al., 2015).

Other research concluded that firms depend upon employees that are capable of linking technical knowledge with business knowledge for the purpose of applying data science insights within an organization. Through these linkages, data science can generate and transfer findings into business opportunities (Henke et al., 2016; Chin et al., 2017). Without these linkages, however, organizations might easily overlook the potential inherent in data science-driven practices. This result is also reflected in a lack of coherent data strategies or benchmarks for measuring success that can be traced back to insights generated by data science (Brown, et al., 2013; New Vantage Partners, 2017). In general, studies have found that firms to date have not been able to make use of a data-driven culture (New Vantage Partners, 2017), or so-called "analytics-culture" (Brown et al., 2013). Instead, organizations, seem to lack a basic and holistic understanding of how data and the adoption of data science-driven approaches may be able to fundamentally change the character of their business, and thus how the data and analytics gap can be filled. In

Approaching a Data-Dominant Logic

Petra Kugler

the following chapter, the notion of a “dominant logic” will be introduced to conceptualize this challenge and to fill the gap that has been identified.

Dominant logic

The concept of a “dominant logic” deals with why a group of intelligent managers fails when thinking strategically about forthcoming structural changes to their core business (Prahalad & Bettis, 1986). Members of the top management team tend to “conceptualize the business and make critical resource allocation decisions - be it in technologies, product development, distribution, advertising, or in human resource management”, in a largely similar way, which is a consequence of their shared dominant logic (Prahalad & Bettis, 1986). More concretely, a “dominant logic represents the shared cognitive map (Prahalad & Bettis, 1986) and strategic mindset of the top management team or the dominant coalition, and it is closely associated with the process and tools used by top management” (Bettis et al., 2003).

A dominant logic in business can be traced back to the fact that a group of managers use similar tools, share implicit and explicit knowledge, and also interpret the tools and knowledge in a way that aligns. Established cognitive models of business have been used to serve as a simplifying filter mechanism, especially when confronted with complex or ambiguous situations. Cognitive models help individuals to focus on certain aspects they are familiar with, while other (unknown or unclear) factors remain largely ignored (Bettis & Prahalad, 1995). Some researchers have found that cognitive structures are not limited to only top management teams, as suggested by Prahalad and Bettis (1986; Bettis & Prahalad, 1995). These ways of thinking can also be found in other organizational groups, including software development teams (Espinosa et al., 2001, 2002) and airplane flight deck crews (Weick & Roberts, 1993), all of which find themselves in highly dynamic and uncertain settings. The characteristics of a dominant logic overlap with other cognitive approaches, such as “shared mental models” (Espinosa et al., 2001, 2002), “organizational cognition” (Smircich, 1983), “underlying assumptions” (Schein, 1995), and a “collective mind” (Weick & Roberts, 1993).

Bergman and colleagues (2015) indirectly proved the stated meaning of “dominant logic” in the context of innovation. Vargo and Lusch (2004; Lusch & Vargo, 2006a; Vargo et al., 2010) found it to prevail in the

context of typical manufacturing-oriented firms in contrast with service-oriented firms. These two types of firms rely on different business logic, either a “goods-dominant logic” (GDL) or a “service-dominant logic” (SDL). While a GDL puts a physical product and tangible, inert resources in the center of value creation, the emphasis of a SDL rather lies in intangible, dynamic resources, co-creating the process of exchange. While GDL can be characterized as “exchange paradigm”, SDL serves rather as a “relationship paradigm” (Prahalad, 2004; Vargo & Lusch, 2006a).

Lusch and Vargo (2006b) conclude that applying SDL instead of GDL leads to numerous changes in how value creation and exchange take place within a company. In short, this shift requires a new set of “specialized competences (knowledge and skills), through deeds, processes, and performances for the benefit of another entity or the entity itself” (2006b). Generally speaking, SDL offers a new lens on how organizations function and how organizational members interpret their role in an organization. Therefore, SDL bears the potential to constitute a new paradigm for economic exchange and value creation (Vargo & Lusch, 2006).

Indicators of a dominant logic

Although the intangible concept of a “dominant logic” has been discussed in a vast body of literature, it is noteworthy that “the exact contents in the dominant logic are usually left unspecified” (Bettis et al., 2011). The construct itself does not refer to a single theme or discipline; rather it should be conceptualized as a set of “main themes” or “configurations” (Obloj et al., 2010). Although the concept is “intellectually appealing, the empirical support for its impact has been weak to date” (Obloj et al., 2010). Attempts to study and measure dominant logic are methodologically challenging because it is an intangible and cognitive concept (Lampel & Shamsie, 2000). Thus, when people have written of a dominant logic, it can only be captured indirectly, and the literature presents a variety of approaches to do so.

