Challenges Concerning Data-Driven Innovation

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Abstract

Digital transformation is highly relevant to most organisations in the business and the government sectors. One important aspect of digital transformation is the capability to exploit data in order to develop new services. For a number of businesses, this capability has become an imperative to their survival in an ever more competitive market. Today, data exploitation is of vital importance for innovation and economic growth. However, there is a lack of consolidated knowledge about the challenges of managing processes for data-driven innovation. Therefore, the purpose of this study is to elaborate on challenges concerning data-driven innovation. We have used the Grounded Theory approach to identify such challenges which are: lack of a systematic process, problems with data access, distrust of data, lack of appropriate digital tools and insufficient competence. Our conclusions reveal that data is rarely used as a strategic resource in data-driven innovation and that there is a lack of data management.

Keywords Data-driven innovation, service innovation, data exploitation, IT service management, data utilisation.

1   Introduction

Data-driven innovation has become the key pillar in 21st century of growth (OECD, 2016). Contemporary organisations show an increasing interest in data-driven innovation and the exploitation of new data sources that can foster new innovations and create significant competitive advantage. The possibilities of capitalising on data have escalated, due to increased Internet activities and decreased cost of activities such as data collection, data analysis and data storage. Jetzek et al. (2014) claim, *"The exponentially growing production of data and the social trend towards openness and sharing are powerful forces that are changing the global economy and society"* (p. 100). Another striking quote reads, *"It is difficult to imagine the power you are going to have when so many sorts of data are available"* (Berners-Lee 2007). Besides capturing data from human activities on the Internet (e.g. social media, web services, consumer behaviours), data is also captured in the physical world by sensors and cameras, which today exist almost everywhere. These new data sources generate huge amounts of data, which can accelerate value creation and spur completely new business models. OECD defines data-driven innovation in the following way, *"the strategic utilization of data and analytics to improve or foster new processes, products, services, and markets"* (OECD, 2015 p. 17).

One purpose of data-driven innovation is to develop new or significantly improve existing products, processes, methods or services. Hence, the exploitation of data, with respect to decision-making, is of major concern. Brynjolfsson et al. (2011) show statistically that the more data-driven a firm is, the more productive it is. They report that firms which adopt data-driven decision-making have output and productivity that are 5- 6% higher than expected, compared to other investments and information technology usage.

Data is often proclaimed to be of vital importance for innovation and economic growth (European Commission 2011a). Moreover, data is viewed as raw material and as the most valuable resource for innovation. However, the exploitation of data is not an easy and straightforward process. According to OECD (2015), *"The low-hanging fruit of data-driven innovation may be clear, but the full scope of potential benefits is much more difficult to grasp, resulting in opportunities that may be lost"* (p. 3). Today, few organisations are successful in their efforts to achieve data-driven innovation (Dougherty and Dunne 2012). OECD (2015) claims that only a few firms have managed to change their internal procedures to fully take advantage of data. In other words, newfound data sources remain largely underexploited because challenges such as data barriers, data overloads, and analysis bottlenecks, effectively hamper such innovation. We define 'challenge' as a constraint or a factor that inhibits innovation (Lee et al. 2010) and we define 'innovation' as "*a complex, diversified activity with many interacting components, and sources of data need to reflect this*" (OECD 2013, p.7).

In this study, we focus on challenges concerning data-driven innovation. Our focus is not restricted to search for technical challenges. We are interested in challenges that can be both technical and organisational in character. The purpose is to create a foundation for the further studies that concern the development of innovations that improve the exploitation of data and the development of data-driven innovations. A number of scholars (e.g. Hjalmarsson et al. 2014; Jetzek et al. 2014) have identified innovation challenges (sometimes referred to as barriers, obstacles or hinders). All these studies provide valuable insights into *general innovation challenges*. However, they do not particularly focus on challenges concerning *data-driven innovation*. Our research question reads, *what challenges exist for the exploitation of data-enabled innovation in the business sector?* According to several scholars little is still known about innovation challenges (e.g. Lüttgens et al. 2014; Ghobadi and Mathiassen 2014; Hjalmarsson et al. 2014: Hjalmarsson et al. 2015).

