STRATEGIES FOR THE INITIATION PHASE OF IT INNOVATION ADOPTION

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Abstract

For decades, enterprises have to face transformational processes triggered by technological progress. At present, digital transformation and its effects are in the focus of companies in all industries. Compared to previous information technology enabled transformations, the digital transformation goes far beyond organization's processes and changes enterprises, markets and society. The technological advances that are associated with this development present companies both game-changing opportunities and existential threats. New technologies are ubiquitous, available at low cost and can be applied and combined in various ways. Companies must therefore orient themselves in a multitude of technological possibilities and evaluate which technologies are most beneficial for them. Simultaneously, the digital transformation requires companies not only simply introduce new technologies, but also exploit them in innovative ways. Using the example of two current IT trends that reflect this development, this dissertation examines the research question of what approaches can be identified when organizations explore the potentials of IT driven innovations and what factors influence the choice of approach. Based on multiple case studies, it investigates how companies approach the adoption of big data and how cities adopt new technologies for smart services. Both trends are triggered by a large bundle of mostly similar technologies and methods. The diversity of new possibilities challenges organizations to identify and leverage the most valuable ones. In particular, the initiation phase, where organizations initially explore the manifold options of new technologies, poses a first serious obstacle. To study this in detail, two theories are used: The innovation adoption process of Rogers as a theoretical lens for the activities of organizations and the technology-organization-environment framework to structure decision criteria during innovation adoption. The results from the big data cases show that three different approaches exist: Companies start (1) with the identification of big data use cases considering only business aspects, (2) with a systematic build-up of a big data technology and data platform, (3) or with reducing data silos for traditional data analyses and a later systematic build-up of a big data platform. Two approaches could be recognized in the initiation phase of smart service adoption in cities: Smart city initiatives start either (1) with identifying use cases for smart services solving urban challenges or (2) with lowering the hurdles for the implementation of future use cases by a systematic build-up of a technological platform. Summing up the results, this thesis contributes to a better understanding of IT innovation adoption in the era of digitalization. Practitioners can compare and restructure their approaches for IT innovation adoption. Researchers gain insights into how innovation adoption is shaped by organizations and how innovation adoption theories can be applied to understand such phenomena.

Contents

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Bremser, Christian[1]; Piller, Gunther[1]; Rothlauf, Franz[2] (2017). *Strategies and Influencing Factors for Big Data Exploration.* In: Proceedings of the American Conference on Information Systems (AMCIS 2017), Boston (USA), August, 10-12, 2017.

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Bremser, Christian[1]; Piller, Gunther[1]; Rothlauf, Franz[2] (2018). *Vorgehensweisen zur Einführung von Big Data in Unternehmen.* In: Proceedings of the Multikonferenz Wirtschaftsinformatik (MKWI 2018), Lüneburg (Germany), March, 6-9, 2018.

Chapter 4
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Chapter 5
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1 Introduction

1.1 Motivation

Constant change and adaptation to new circumstances are prerequisites for the sustainable success of companies. For several years now, the digital transformation and associated changes have been a pre-dominant topic for companies in all industries (Sebastian et al., 2017). The recent advances in information technology (IT) and their adoption in business environments are thereby one of the key challenges companies face (Matt, Hess, & Benlian, 2015). In general, the digitalization of business processes and activities is nothing new for companies. Transformative processes due to technology innovations already existed in the past (Hwa Chung & Snyder, 2002).

The challenges resulting from the digital transformation, however, go much further than previous IT enabled transformations (Vial, 2019). In the era of digitalization, companies have a multitude of possibilities at their disposal. Many new technologies are available at low cost and their applications are manifold (Porter & Heppelmann, 2014). Moreover, the speed at which IT innovations emerge and change is constantly accelerating (Neumeier, Wolf, & Oesterle, 2017; Porter & Heppelmann, 2014). As a result, classical approaches for the adoption of innovations fall short (H.-M. Chen, Kazman, & Matthes, 2015).

Business leaders have recognized that recent IT innovations present both, game-changing opportunities and existential threats to their business (Sebastian et al., 2017). Digital pioneers such as Google or Amazon have shown how to use IT innovations efficiently and grown from startups to powerful giants. In consequence, senior executives in all industries have started dedicated initiatives to evaluate the potentials new technologies may provide for their business (Berghaus & Back, 2017; Davenport & Bean, 2018).