Some authors use analogies to circumscribe the construct, such as, for instance, likening it to a medical diagnosis (Bettis & Prahalad, 1995; Prahalad, 2004). Other authors have broadly compared how closely the empirical setting conforms to descriptions of dominant logic in the literature (for example, Lampel & Shamsie, 2000, in the case of Jack Welch and General Electric). Similarly, the literature has discussed a broad set of characteristics and typical settings that indicate the

Approaching a Data-Dominant Logic

Petra Kugler

Table 1. Indicators of dominant logic on the individual and organizational level, based on a literature review

Level of Analysis	Tangible, directly observable, "acting"	Intangible, indirectly observable, "thinking"
Individual	Individual acting (7) Individual decision making, e.g. resource allocation (1, 3) Individual problem-solving behavior (2)	Beliefs, assumptions, expectations, interpretation, propositions (1, 3, 4, 7, 10) Cognitive schemas, mindset, world view, cognitive map (1, 2, 3, 6) Conceptualization of business (1, 2, 3, 10) Constraints to search spaces associated with problems (3) Criteria for choice, evaluation, decision making (10) Individual routines (5) Information filter (5, 9) Key features of acceptable solutions (3) Learning, unlearning, forgetting curve (1, 5) Reinforced behavior (1) Specific set of premises (6)
Organizational	Performance of the organization (2) Administrative tools, organizing and management principles, formal procedures, control (2, 3, 7, 8, 10) Culture (3) Use of technology (4) Goal setting, e.g. performance targets (5) Systems, structure, locus of decisions (1, 2, 3, 4) Processes, procedures (3, 4, 7, 9) Resource allocation (4, 5, 8) Strategy (1, 2, 3, 5, 7, 8) Products, brand (3, 4) Value exchange and creation (4, 11) Tasks critical to success, core activities (5, 10)	Cultural values and norms (1, 3, 5, 10) Organizational identity, image (7) Organizational Routines (5, 8) Procedural memory (7) Social architecture of the firm, socialization (7) Social control (3) Top management team thinking (7)
Literature Source		
1 Bettis & Prahalad, 1995		6 Lampel & Shamsie, 2000
2 Prahalad & Bettis, 1986		7 Jarzabkowski, 2001
3 Bettis, Wong & Blettner, 2011		8 Grant, 1988
4 Prahalad, 2004		9 Pan, 2017
5 Obloj, Obloj & Pratt, 2010		10 Côté, Langley & Pasquerc, 1999
		11 Vargo & Lusch, 2004

Approaching a Data-Dominant Logic

Petra Kugler

prevalence or absence of a certain dominant logic. However, these characteristics have often been presented in broad categories that only give an idea where to search for a dominant logic, instead of showing a clear list of indicators (see Table 1).

Dominant logic typically refers to thinking and acting in organizations (Jarzabkowski, 2001). It is a multi-level construct that relates to both the individual and the organizational levels of analysis. On an *individual level*, dominant logic refers to the thinking and of framing a specific situation or problem definition by an organizational member or the top management team. The indicators mentioned in the literature include, among others, cognitive schemas, mindset, and cognitive maps (Pralhalad & Bettis, 1986; Bettis & Prahalad, 1995; Bettis et al., 2003; Vargo & Lusch, 2004) that serve as information filter (Obloj et al., 2010), criteria for choice, evaluation, decision making (Côté et al., 1999), business conceptualization (Pralhalad & Bettis, 1986; Bettis & Prahalad, 1995; Côté et al., 1999; Bettis et al., 2003), and beliefs, assumptions, expectations, and interpretations (Bettis & Prahalad, 1995; Côté et al., 1999; Jarzabkowski, 2001; Bettis et al., 2003; Prahalad, 2004). These indicators are admittedly intangible and hard to observe in a direct way.

“Thinking” on an individual level only turns into “acting” on an *organizational level*, where intangible cognition turns into tangible activities or structures. On an organizational level, dominant logic becomes visible through management principles, formal procedures, and control actions (Pralhalad & Bettis, 1986; Grant, 1988; Côté et al., 1999; Jarzabkowski, 2001; Bettis et al., 2003; Prahalad, 2004), culture, processes, and procedures (Jarzabkowski, 2001; Bettis et al., 2003; Prahalad, 2004), resource allocation (Grant, 1988; Prahalad, 2004; Obloj et al., 2010), and strategies (Pralhalad & Bettis 1986; Grant, 1988; Bettis & Prahalad, 1995; Jarzabkowski, 2001; Bettis et al., 2003; Obloj et al., 2010).

A company’s dominant logic that is anchored in individual and organizational thinking and acting provides an organization with a specific *repertoire to act* that fits certain situations. A dominant logic under stable conditions of exploitation (March, 1991) leads to efficiently and informally coordinating a company. Instead, when operating under conditions of fundamental change (“exploration”, March, 1991) or disruption (Christensen, 1997; Christensen & Raynor, 2003), a certain dominant logic can be a hurdle to

timreview.ca

organizational adaptation.