The following section describes the state of the art concerning claims and considerations with respect to challenges in data-driven innovation. Section 3 argues for why data exploitation is important and section 4 describes the research method. Thereafter, section 5 presents the findings and in section 6 the conclusions drawn.

2   The importance of Data-Driven Innovation

Our literature review has included a search for successful examples of data-driven innovation or arguments that motivate why the exploitation of data as a strategic resource in data-driven innovation is important. Barua et al. (2012) examine the impacts of effective data use for business, based on a sample of 150 companies. They claim that relatively small improvements in terms of effectiveness in the use of data lead to a significant increase of financial returns. Another example, based on a global sur-

vey of 3 000 business people, is provided by Lavalle et al. (2011). They argue that higher-performing organisations are more likely to apply data analytics when making decisions compared to lower-performing organisations. Another claim that strengthen the importance of data exploitation is that new data will enable novel opportunities for the development of new products and services which will change existing business models (Sathi 2011). ComputerWeekly (2013) adds that predictive data analysis improves the speed of decision-making. The magazine states, "*Within the context of customer relationship management (CRM), however, predictive analytics is more at the experimental stage rather than a de facto modus operandi*". Furthermore, Google Analytics Solutions (2017) states that the top-performing enterprise marketers are five times more likely to use data-driven attribution. Finally, Brynjolfsson et al. (2011, p.2) state "*Leading-edge firms have moved from passively collecting data to actively conducting customer experiments to develop and test new products*". We regard all these examples or arguments as encouragements or recommendations to companies, which have not yet started to strategically exploit data in order to innovate services.

The importance of exploiting data has also been discussed in connection to the concept of open data. Open data is often regarded as an enabler of economic growth due to its high potential for service innovation (e.g. European Commission 2011b; Borzacchiello, and Craglia 2012; Manyika et al. 2013; Smith et al. 2016). Zuiderwijk et al. (2014) state that open data not only creates possibilities for private sector innovation but also for public sector innovation. At the same time the authors acknowledge that "*A substantial body of research concentrates on innovation in the private sector (Windrum and Koch 2008), while the public sector is often considered less amenable to innovation (Borins 2001)*" (p.I). Moreover, Smith et al. (2016) propose an open data marketplace that can support knowledge-sharing activities and can function as a meeting place for open data providers and open data users. The authors argue that an open data marketplace will increase knowledge transfer within ecosystems. They identify five values for open data users: less task complexity, more access to knowledge, more possibilities to influence, lower risk and higher visibility. Avital et al. (2015) add that the disruptive nature of the sharing economy has caused challenges in terms of mixed responses ranging from active conflict to adoption and assimilation

The sharing of knowledge based on open data in an ecosystem is closely related to service innovation (e.g. Lush and Nambisan, 2015) and open innovation (e.g. Chesbrough 2011). Since data is often represented as symbols (e.g. Ackoff 1989), it needs to be transformed into information and knowledge that can be utilized in the service innovation process. In this respect, data exploitation plays a central role in the service innovation process. At the same time, it is important to apply a perspective on data exploitation which includes an open view that companies offering value propositions (through services), and that multiple actors co-create value propositions through the integration of knowledge and skills (e.g. Skålén et al. 2015). The potential benefits in applying an open innovation perspective on data exploitation are numerous: the ability to share and access new knowledge and skills, an increase of innovation capabilities, the fostering of sustainability, and a strengthened relationship between service providers and customers (e.g. Lusch et al. 2007; Chesbrough 2013).