Companies have to leave the beaten track of innovation adoption to succeed (Berghaus & Back, 2017; Sebastian et al., 2017; Vial, 2019). Digital transformation as a major strategic issue requires that IT innovations are used to create business innovations that meet the demands of a digital environment (Berghaus & Back, 2017; Sebastian et al., 2017). It is not enough to simply introduce an IT innovation, it is crucial to use it innovatively within an organizations business ecosystem. Thus, the ultimate value an IT innovation can leverage depends on innovative use cases (i.e. how to use a new technology) a company discovers and the ability to deploy them at full-scale (H. M. Chen, Kazman, & Haziyev, 2016; Vial, 2019).

Previous studies on innovation adoption and product development have shown, that the initiation phase in which organizations search for ways to use a new technology, is often perceived as complex, vague and ill-defined (Reinertsen, 1999; Rogers, 2003). At the same time, it is the phase that can most positively influence the outcome of innovation adoption (Gregor & Hevner, 2015; Markham, 2013). Describing and structuring this stage, bears therefore great potential for the success of innovation adoption. Despite the importance of this phase, there have been few attempts to understand the initiation phase of innovation adoption in the current era of digitalization with its tremendous multitude of different options. This dissertation aims to address this gap by examining two IT trends: Big data in companies and smart services in smart cities. They are used as examples reflecting the possibilities and challenges of current opportunities from digitalization. Both are triggered by numerous and similar innovative technologies and methodologies (Gandomi & Haider, 2015; Yeh, 2017); both represent a new complexity organizations have to cope with (Davenport, Barth, & Bean, 2012; Porter & Heppelmann, 2014); and both have undergone a remarkable development in recent years (LaValle et al., 2011; Zelt, 2017).

The following two sections summarize both trends, introduce the current literature and emphasize the gaps in innovation adoption research this dissertation aims to fill.

1.1.1 Big Data in Companies

The TechAmerica Foundation (2012) defines big data as "a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information." Following this definition, big data is a bundle of new technological and methodological possibilities that allow to process and analyze large, complex and rapidly growing data sets. In accordance with many other current definitions[1], the TechAmerica Foundation use in particular volume (i.e. the amount of available data), velocity (i.e. the rate that data is generated and should be analyzed) and variety (i.e. the structural heterogeneity of data) to describe the data management challenges associated with big data. However, the literature shows that there are ambiguities about limits on the three Vs (Mikalef, Pappas, & Krogstie, 2017). These depend on size, industry and location of a company and result in a "three-V tipping point". Beyond this tipping point traditional data management and analysis technologies become inadequate for deriving intelligence within a sufficient period of time. Therefore, this tipping point poses a threshold beyond which firms start dealing with big data and examine the value of new technologies (e.g. in-memory data processing, NoSQL databases, Hadoop) compared with their present implementations (Gandomi & Haider, 2015).

Despite the high relevance and topicality of big data, only a handful of studies in the adoption of big data exist. Previous work in this context focuses on the investigation of factors that influence the general adoption of big data[2]. Within these studies, the Technology-Organization-Environment (TOE) framework (Tornatzky, Fleischer, & Chakrabarti, 1990) which classifies influencing factors into a technology, organization and environmental dimension, has been well-established. The results of these studies show that the protection and integration of data are considered as important technological challenges (Agrawal, 2015; Malaka & Brown, 2015; Sun et al., 2016). Organizational aspects, such as unclear processes, lack of analytical skills or indistinct prioritization of use cases are further obstacles to the successful adoption of big data. However, the adoption is most often positively influenced by company size and competition intensity. Nam et al. (2015) have investigated the change of influencing factors during the

[1] see e.g. the big data literature review of Mikalef et al. (2017) or Epinosa et al. (2019)
[2] see e.g. (Agrawal, 2015; Malaka & Brown, 2015; Sun et al., 2016)

adoption process. As a result, they identified that existing information system (IS) competence has a positive impact in the beginning of the adoption process, while competitive intensity and financial readiness significantly support the successful implementation of big data.

A study on the innovation adoption process of big data was only conducted by Chen et al. (2015). They investigated the implementation phase and identified a “limbo stage” in which companies continuously experiment with big data and do not proceed to deployment, despite their intention to adopt. For their research purpose, they utilize the TOE framework and include factors from the diffusion of innovation theory (Rogers, 2003) and the IT fashion theory (Wang, 2010). The diffusion theory describes factors that influence the spreading of an innovation among members of a social system (Rogers, 2003). The IT fashion theory highlights the social settings of emerging IT trends, e.g. the influence of consultants and technology analysts (Wang, 2010). The question of how organizations explore the value of new big data technologies and methods in the initiation phase of innovation adoption remains unexplored.