When confronted with *fundamental structural changes in their environment*, firms therefore also need to change or adapt their respective dominant logic (Bettis & Prahalad, 1995; Bettis et al., 2003). In situations in which firms are unable to adapt to environmental changes, in which they are unable to turn information into actionable knowledge (Bettis & Prahalad, 1995), or in which they use inappropriate (cognitive) schemas (Côté et al., 1999), one of the main problems may be that organizations have not (yet) developed a new, appropriate dominant logic. Consequently, these organizations lack the appropriate *repertoire to act*.

This discussion reveals that a dominant logic can be recognized by a vast array of indicators across organizations. This finding indicates that dominant logic permeates entire organizations, because many of the indicators and characteristics of a dominant logic are interrelated. Consequently, a holistic perspective or integrative framework is required to study the concept of dominant logic (Obloj et al., 2010), while also accepting the concept’s limitations. This requirement will be mirrored in the empirical study below, which approaches the field from a set of four different perspectives.

While the concept of “dominant logic” has been studied in the context of analog firms, to date little to nothing in the literature addresses, first, if digital firms actually need a different, data-related (digital) dominant logic, second, what exactly is different between these two types of dominant logic (analog and digital), and third, how firms can develop a data-dominant logic for their business. The remainder of this paper will focus on the first question to lay a foundation for future research. It discusses the situation of many established SMEs that today lack a data-dominant logic (DDL). The manuscript does not discuss in detail empirical findings of how DDL can be characterized, or what firms should do to build up DDL for their own organization. The paper thus takes only a first introductory step towards a detailed characterization of why a DDL is necessary for firms, how it can be characterized, and what it takes to foster one in organizations.

Method

The paper’s findings emerged from a two-year (2018-2019) rather open exploratory field study that aimed at gaining deeper knowledge of the current state of data

Approaching a Data-Dominant Logic

Petra Kugler

and data science-related practices in SMEs. The study focused on the so-called DACH-region (Austria, Germany, Switzerland) and explored opportunities and threats related to data science practices. The study went through several methodical steps, based upon each other (see Table 2 and succeeding paragraphs). Throughout these steps, the study focused on four specific core themes, namely: (1) strategy and business model, (2) organizational culture, (3) processes and services, and (4) leadership and human resources management (HRM). These groups of core themes were chosen to get a broad picture of the role data science practices play in firms, and also to pre-structure and pre-define the problem space in question.

A dominant logic, or, business mindset, was not explicitly thought to be a focal aspect of the study. Rather, the construct emerged during the course of the exploratory study. Nevertheless, according to Schein (1985), how the members of an organization interpret

their situation (so-called “underlying assumptions”) constitutes one out of three critical components of organization and organizational culture (next to artifacts and an organization’s values and norms), which was one of the core themes that guided the empirical work.

Step 1: Literature analysis

The first methodological step was to perform a literature analysis. About 150 sources in total on the topics “data”, “data science”, “data analytics”, and related terms, as well as on the four core themes that guided the study were compiled. The sources of literature were then analyzed to identify research gaps and gain an overview of the current state of the field. The literature covered studies, scientific articles, and practitioner articles, which delivered mutually complementary insights. The analysis revealed that in recent years data science-related topics have been attracting increased interest within the scientific community and among practitioners. However, the way firms adopt data science-related practices and how all types of

Table 2. Methodological steps, including input and output (own depiction)

Step	Method	Input	Output
1	Literature analysis	Literature on data, data science, data analytics and related topics, as well as on the selected core themes: (1) strategy and business model, (2) organizational culture, (3) processes and services, (4) leadership and HRM.	Insights into opportunities, threats, applications, causalities, research gaps in the context of data and data science Interview guide that covers questions in the fields of all four core themes
2	Qualitative interviews	Interview guide that covers questions in the fields of all four core themes (from step 1) Knowledge of all interviewees	Catalogue of working hypotheses
3	Condensation of working hypotheses	Catalogue of working hypotheses (from step 2) Comparison and evaluation of the hypotheses	Selection of the strongest hypotheses and questions Formulation of questions for the quantitative survey
4	Quantitative survey	Selection of the strongest hypotheses and questions (from step 3)	Quantitative testing and strengthening of selected hypotheses

Approaching a Data-Dominant Logic

Petra Kugler

organizations turn data into value, remains largely nebulous. Also, only a few empirical sources in the literature were found that explicitly discuss the situation of SMEs. The literature review's output was an interview guide structured along the four core themes, which helped to prepare the qualitative interviews in step 2.

Step 2: Qualitative interviews

In a second step, 23 interviews were conducted with 28 individuals (some group-interviews) from 16 firms. All interviews were semi-structured, with guidelines defining the overall structure and broad categories of interest (Table 3). Interviewees were, first, representatives of SMEs in the manufacturing and service industries who have (some) experience with data science-driven approaches (8 firms), or second, IT/data science consultants (8 firms). These two groups of interviewees were chosen to gain insights

into the topic in question from inside and outside of SMEs. The perspectives of both groups of interviewees helped to better understand and interpret the SMEs' situations, because SMEs might not totally be aware of the role of data and data science insights in their respective current business situation. Data science for many firms is a rather unfamiliar topic, and firms do not completely know what they do not know about data science-driven approaches. The interviews typically lasted about one hour in length and were led in person and on-site at the respective companies. The interviews were either recorded and transcribed, or notes were taken during the interview in the minority cases that an interviewee refused the recording.