3   The State of the Art Concerning Innovation Challenges

Our literature review of previous work regarding challenges for data-driven innovation has identified a number of interesting publications. We have identified challenges with respect to: general nature, data-driven innovation, and service innovation. A majority of these challenges have been identified in the public sector. However, there are also few identified in business sector. Hjalmarsson et al. (2014) have compiled an extensive list of challenges concerning general innovation challenges. These challenges have been identified in journals such as: International Journal of Entrepreneurship and Innovation Management, Journal of Product Innovation Management, Long Range Planning, Research Policy, and Technovation. The challenges have been classified according to a grounded theory approach, which has resulted in the following main categories: costs, finance, risk, knowledge, market, organisation, strategy, regulation, society and technology.

Keim et al. (2006, p.9) discuss challenges with respect to data-driven innovation. They state that one major challenge is that "*... the capacity to collect and store new data grows rapidly, the ability to analyze these data volumes increases at much lower pace. This gap leads to new challenges in the analysis process, since analysts, decision makers, engineers, or emergency response teams depend on information "concealed" in the data*". Mathis (2015) discusses challenges related to the process of data-driven innovation, arguing that businesses are often stuck in a dilemma. Employees, who have knowledge of available data, are not engaged in the strategic development of new business models. On the other hand, managers responsible for business models lack knowledge of available data. Another important review of challenges identified in the government sector has been conducted by Jetzek et al.

(2014). They state that the most commonly identified challenges are: a) closed or inaccessible datasets, b) lack of comprehensive data policies, c) lack of validity, completeness and exhaustiveness of datasets, d) insufficient metadata, e) lack of consistency in cross-border access regimes, f) lack of motivation within the public sector, g) lack of technical and semantic interoperability, h) lack of technical ability within public and private sectors, i) the digital divide and j) an overly fragmented and disparate open data community. We can conclude that both these publications provide valuable input with regard to fulfilling the purpose of this paper. Moreover, Lee et al. (2010) conclude that a distinction can be made between actual and perceived challenges in general. They claim that perceived challenges are based on subjective judgements. Nevertheless, a perceived challenge can also be seen as a real limitation; it should be acknowledged that this kind of challenge can cause the same constraint as the actual ones. We agree with this conclusion and our study includes both actual and perceived challenges.

Bitner et al. (2008) discuss different challenges with respect to service innovation. The first challenge relates to the analysis of the process as a whole, including interactions with customers and a thorough understanding of how customers evaluate the service process and how those judgments evolve. The second challenge concerns service experiences with Bitner et al. (2008) questioning whether companies have the capability to systematically managing the experiences of service. The third challenge, called the "fuzzy front end", refers to requirement specification, which is specifically problematic, because it involves imprecise processes and impromptu decision-making (ibid.).

Based on our literature review, we can conclude that the state of the art provides valuable insights. We have identified studies that discuss general challenges concerning innovation, few studies that specifically report on challenges concerning data-driven innovation and few studies that concern challenges with respect to service innovation. We can also conclude that the literature mostly discusses challenges related to the public sector, which we found most interesting. However, challenges in the public sector can of course differ from challenges in the business sector due to different rules, regulations, goals and culture. Thus, one purpose of this study is to complement existing knowledge with challenges concerning data-driven innovation in the business sector.

4   Research Method

In order to contribute knowledge about the challenges of data-driven innovation, a qualitative approach has been conducted. According to Orlikowski and Baroudi (1991), the intention of qualitative studies is not to arrive at statistical generalisations, but to understand the deeper structure of a phenomenon. In other words, we are interested in understanding what challenges exist, why they exist, and what consequences they may cause. The domain of our is IT Service Management (ITSM). ITSM is often regarded as a strategy for adopting and applying a service perspective (e.g. Cronholm and Persson 2016). This strategy supports the whole service life cycle, enabling value for multiple actors in the service ecosystem. However, adopting and applying a service perspective does not just entail a minor change of attitude; it means a paradigm shift for the whole IT sector (Göbel and Cronholm). According to Galup et al. (2009), the purpose of ITSM is to develop services from a customer perspective, which thus plays a critical role in supporting and satisfying business requirements.