1.1.2 Smart Services in Smart Cities

There are over 500 cities worldwide, each with more than one million inhabitants (United Nations, 2018). A total of 1.7 billion people live in these cities. And this number will continue to rise (United Nations, 2018). Already today, cities are facing fundamental challenges of urbanization. Scarcity of housing, air pollution and overburdened infrastructures are only a few examples of the current problems in cities.

The concept of smart city is considered as a chance to tackle these issues. Public authorities want to transform cities into smart cities enabling modern information technology to improve citizens’ quality of life and the efficiency of urban services (Neirotti et al., 2014). To meet these goals, smart cities need to explore new technologies and realize smart services that address the concerns and needs of citizens (Anthopoulos, Janssen, & Weerakkody, 2016; Pourzolfaghar & Helfert, 2017). The term “smart services” refers to the services that a smart city delivers to its stakeholders by the use of the city’s intangible resources (e.g. people, knowledge, methods) and tangible resources, in particular information systems, data, and corresponding technologies (Angelidou, 2017; Anthopoulos et al., 2016; ITU-T Focus Group on Smart Sustainable Cities, 2014).

Previous work in the context of smart service adoption in cities is still scarce. Existing adoption studies predominately focused on influencing factors for general adoption of the smart city concept. For example, Neirotti et al. (2014) used in an empirical analysis a sample of 70 cities to investigate context variables that support the adoption of the smart city concept. As a result, they show that economic development and structural urban variables (e.g. demographic density, city area) drive the initiation of smart city programs in urban areas. Nam and Pardo (2011) and Caragliu et al. (2009) argue that a successful adoption of the smart city concept depends on investments in human and social capital, investments in modern and traditional infrastructure and the participation of citizens.

In the context of smart service adoption, Ben Letaifa (2015) developed a strategy framework and described five stages the city’s services have to pass through in order to get smart. These stages range from a strategy phase, in which a city decides how to become a smart city, to a technology phase, in which necessary technologies are identified to fulfil the strategic direction. Moreover, Chatterjee and Kar (2018) and Yeh (2017) investigated factors that influence the adoption of smart services from a citizens' perspective. They found that, from the citizens' perspective, data privacy and quality of service are factors that are most important for the successful adoption of a smart service.

So far, an investigation of the innovation adoption process in smart cities has only been conducted by van Winden and van den Buuse (2017). They utilized a multiple case study to investigate the implementation phase of smart city projects in general. Based on twelve smart city initiatives they identify three types of full-scale deployments in smart city projects: roll-out, expansion, and replication. They also identify corresponding influencing factors, e.g. upscaling in the implementation stage is often hindered by an absence of knowledge transfer, a lack of funding and missing standards such as data models or IT systems. How smart city initiatives approach in the initiation phase for the adoption of smart services has not yet been investigated.

1.2 Research Goal

In the previous sections, it has been explained that the initiation phase in the innovation adoption bears great potential, but corresponding investigations are rare. The dissertation intends to close this research gap and addresses the research question:

RQ: *What approaches can be identified when organizations explore the potentials of IT driven innovations in the era of digitalization during the initiation phase of innovation adoption and what factors influence the choice of approach?*

This question is studied in detail for big data in companies and smart services in smart cities. For this purpose, multiple case studies with ten companies from different industries and eight major European cities have been conducted. The organizational innovation adoption process of Rogers (2003) in combination with the Technology-Organization-Environment framework (Tornatzky, Fleischer, & Chakrabarti, 1990) were used as a theoretical basis and will be introduced in the next two sub sections.

1.2.1 Conceptual Framework

The theoretical foundation of this dissertation are innovation adoption theories. The theories on innovation adoption typically describe the process of introducing an innovation in organizations and factors that have an influence on the process (Damanpour & Schneider, 2006). Since the research aims at gaining understanding of the initiation phase of IT innovation adoption in organizations, this research applies the innovation adoption process of Rogers (2003) and the TOE framework of Tornatzky et al. (1990). Both theories are well-established in organizational adoption research.