Step 3: Condensation of working hypotheses

In the third step, the interviews were analyzed using content analysis (Mayring, 2015). For this purpose, categories and hypotheses on possible causalities and

Table 3. Interview guide: Overview of core themes and subtopics (summary, abridged)

Question block #	Core theme	Subthemes
1	General initial questions	<ul style="list-style-type: none"> ▪ general situation of the interviewee and the company ▪ understanding of data science and current state of data science practices in the company ▪ opportunities and threats, goals and expectations that relate to data science
2	Strategy and business model	<ul style="list-style-type: none"> ▪ data science and formal / informal company strategy ▪ role of data science on the market, competition, rules of competition ▪ role of data science in business models, types of business models
3	Organization and Organizational culture	<ul style="list-style-type: none"> ▪ role, meaning and awareness of data, data science practices in the firm ▪ relationship between data, data science practices and actionable knowledge, opportunities in the company ▪ artefacts, norms and values, underlying assumptions regarding data and data science (practices)
4	Processes and services	<ul style="list-style-type: none"> ▪ data and (smart) products, services, smart service design processes ▪ value of data and data science practices ▪ infrastructure, workflow, tools, data security
5	Leadership and HRM	<ul style="list-style-type: none"> ▪ roles, tasks, challenges of a data scientist in the company ▪ required skills, competences, knowledge ▪ distribution of data-related tasks within the firm / across firm boundaries
6	Closing questions and remarks	<ul style="list-style-type: none"> ▪ various closing questions

Approaching a Data-Dominant Logic

Petra Kugler

relationships between the categories were compiled. Categories and causalities were established within and between the four core topics that guided the interviews. Each category was filled with quotes from the interviews that addressed or justified the working hypotheses.

A selection of 20 hypotheses on all four core themes formed the basis for the formulation of a quantitative survey (step 4). In comparison to the hypotheses that were not selected for the survey, the selected hypotheses could be classified as 'strong' in the sense that more quotes from the interviews are attributable to them. However, it was not possible to clearly determine the strength of all hypotheses. This is because some topics were touched on in most of the interviews, while other topics were addressed only in one or a few, or the topics were mentioned only by one or few interviewees.

Step 4: Quantitative survey

In a fourth step, based on insights gained from the interviews, a quantitative online survey was designed that primarily included 42 closed questions. The goal of the survey was to gain a deeper understanding of selected issues and hypotheses from the proceeding steps. It was distributed over a variety of channels (multiple university-owned databases, social media, newsletters), so a response rate cannot clearly be defined. 280 respondents replied to the survey, of which 110 individuals answered all questions. This constitutes the sample that was analyzed for the purpose of this paper.

Some respondents did not answer all sub-questions. For some variables, the sample size is therefore smaller than 110. Representatives of SMEs (<250 employees) from all industries make up 75% of the answers. The situation of large firms as compared to SMEs was compared for the purpose of analysis. The survey covered all core topics that also guided the interviews, as well as some general questions about the firms. The survey results were primarily analyzed using descriptive statistics.

This paper's focus on organizational and managerial aspects of DDL in SMEs is only one of several insights generated from the field study. The following section summarizes some of the key findings that emerged from the empirical data.

Findings: Approaching Data-Dominant Logic

The analysis of the qualitative and quantitative data both directly and indirectly indicate that in the SMEs under consideration, first, the expectation of *fundamental structural changes in firms' competitive environments* can often be traced to the growing use of data science-related practices. Second, the collected data reveals that many of the firms under study have been *unable to yet develop an appropriate organizational repertoire to act* with a data science strategy under the current circumstances. These observations, third, lead to the hypothesis that many of these firms have not yet been able to adapt their dominant logic to the changing situation, by putting data and data science-related practices at the center of their thinking and acting. One conclusion to be drawn is that up until now they are *missing data-dominant logic*.

Firms expect fundamental structural changes

The respondents to the quantitative study expect fundamental structural changes in their respective industries. This situation requires a shift in managers' dominant logic (Bettis & Prahalad, 1995). Today, data science-driven approaches can have the biggest benefit for SMEs in creating customer proximity and optimizing processes or products (in roughly 55% of the cases), while new products and services have less relevance (in roughly 35% of the cases). Generating new business models does not have a significant impact on most SMEs today (only in roughly 15% of the cases). However, the respondents expect the situation to fundamentally change within five years, to a situation in which more new business models will be required. Almost 50% of respondents from companies expect products that build on data science insights to be important for their future business.

SMEs are usually well aware of the general strategic consequences to which the expected changes might lead. While today data science-driven practices are of great or very large importance for 15% of firms, in five years almost 60% of firms expect this to be the case. Also, only about 25% of the respondents stated that the use of data science insights today changes the competitive situation of their industries. In five years, this is projected to be the case for more than 55% of the represented firms.