In order to answer the research question, data has been collected from eleven interviews with seven companies (see table 1). All the informants are working with tasks related to ITSM. They represent small, medium and large companies and are all experienced in their work with the development and maintenance of digital services in relation to business needs. We have used semi-structured interviews (e.g. Silverman, 2013) consisting of open-ended questions such as: Do you use data to enhance innovation? Do you have an established process with respect to data-driven innovation? What challenges concerning data-driven innovation have you experienced? The reason for using open-ended questions was due to the fact that we preferred to gather as broad a range of experiences as possible (Cronholm and Melin 2006). Each interview lasted for approximately two hours. We used Grounded Theory to analyse the interviews and we have followed the processes of open coding, axial coding and selective coding (e.g. Strauss and Corbin 1998; Corbin and Strauss 2008). In the open coding process the interviews analysed in order to find patterns in the data and to generate categories. Typical questions asked during the open coding process included: What does this concept mean? What is this about? What examples of this concept exist? What is this concept an example of? What other concepts relate to this concept? The result of the open coding process was a conceptualisation of data into categories and sub-categories. The purpose of axial coding is to contextualise and to relate the categories and sub-categories identified in the open coding process. We have related categories and sub-categories by using a specific coding paradigm. According to Strauss and Corbin (1998), the coding paradigm includes the following meta-categories: conditions (e.g. circumstances, situations), actions/interactions and consequences (outcomes, results of actions). The purpose of the coding paradigm is to form a co-

herent and logical structure. According to Struss and Corbin (1998), open and axial coding are two intertwined processes. In other words, our analysis has continuously shifted between the process of categorisation and contextualisation. The results of the open and axial coding processes are presented in sections 5.1-5.5. The purpose of the process of selective coding is to find a core category that represents an overarching theme and integrates all the categories. Based on the contextualisations created in the process of axial coding, we have extracted one core category that represents the overarching theme (see section 5.6).

The Grounded Theory analysis, comprising the three processes of open, axial, and selective coding, was carried out in two iterations. The first iteration included an analysis of the eleven interviews. In the second iteration, the result of the first iteration was returned to the informants for the purposes of collecting feedback that could enrich and/or validate the findings. The second iteration also included validating the core category (see section 5.6). The feedback constituted valuable input that was used to both refine the categories and to identify new relations between sub-categories.

Company	Sector	Company size	Role of informant
A	Telecom	Large	Supply Chain Manager
B	IT	Medium	Manager Consumer Sales
C	IT	Small	Senior consultant
D	IT	Medium	Delivery Manager
E	Telecom	Large	Manager Service and Support
E	Telecom	Large	Customer Experience Design
F	IT	Medium	Senior Consultant
F	IT	Medium	Senior Consultant
G	Car industry	Large	IT Quality Manager
G	Car industry	Large	ITSM Process Owner
G	Car industry	Large	IT Process Framework Manager

Table 1. Description of companies and informants

5   Findings

We have identified five categories (see sections 5.1-5.5) of with each corresponds to a context of challenges that includes related sub-categories in terms of conditions, actions, and consequences. The five categories are: lack of a systematic process, problems with data access, distrust of data, lack of appropriate digital tools, and insufficient competence. These five categories have been assembled into a larger context that describes the core category as *data is rarely used as a strategic resource* (see section 5.6).