The process of innovation adoption can be divided into two phases (Rogers, 2003): initiation and implementation. Both are separated by an adoption decision. The initiation phase starts with the stage agenda-setting, which is triggered by an organizational problem or by the perception of an innovation. The organizational problem manifests itself through a perceived performance gap, which is the result of internal inefficiency or altered environmental conditions (Damanpour & Schneider, 2006). The observation of an innovation is achieved by continuously scanning the business environment (for example, monitoring competitors or technological developments). Both triggers force enterprises to consider the potentials of innovations. Within the agenda-setting stage the entrepreneurial range of possible reactions with respect to innovations is weighed. For example, a company decides how to react on the availability of a new technology. The second stage matching includes all activities that proof whether an identified innovation is suitable for fulfilling the organizational needs in context of the current situation of a company. Typically, some members of an organizational unit explore the capabilities of the innovation to make a prediction on its potential for specific use cases. If this forecast is positive, the implementation phase is triggered in the adoption process. This phase consists of the stages redefining, clarifying and routinizing, and includes all the activities and decisions that are necessary to put the innovation into production.

Figure 1.1 presents the innovation adoption process (Rogers, 2003).

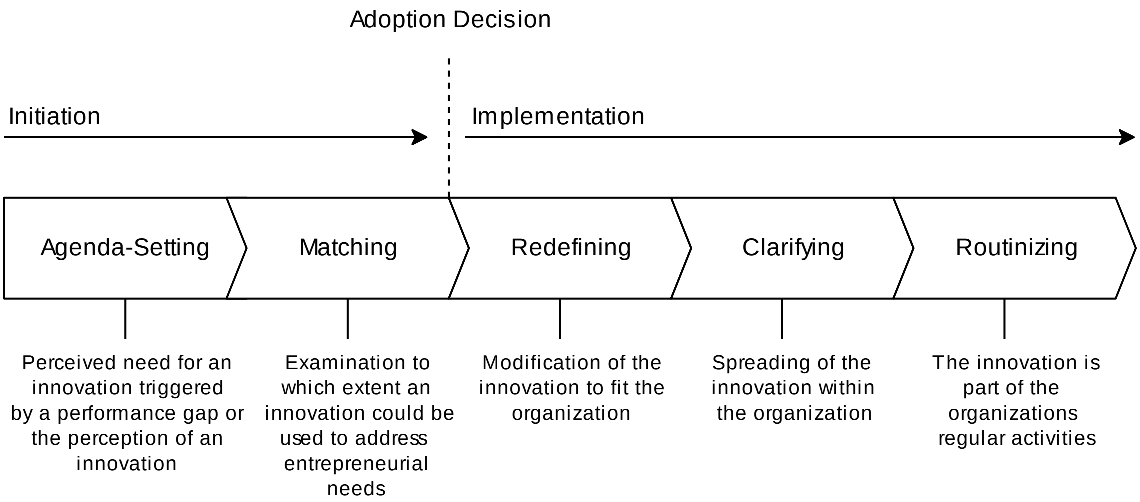

Figure 1.1 Conceptual framework (1) Innovation adoption process (Rogers, 2003)

The TOE framework describes the main factors that influence the adoption of technology innovations. These factors are clustered into three dimensions: technology, organization and environment (Tornatzky et al., 1990). The technology dimension encompasses the characteristics of available technologies that are relevant to a company. The organizational dimension covers company attributes, such as size, formal and informal linking structures, competencies and the amount of slack resources. The firm's environment and its influence are described in the environmental dimension. It includes competitors, industry specifics and governmental regulation. As a very generic framework, the TOE framework can be applied to different research contexts in a straight forward way (Oliveira & Martins, 2011). Figure 1.2 illustrates the TOE (Tornatzky et al., 1990).

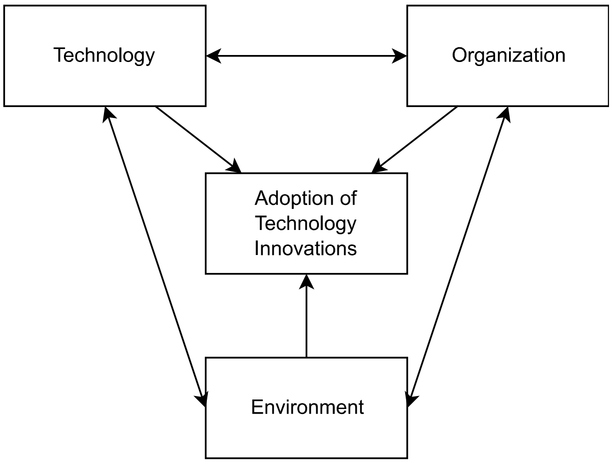

Figure 1.2 Conceptual framework (2) Technology-Organization-Environment framework (Tornatzky et al., 1990)

1.2.2 Findings

The principal goal of this dissertation is to examine the question of how organizations approach the adoption of IT driven innovations in the era of digitalization and what factors influence their choice of approach. Two current IT trends were therefore analyzed. Figure 1.3 illustrates the central findings.