Approaching a Data-Dominant Logic

Petra Kugler

These findings were also mirrored in the interviews. One interviewee claimed, “There is still a point that indicates a paradigm shift. I can summarize this fact in one sentence. Formerly, producing firms could influence the market. Today it's completely different. Completely” (J.E., IT and data science consultant).

However, the incoming changes suggested above are often not (yet) mirrored in firms’ strategic behavior. SMEs largely use data science insights to improve their cost situation and to become more efficient players (see above, in approx. 55% of the cases). In doing so, they rather focus on staying in business today, than on coming up with innovative solutions for the future.

One may conclude that for SMEs, data science-driven approaches today are a set of tools that are more often used for operational rather than strategic purposes. But also, that data science insights will gain importance for more strategic and innovation-related issues in the near and foreseeable future. These insights might lead to, and at the same time are a consequence of, fundamental structural changes in how business is conducted digitally.

Firms have no repertoire to act

Many SME’s have not yet developed a clear repertoire of what they could concretely do with data and data sciences-driven practices. In the interviews, the respondents claimed that using data science insights is related to a high degree of uncertainty, and today many crucial questions still lack a clear answer. These questions comprise, for instance, “Where does data come from?”, “Which data is relevant?”, “Is an inductive or rather a deductive approach for analyzing and using data adequate for a specific situation?”, “(How) can we use data, at all?”, etc. Some of the interviewed individuals reported that their firms approach data science-related practices through a process of trial-and-error. The firms test and compare stepwise different data-based products or services that could help them to design data-based business models.

The respondents to the quantitative survey claimed that both C-level and other managers (55%), as well as employees (70%), strongly or very strongly lack knowledge and competences that could help them to cope with data and data science insights. One interviewee claimed that, “The companies have a big problem. I always call this a ‘knowledge problem 4.0’.”
timreview.ca

The knowledge does not exist. [...] They don't have the know-how at the C-level, they don't have the potential to change and they don't even know what they want to develop.” (J.E., IT and data science consultant).

Instead, the interviewees reported a lot of fear from employees on all hierarchical levels, as job descriptions that refer to data-oriented positions are still lacking. Many people wonder if their jobs will still exist in the future, and if or how their job might change. The fear rather leads to inertia instead of actively changing today’s situation by learning more about what data and data science can do for business. Mentally, the people interviewed seem to displace the expected situation that data science-driven approaches might bring for their company’s future.

Lack of an appropriate culture and mindset; missing a data-dominant logic

The survey revealed that the biggest hurdles for using data science-driven practices are related to the so-called “soft factors” that lie inside of organizations. Soft factors include a lack of knowledge (40%), unsolved organizational issues (39%), no urgency to use the data (37%), or an unclear vision of how to use data for company business (34%). 70% of the firms claimed that their employees very strongly or strongly lack skills for dealing with data and data science insights. This finding was also reflected in the interviews, in which the interviewees referred to the need for change in the firms’ mindset or organizational culture (both terms have been used by the interviewees).

The interviewees also referred to the need for one or several data-oriented change agents in their firms. Managers and employees alike seem to have difficulties including data-related aspects into their established mindset, or into their prevailing dominant logic (Pralhad & Bettis, 1986). This research concludes that the way companies function today is not (yet) designed to make fundamental use of data science-driven approaches for business.

According to the study’s findings, for respondents’ businesses, “soft factors” are a higher hurdle than the so-called “hard factors”. Hard factors refer to security concerns (28%), costs (24%), other technologies (24%), or firm size (too small, 22%). Perhaps surprisingly, “inadequate data” (SMEs: 4%, large firms: 17%) is the least important hurdle for the use of data. One interpretation of this finding is that companies often

Approaching a Data-Dominant Logic

Petra Kugler

do not even know what they don't know, or, stated differently, they are lacking sensitivity regarding their insufficient use of business-relevant data sets.

It can be concluded that firms require a holistic approach that covers adapting their culture and mindset, knowledge and capabilities, as well as their business model and services, in a way that is grounded together in the use of data and data science insights. All of these are reflected and stored in a firm's dominant logic (Pralhad & Bettis, 1986; Bettis & Prahalad, 1995). Thus, a new type of dominant logic seems to be required to cope with situations for firms that deal with data and data science-driven practices. I term this new dominant logic as data-dominant logic (DDL), which is the guiding way in which the members of a data-driven company think, act, and design their value creation process within and across the boundaries of their organization.

Discussion and Conclusions

This paper asked for organizational and managerial requirements that facilitate data and data science-driven value creation, focusing especially on the situation faced by SMEs. A literature review and multi-step field study was conducted in the DACH-region. The study's findings suggest, first, that the firms under consideration expect incoming fundamental structural changes caused by the application of data-driven practices. Also, the study revealed that many firms have no clear repertoire to act on a data strategy within the changing setting and therefore cannot fully exploit the potential inherent to data science practices. These findings indicate that SME organizations often lack an appropriate dominant logic for coping with data science-driven approaches. Therefore, second, the paper concludes that to facilitate a data-driven business, firms need to transform their traditional dominant business logic into a data-dominant logic (DDL), thus a new construct was introduced through this work. DDL proposes to add value to both the scientific community and market practitioners, because it helps to clarify and remove hurdles that hinder (established) organizations from more deeply making use of data science principles and practices for their value creation process.