5.1   Lack of a Systematic Process

The category 'Lack of a systematic process' refers to the fact that there is no systematic and established systematic process for conducting data-driven innovation (see figure 1). A representative quote from the interviews reads, "*We do not have a systematic process that can guide us to utilise data. Analysis of data is carried out on individual basis*". Our analysis has revealed that only few attempts are made to exploit data for innovation. However, these attempts are carried out as an ad-hoc activity, which means it is conducted in different ways. We also found that there is also a lack of governance or encouragement from management to standardise or systematise the process. This is problematic because the absence of a systematic process concerning data-driven innovation also means there is no accumulation of learning from mistakes and process errors. Moreover, a non-existent systematic process cannot support shared process understanding, which leads to a lack of consistency.
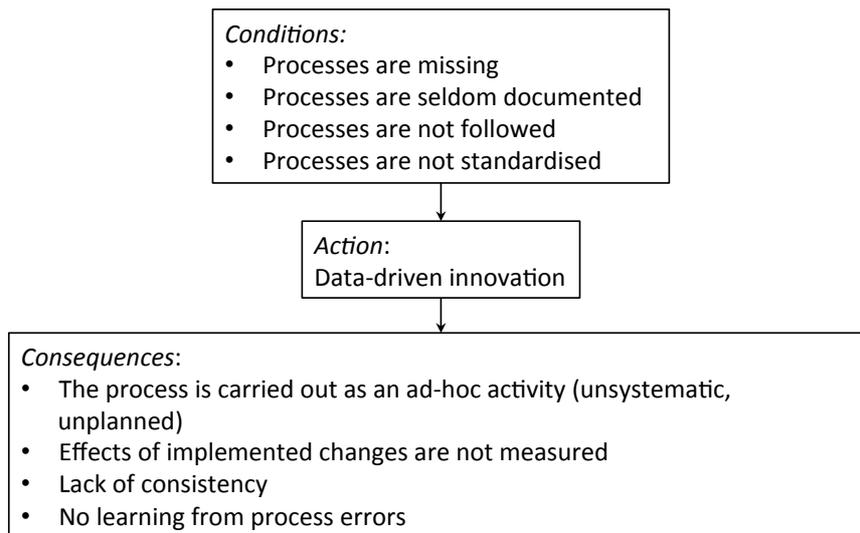
Conditions:
- Processes are missing
- Processes are seldom documented
- Processes are not followed
- Processes are not standardised

Action:
Data-driven innovation

Consequences:
- The process is carried out as an ad-hoc activity (unsystematic, unplanned)
- Effects of implemented changes are not measured
- Lack of consistency
- No learning from process errors

Figure 1: Lack of a systematic process

5.2   Problems with Data Access

Our analysis has shown that data is difficult to access due to several factors (see figure 2). One such factor is that the storage of data follows the organisational schema. This means that a company structured as different silos will also store data in silos. Such as data storage structure restricts data access and data sharing which, in turn, makes the analysis of complete set of data difficult. One of the informants stated, "*The storage of data is distributed in several systems that are not communicating which each other, thus it is almost impossible to get the full picture*". In addition, there is a lack of data management, which also prevents the flow of data between different departments. This silo mentality affects the motivation of employees because it counteracts peoples' drive to bond (Nohria et al. 2008). Another factor is that localising data in such companies is difficult, which resulted in inefficient data collection and the obstruction of data use. Consequently, all these factors contribute to insufficient information for decision-making and sub-optimisation due to incomplete sub-sets of data.
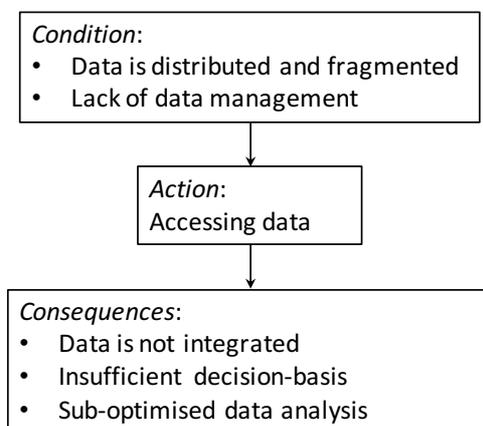
Condition:
- Data is distributed and fragmented
- Lack of data management

Action:
Accessing data

Consequences:
- Data is not integrated
- Insufficient decision-basis
- Sub-optimised data analysis