Big Data

The results of the big data cases show that three different approaches in the initiation phase of big data adoption exist: Business First, Platform Building and Data Integration. In the approach Business First, enterprises explore big data potentials entirely from a business perspective. They search for use cases with high expected business value. In Platform Building the integration of technologies is of primary interest and seen as a necessary step towards the successful adoption of big data. Only after that, use cases with high potential value are searched for. Data Integration can be seen as an antecedent of the Platform Building approach. This approach is first used for reducing data silos to conduct traditional data analyses. If these proof successful, the integration of big data technologies is considered as a next step and a big data platform is aspired.

The decision which approach to choose is made by the senior management in the agenda-setting stage of the adoption process. This choice is influenced by the expected unique benefits from big data, an innovation driven business strategy, the financial readiness of the company and the maturity of the data architecture.

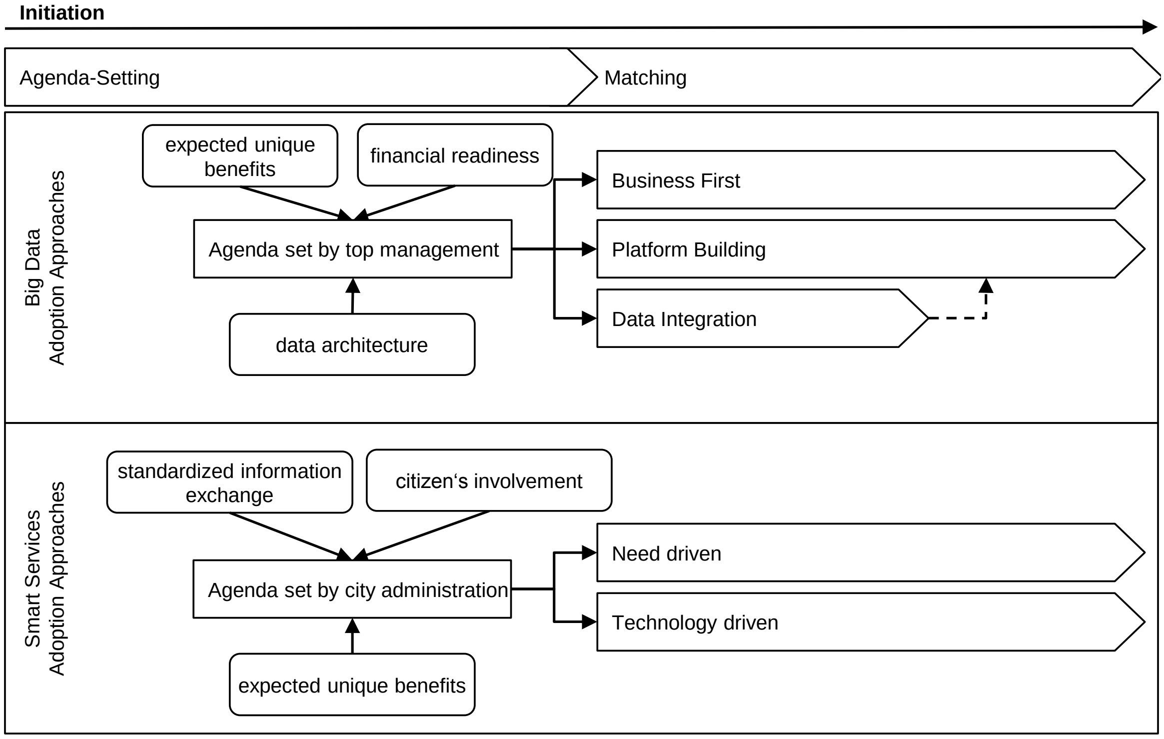

Figure 1.3 Central findings

Smart Services

Based on the analysis of the smart city cases, two different approaches for the initiation phase of smart service adoption could be identified: A need driven, and a technology driven approach. The need driven approach focuses initially on the identification of valuable use cases for smart services to solve urban challenges. After that, appropriate technologies for prototyping and testing are implemented on a small scale, e.g. in testbeds, living labs. This is in contrast to the technology driven approach. There, the systematic implementation of new technologies is of primary interest. These technologies are considered as the basis for a subsequent identification and implementation of use cases for smart services.