The findings of this research suggest the importance of learning for firms that seek to ground their business in data and data science insights. First, the research shows that firms, especially SMEs, should take some

initial steps to become digital, even though to date it is not yet clear what it takes for firms to be a "digital player". To sensitize their management team and build up DDL, firms need to learn how to cope with both the opportunities and also the constraints of data science-driven approaches. It might be that firms will have to learn from mistakes, which sometimes can be costly, but necessary.

Second, firms can also recruit data science experts or develop the data science competencies of their own employees. This study indicates that individuals who are familiar with data science-driven principles, practices, and digital technologies can take over the role of a "digital change agent", who serves as a translator and facilitator between the established analog and the new digital paradigms.

Third, a digital change agent might help with a company's change processes. This may be because dominant logic is not restricted to a certain individual's cognition, but is also closely related to a firm's organizational structure, management methods, business model, and value creation processes (Pralhad & Bettis, 1986). To link a firm's business with data science insights, it thus might be necessary to also change organizational structures, as shown by the field study in question.

Fourth, in the case of organizational changes, DDL might not only be helpful for members of the top management team, as suggested by Bettis and Prahalad (1995, Prahalad & Bettis, 1986), but also for other members of the organization, employees, and stakeholders. The notion of DDL in this way becomes a broader concept than originally introduced by these authors.

Research on the requirements and challenges of data science-driven approaches in strategy and management is still at an infant stage. We have only begun to understand what it takes for firms to efficiently use data for their businesses, for example, with new products, services, or business models. This work thus can only be considered as a starting point for discussion and research on data-dominant logic, and other organizational and managerial requirements of digital firms. However, this situation leaves room for future research.

First, this paper primarily focused on the construct of data-dominant logic. However, the empirical study did

Approaching a Data-Dominant Logic

Petra Kugler

not aim explicitly at studying (data) dominant logic. The construct of DDL rather emerged during the process of conducting the empirical study, as an effective way of targeting a current business need. The paper was therefore not able to explore and clarify in detail, how exactly the dimensions and features of DDL can be characterized, or what firms should do in order to establish or enhance it in their organizations. Both questions are open issues that should be clarified through future research.

Future studies could compare the similarities and differences of the dominant logic of organizations that can be characterized as analog or digital and focus on both how and how much firms are making use of data-driven approaches. To do so, it might be helpful to explicitly compare the situation of firms that already clearly take a DDL approach (firms in which data science is at their very core), with those that do not have such an approach (firms that do not focus on working with data science). Such research would respond to the conclusion and challenge of Bettis et al. (2003) that “there is considerable potential for exploring the emergence of a dominant logic based on the competition of multiple logics”.

Finally, it would be interesting to learn which kinds of firms can adopt a data-dominant logic and if it is easier for some types of organizations than others (for example, small vs. large firms, young vs. established, or certain industries)? If so, (how) can the transformation process towards DDL be designed to give more SMEs a data-driven development roadmap? DDL in sum might therefore bear the potential to open a new organizational paradigm for the digital economy.

Acknowledgment

This study was supported by the grant "IBH-Lab KMUdigital" within the framework of the Interreg V-programme "Alpenrhein-Bodensee-Hochrhein" (DE/AT/CH/LI) whose funds are provided by the European Regional Development Fund (ERDF) and the Swiss Confederation. The funders had no role in study design, data collection and analysis, decisions to publish, or preparation of the manuscript.