Figure 2: Problems with data access

5.3   Distrust of Data

Several companies experience distrust of data (see figure 3). One reason is that the employees' individual experiences are contrary to the companies' statistical reports based on data analysis. This is often due to the use of vague critical success factors (CSFs) and poor key performance indicators (KPIs) that are not sufficiently linked to strategic goals. One of the informants stated that "*many times you get a report that informs about 100 errors, which are related to vast number of KPIs. It is almost impossible to understand which of these errors are crucial and should be prioritised*". Distrust of data also includes problems with formulating KPIs in such a way that ensures they actually measures what should be measured. Operating with poor KPIs not only increases the risk of failure, it also decreases the risk of success. Often, the result of measurements is visually represented and the main purpose of

visual representation is to support managers in gaining insight, to drawing conclusions, and, ultimately in making better decisions (Keim et al. 2006). One challenge related to visualisation is the problem of interpretation of data. Keim et al. (2006, p.9) state that "*Interpretability or the ability to recognize and understand the data is one of the biggest challenges in visual analytics*". To a large extent, the interpretability relies on visualisations that are based on data. Therefore, the ability to draw conclusions largely depends on the quality of measurements and the quality of data. Factors that affect the quality of data are: data capture errors, low precision, missing values, and double counts. These challenges concerning distrust of data lead to low levels of confidence in companies regarding the outcome of performance measurements.
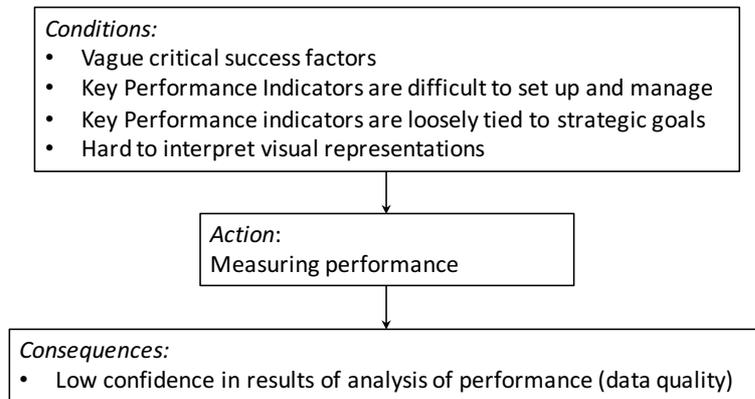

Figure 3: Distrust of Data

5.4   Lack of Appropriate Digital Tools

An abundance of tools for analysis of digital data is available on the market today. However, our analysis reveals that many companies consider these tools to be unduly advanced and complex (see figure 4). Therefore, they require substantial pre-knowledge in order to be used in a productive way. These tools also have a high learning threshold and the effort of learning is regarded as too time-consuming. A quote from one of the informants reads, "*Due to the lack of appropriate tools, many times the colleagues are using Excel and PowerPoint for data analysis and visualisation, which is not optimal and inefficient*". The challenge for small and medium-sized businesses is that they need to realise the payoff quickly and cannot dedicate staff to work solely with advanced data analysis. The challenge for larger companies is that although dedicated and competent staff is available to conduct data analysis, access to this competence is difficult because there is often a long wait between 'ordering' a specific data analysis and its 'delivery'. All these obstacles lead to challenges concerning efficiency, which means the need of appropriate support for advanced data analysis remain.
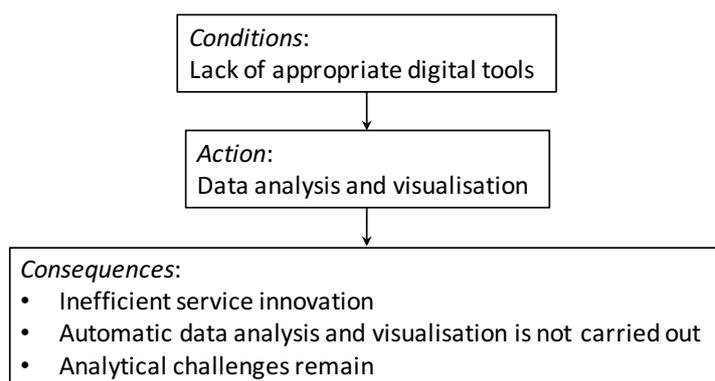