The decision on a particular approach is made by the city administration in the agenda-setting stage. Perceived importance of standardized information exchange, expected unique benefits of new technologies and citizen’s involvement could be identified as discriminatory influencing factors for decision-making in the agenda-setting stage.

1.3 Methodology

The research on IS has two major methodological streams: design-oriented and behavioristic-oriented research (Hevner et al., 2004; Österle et al., 2011). Design-oriented research aims on the development of innovative ideas, practices, technical capabilities and products (so called artifacts) for the design, implementation and use of IS (Hevner et al., 2004). The behavioristic-oriented research analyzes existing IS and seeks to explain and understand organizational and human phenomena surrounding IS (Hevner et al., 2004; March & Smith, 1995).

This dissertation follows a behavioristic-oriented research approach and applies a qualitative research method. Qualitative research can help to describe and understand how organizations operate and how they interact (Miles, Huberman, & Saldana, 2013). As emphasized in the motivation section, there is little understanding of how organizations explore the potentials of IT driven innovations and why they choose certain strategies. A qualitative approach allows obtaining detailed descriptions of the companies' decisions, influences and behavior. In this context, a case study method is appropriate, because this research deals with "how" and "why" questions and focuses on analyses of contemporary phenomena in a real world context (Benbasat, Goldstein, & Mead, 1987; Darke, Shanks, & Broadbent, 1998; Dubé & Paré, 2003; Yin, 2003).

In the sense of a strict implementation of the case study research design, four established quality criteria were used (Yin, 2003):

- internal validity
- external validity
- construct validity
- reliability

Following Eisenhardt (1989), an a priori specification of constructs helps to shape the initial design of theory-building research. In order to ensure **internal validity**, the interview guideline was developed based on the conceptual frameworks presented in section 1.2.1. The expert interviews to record the cases were semi-structured and the questions open to allow interviewees freely to speak. Interview participants were persons responsible for big data initiatives or smart city representatives.

The **external validity** focusses on the generalizability of the results. This is ensured by replicating the case studies. Therefore, the case selection followed the "literal replication logic". The literal replication logic ensures an analytical generalization by selecting cases from a similar contextual background to predict similar results (Dubé & Paré, 2003; Yin, 2003). In order to ensure a comparable organizational and technological context, companies and cities were selected on the basis of predefined characteristics[3]. Table 1.1 and table 1.2 provides an overview of the investigated cases.

[3] for companies e.g.: more than 10,000 employees, headquarter in Germany, active big data initiative; for cities e.g.: more than 1 Mio. inhabitants in urban area, matured city infrastructure, active smart city initiative

#	Industry	# employees	Role of interviewee
1	Transport	>50,000	Head of Domain Architecture
2	Banking	>50,000	Head of IT Architecture
3	Insurance	>10,000	Head of Group strategy
4	Manufacturing Vehicle	>50,000	IS Chief-Architect
5	Retail Trade	>50,000	Head of Business Intelligence
6	Utilities	>50,000	Chief Digital IT Strategist
7	Manufacturing Vehicle	>50,000	Head of Analytics Lab
8	Manufacturing Apparel	>50,000	Head of Data Analytics Lab
9	Manufacturing CPG	>10,000	Head of Marketing & Analytics
10	Manufacturing Chemicals	>10,000	Head of BI Architecture

Table 1.1 Cases for big data adoption in companies

#	City	Inhabitants of urban area	Role of interviewee
1	Amsterdam	>2.3 Mio.	Program ambassador
2	Barcelona	>5.3 Mio.	Catalan smart city coordinator
3	Dublin	>1.9 Mio.	Smart city coordinator
4	Cologne	>2.1 Mio.	Smart city project manager
5	Copenhagen	>1.3 Mio.	Head of IT
6	Berlin	>4.1 Mio.	Policy advisor smart city
7	Vienna	>1.7 Mio	Expert for urban innovation
8	Zurich	>1.6 Mio	Dep. director urban development

Table 1.2 Cases for technology adoption in smart cities

Yin (2003) suggests triangulation to ensure **construct validity**. Within the case studies, different data sources were therefore used. In addition to the key-informant interviews, public and - if available - internal documents were analyzed to validate the information retrieved from the key-informant interviews. While for cities a large number of public documents were accessible, the number of documents from companies was very limited. To compensate this, interviews with other organizational members, consultants and software vendors specialized on big data adoption were conducted.