References

- Bange, C., Grosser, T., & Janoschek, T.N. 2015. Big Data Use Cases: Getting Real on Data Monetization. *BARC Research Study*.
- Barton, D., & Court, D. 2012. Making Advanced Analytics work for You — A practical Guide to Capitalizing on Big Data. *Harvard Business Review*, 90(10): 78-83.
- Bergman, J.-P., Jantunen, A., & Tarkiainen, A. 2015. Managerial Cognition and Dominant Logic in Innovation Management: Empirical Study in Media Industry. *International Journal of Business Innovation and Research*, 9(3): 253-271.
<http://dx.doi.org/10.1504/IJBIR.2015.069136>
- Bettis, R.A., & Prahalad, C.K. 1995. The Dominant Logic: Retrospective and Extension. *Strategic Management Journal*, 16 (1): 5-14.
<https://doi.org/10.1002/smj.4250160104>
- Bettis, R.A., Wong, S.S., & Blettner, D. 2003. Dominant Logic, Knowledge Creation, and Managerial Choice. In J. Baum, & S. Dobbings (Eds.), *Economics Meets Sociology in Strategic Management*. Stamford: JAI Press: 369-381.
- Brown, B., Court, D., & Willmott, P. 2013. Mobilizing Your C-Suite for Big-Data Analytics. *McKinsey Quarterly*, November.
- Brynjolfsson, E., & McAfee, A. 2014. *The Second Machine Age. Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: Norton.
- Chin, J.K., Hagstroem, M., Libarikian, A., & Rifai, K. 2017. Advanced Analytics: Nine Insights from the C-Suite. *McKinsey Analytics*, July.
- Christensen, C.M. 1997. *The Innovator's Dilemma: When new Technologies cause great Firms to fail*. Boston: Harvard Business School Press.
- Christensen, C.M., & Raynor, M.E. 2003. *The Innovator's Solution: Creating and Sustaining Successful Growth*. Boston MA: Harvard Business School Press.
- Côté, L., Langley, A., & Pasquero, J. 1999. Acquisition Strategy and Dominant Logic in an Engineering Firm. *Journal of Management Studies*, 36(7): 919-952.
- Espinosa, J.A., Kraut, R.E., Lerch, J.F., Slaughter, S.A., Herbsleb, J.D., & Mockus, A. 2001. Shared Mental Models and Coordination in Large-scale, Distributed Software Development. *ICIS 2001 Proceedings*, 22nd International Conference on Information Systems at New Orleans.
- Espinosa, J.A., Kraut, R.E., Lerch, J.F., Slaughter, S.A., Herbsleb, J.D., & Mockus, A. 2002. Shared Mental Models, Familiarity, and Coordination: A multi-method Study of Distributed Software Teams. *ICIS 2002 Proceedings*, 23rd International Conference on Information Systems at Barcelona, Spain.

Approaching a Data-Dominant Logic

Petra Kugler

- Fosso Wamba, S.F., Akter, S., Edwards, A., Chopin, G., & Guanzou, D. 2015. How 'Big Data' can make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study. *International Journal of Production Economics*, 165: 234-246. <https://doi.org/10.1016/j.ijpe.2014.12.031>
- Fosso Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J., Dubey, R., & Childe, S.J. 2017. Big Data Analytics and Firm Performance: Effects of Dynamic Capabilities. *Journal of Business Research*, 70: 356-365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
- Grant, R.M. 1988. On 'Dominant Logic', Relatedness and the Link between Diversity and Performance. *Strategic Management Journal*, 9(6): 639-642. <https://doi.org/10.1002/smj.4250090610>
- Gruber, M., & Henkel, J. 2004. New Ventures based on Open Innovation —an Empirical Analysis of Start-up Firms in embedded Linux. *International Journal of Technology Management*, 33(4): 356-372. <https://doi.org/10.1504/IJTM.2006.009249>
- Gupta, M., & George, J.F. 2016. Toward the Development of a Big Data Analytics Capability. *Information and Management*, 53(8): 1049-1064. <https://doi.org/10.1016/j.im.2016.07.004>
- Hagstrom, M. 2012. High-performance Analytics fuels Innovation and Inclusive Growth: Use Big Data, Hyperconnectivity and Speed to Intelligence to get True Value in the Digital Economy. *Journal of Advanced Analytics*: 3-4.
- Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, T.G. 2016. The Age of Analytics: Competing in a Data-Driven World. *McKinsey Research Report*, McKinsey Global Institute in Collaboration with McKinsey Analytics. London et al.
- Iansiti, M., & Lakhani, K.R. 2017. Managing our Hub Economy. Economy, Strategy, Ethics and Competition in the Age of Digital Superpowers. *Harvard Business Review*, 95(5): 84-92.
- Jarzabkowski, P. 2001. Dominant Logic: An Aid to Strategic Action or a Predisposition to Inertia? *Working Paper of Aston Business School Research Institute*, RPO 110.
- Kugler, P. 2019. When Less is More: Coordinating Innovation in Open versus Closed Source Software Development. *International Journal of Entrepreneurship and Small Business*, 37(1): 87-108. <https://doi.org/10.1504/IJESB.2019.10021494>
- Lampel, J., & Shamsie, J. 2000. Probing the Unobtrusive Link: Dominant Logic and the Design of Joint Ventures at General Electric. *Strategic Management Journal*, Vol. 21(5): 593-602. [https://doi.org/10.1002/\(SICI\)1097-0266\(200005\)21:5<593::AID-SMJ100>3.0.CO;2-0](https://doi.org/10.1002/(SICI)1097-0266(200005)21:5<593::AID-SMJ100>3.0.CO;2-0)
- Lusch, R.F., & Vargo, S.L. 2006a. Service-dominant Logic as a Foundation for a General Theory. In R.F. Lusch, & S.L. Vargo (Eds.), *The Service-Dominant Logic of Marketing: Dialog, Debate, and Directions*, 406-4290. Armonk: M.E. Sharpe.
- Lusch, R.F., & Vargo, S.L. 2006b. Service-dominant Logic: Reactions, Reflections, and Refinements. *Marketing Theory*, 6(3): 281-288. <https://doi.org/10.1177/1470593106066781>.
- Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A.H. 2011. Big Data: The next Frontier for Innovation, Competition and Productivity. *McKinsey Research Report*, McKinsey Global Institute.
- March, J.G. 1991. Exploration and Exploitation in Organizational Learning. *Organization Science*, 2(1): 71-87. <https://doi.org/10.1287/orsc.2.1.71>
- Mayring, P. 2015. *Qualitative Inhaltsanalyse. Grundlagen und Techniken*. 12th Edition, Weinheim/Basel: Beltz.
- McAfee, A., & Brynjolfsson, E. 2018. *Machine, Platform, Crowd. Harnessing our Digital Future*. New York: Norton.
- Meierhofer, J., Kugler, P., & Etschmann, R. 2019. Challenges and Approaches with Data-driven Services for SMEs: Insights from a Field Study. *Proceedings of the Spring Servitization Conference on Delivering Services Growth in the Digital Era*, May 13-15, Linköping, Sweden.
- New Vantage Partners LLC. 2017. Big Data Business Impact: Achieving Business Results through Innovation and Disruption. *Research Report*, Boston et al.
- Obloj, T., Obloj, K., & Pratt, M.G. 2010. Dominant Logic and Entrepreneurial Firms' Performance in a Transition Economy. *Entrepreneurship Theory and Practice*, 34(1): 151-170. <https://doi.org/10.1111/j.1540-6520.2009.00367.x>
- Pan, G. 2017. A Dominant Logic View of Managing Innovation. *Journal of Information Technology Management*, 28(4): 1-17.
- Parker, G.G., Van Alstyne, M.W., & Choudary, S.P. 2017. *Platform Revolution: How Networked Markets Are Transforming and How to Make Them Work for You*. New York: Norton.
- Pralhalad, C.K. 2004. The Blinders of Dominant Logic. *Long Range Planning*, 37(2): 171-179. <https://doi.org/10.1016/j.lrp.2004.01.010>
- Pralhalad, C.K., & Bettis, R. 1986. The Dominant Logic: A New Linkage Between Diversity and Performance. *Strategic Management Journal*, 7: 485-501. <https://doi.org/10.1002/smj.4250070602>