Figure 4: Lack of appropriate digital tools

5.5   Insufficient competence

Based on our analysis, it is evident that none of the companies offer an education program in advanced data analysis (see figure 5). This is surprising, because skilled employees are the key to innovation success (Lusch and Nambisan, 2016). One of the informants stated, "*In general there is a lack of advanced competence with respect data analysis. In order to utilise the full potential of the staff, we*

need to educate them in data analytics, statistics and to use modern analytical tools". Consequently, the potential of data is not being exploited. It also results in unmotivated employees because their natural ambition to learn and gain new skills is not encouraged. The consequent lack of advanced skills affects the way in which data is interpreted. An advanced analyst is less likely to interpret data incorrectly and subjectively. Instead, a skilful analyst will detect patterns in the data and provide more useful information for decision-making. Maintaining and developing the competence of employees is of great importance; a loss of competence will undoubtedly lead to a loss of competitiveness.
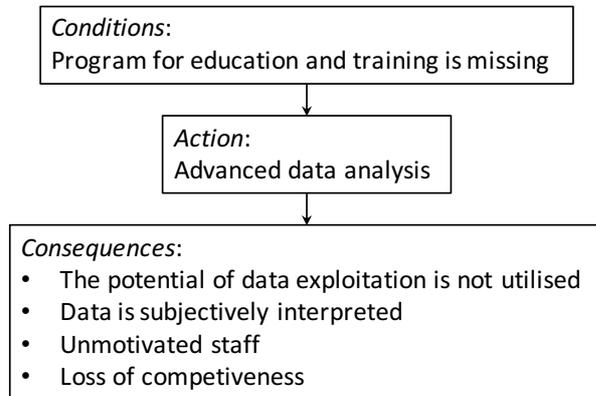
Conditions:
Program for education and training is missing

Action:
Advanced data analysis

Consequences:
- The potential of data exploitation is not utilised
- Data is subjectively interpreted
- Unmotivated staff
- Loss of competiveness

Figure 5: Insufficient competence

5.6   Core Category: Data is Rarely Used as a Strategic Resource

In this section, all the categories presented above are related to the core category *Data is rarely used as a strategic resource* (se figure 6). The purpose of the core category is to include all the categories mentioned above in this larger context. All the categories are regarded as conditions that hamper data-driven innovation. The consequences of such impediments are derived from the interviews and confirmed by the informants in the second iteration of analysis. Several of the consequences are linked to the relationship with the customer. In other words, the failure to use data as a strategic resource in data-driven innovation clearly prevents the service providers from developing their customer relationship. It also affects the service providers' competitiveness. Together, these consequences effectively prevent service providers from improving their organisational capability of developing new business models.
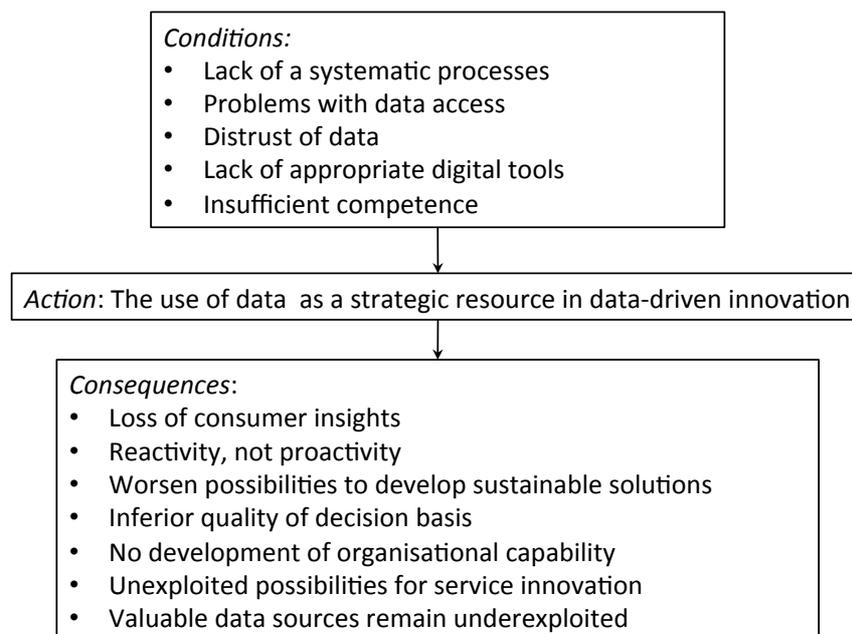
Conditions:
- Lack of a systematic processes
- Problems with data access
- Distrust of data
- Lack of appropriate digital tools
- Insufficient competence

Action: The use of data as a strategic resource in data-driven innovation

Consequences:
- Loss of consumer insights
- Reactivity, not proactivity
- Worsen possibilities to develop sustainable solutions
- Inferior quality of decision basis
- No development of organisational capability
- Unexploited possibilities for service innovation
- Valuable data sources remain underexploited

Figure 6: Data is rarely used as a strategic resource

6   Conclusions

In this study, we have used the method Grounded Theory to develop a grounded theory that elaborates on challenges concerning data-driven innovation. A grounded theory constitutes "A set of well-developed concepts related through statements of relationship, which together constitute an integrated framework that can be used to explain or predict phenomena" (Strauss and Corbin, 1998, p.15). The theory of challenges concerning data-driven innovation consists of five categories (concepts) and each category includes a structure of related sub-categories, which are classified as conditions, actions or consequences. Challenges concerning data-driven innovation are seen as a sub-class of the general class 'challenges concerning innovation'. We claim that our study complements existing knowledge about general innovation challenges with specific knowledge concerning data-driven innovation. Our study contributes with five categories that together form a structured model (framework) that explains the identified challenges with respect to data-driven innovation.

The main conclusion, which corresponds to the core category, is that data is rarely used as a strategic resource in data-driven innovation (see section 5.6). We have in a transparent way arrived at this conclusion by illustrating how the core category logically builds on other categories and sub-categories. Another conclusion refers to the lack of data management. In other words, there is no clear authority that is responsible for the storage, access, management, collection and analysis of data. In the field of IT Service Management, the roles concerning process owner and system owner are well established, but the role of data manager or data owner is seldom prominent. This is surprising, because data is one of the most valuable assets of the companies and data management relies heavily on the ability of companies to exploit data. A third conclusion is that the lack of appropriate digital tools hampers the use of data as a strategic resource. This challenge is a recurrent theme in the interviews and the need of tools is supported by Lee et al. (2014, p.3), who state, "*In today's competitive business environment, companies are facing challenges in dealing with big data issues of rapid decision-making for improved productivity. Many manufacturing systems are not ready to manage big data due to the lack of smart analytic tools*". We claim that these conclusions contribute to theory and extend prior knowledge described in section 3. Our contributions specifically advance the challenges of general character that are presented in Hjalmarsson et al. (2014), elaborates and refine the challenges discussed by Keim et al. (2006), and complement the process-related challenges identified by Mathis (2015).

The conclusions drawn are based on nascent results consisting of eleven interviews conducted in seven companies. Thus, we recommend that further research conduct a more comprehensive survey with respect to the findings in this study. A limitation of our study is that the challenges have been identified in the context of data-driven innovation in the business sector. Therefore, we are not able to generalise the findings to include the government sectors. However, we have not found anything that would invalidate the consideration of the findings in other contexts. Consequently, in order to make further generalisations, we propose that future research seeks to validate the challenges in other contexts. A further limitation of this study is that we have not proposed solutions, innovations or possible measures for the challenges we have presented. Therefore, we recommend that future research elaborates on possible solutions with respect to the challenges identified in this study.

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