Approaching a Data-Dominant Logic

Petra Kugler

- Remane, G., Hanelt, A., Nickerson, R.C., & Kolbe, L.M. 2017. Discovering Digital Business Models in Traditional Industries. *Journal of Business Strategy*, 38(2): 41-51.
<https://doi.org/10.1108/JBS-10-2016-0127>
- Schein, E.H. 1985. *Organizational Culture and Leadership*. San Francisco: Jossey-Bass Wiley.
- Smircich, L. 1983. Concepts of Culture and Organizational Analysis. *Administrative Science Quarterly*, 28: 339-358.
<https://doi.org/10.2307/2392246>
- Tabesh, P., Mousavidin, E., & Hasani, S. 2019. Implementing Big Data Strategies: A Managerial Perspective. *Business Horizons*, 62(3): 347-358.
<https://doi.org/10.1016/j.bushor.2019.02.001>
- Vargo, S.L., & Lusch, R.F. 2004. Evolving to a New Dominant Logic for Marketing. *Journal of Marketing*, 68(1): 1-17.
<https://doi.org/10.1509/jmkg.68.1.1.24036>
- Vargo, S.L., & Lusch, R.F. 2006. Service-dominant logic: What it is, what it is not, what it might be. The service dominant logic of marketing: Dialog debate and directions. *Journal of the Academy of Marketing Science*, 6(3): 281-288.
- Vargo, S.L., Lusch, R.F., Archpru Akaka, M., & He, Y. 2010. Service-Dominant Logic: A Review and Assessment. *Review of Marketing Research*, 6: 125-167.
[https://doi.org/10.1108/S1548-6435\(2009\)0000006010](https://doi.org/10.1108/S1548-6435(2009)0000006010)
- Weick, K.E. & Roberts, K. 1993. Collective Mind in Organizations: Heedful Interrelating on Flight Decks. *Administrative Science Quarterly*, 38: 357-381.
<https://doi.org/10.2307/2393372>

About the Author

Petra Kugler is a Professor of Strategy and Management at OST-Eastern Switzerland University of Applied Sciences, Switzerland. Her research focuses on the intersection of innovation, strategy and management, and how firms can generate and protect sustainable competitive advantages in turbulent times. She is especially interested in strategic innovation, management innovation, technology, and the contradictory nature of innovation and coordination in organizations. She obtained her PhD from the University of St. Gallen (HSG), has also worked in advertising, and has gained international academic experience through various scholarships, among others a Swiss National Science Foundation Grant for a research year at the University of California, Berkeley.

Citation: Kugler, P. 2020. Approaching a Data Dominant Logic. *Technology Innovation Management Review*, 10(10): 16-28.

<http://doi.org/10.22215/timreview/1393>



Keywords: Data science, dominant logic, data-dominant logic, empirical study, organizational and managerial requirements, SMEs.