The first phase of data collection started June 2016 and stretched over a period of seven months. During this period, data were collected from the case companies. The second phase started in February 2018 and lasted five months. In this phase, the interviews with the smart city initiatives were conducted. All conversations were recorded and transcribed. Shortly after each interview, the main points and key findings were recapitulated in a contact summary sheet (Miles, Huberman, & Saldana, 2013).

The analysis of the cases was carried out in a twofold way. First, a within-case analysis (Yin, 2003) was conducted to extract all characteristic content (i.e. trigger of the process, activities in agenda-setting and matching) and influencing factors related to the adoption process of individual cases. For this purpose, the deductive content analysis method (Mayring, 2008) was utilized and first-level coding (Miles et al., 2013) applied. In the second step, a cross-case analysis (Yin, 2003) was performed and the cases were compared to each other.

In order to minimize errors and biases, the **reliability** of the case study analysis was ensured by establishing a case study database. There, all information about the data collection process, the data itself and the case study results were stored. According to Yin (2003), this helps to provide the same results in repeated trials and makes the data available for independent inspections.

Figure 1.4 illustrates the research design.

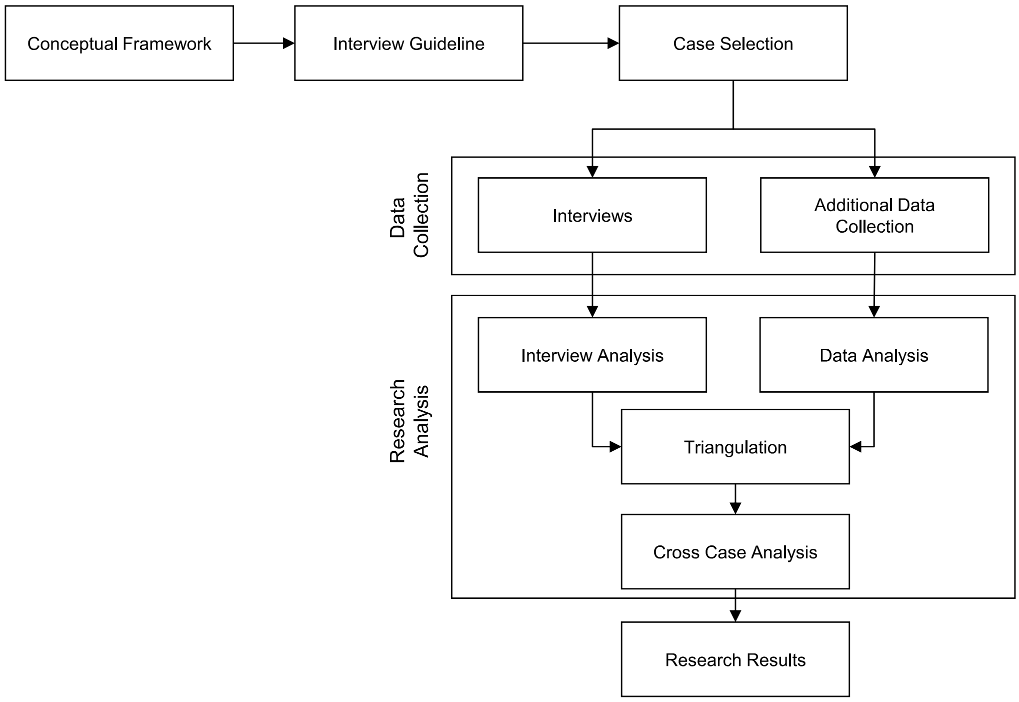

Figure 1.4 Research design

1.4 Structure of the Thesis

This dissertation is structured into six chapters. Figure 1.5 illustrates the structure of the thesis. In chapter 1, the research project is introduced and motivated. In chapters 2 to 5, the objective and research question of the thesis are addressed by several independent research contributions. Each research contribution answers a sub-research question that serves to answer the central research question. The sub-research questions are listed below the summary of the chapters and help to later structure the results in chapter 6. In order to ensure a uniform presentation, the four contributions were consistently formatted and a uniform citation style is applied. The references of each contribution are summarized in a combined bibliography at the end of this thesis.

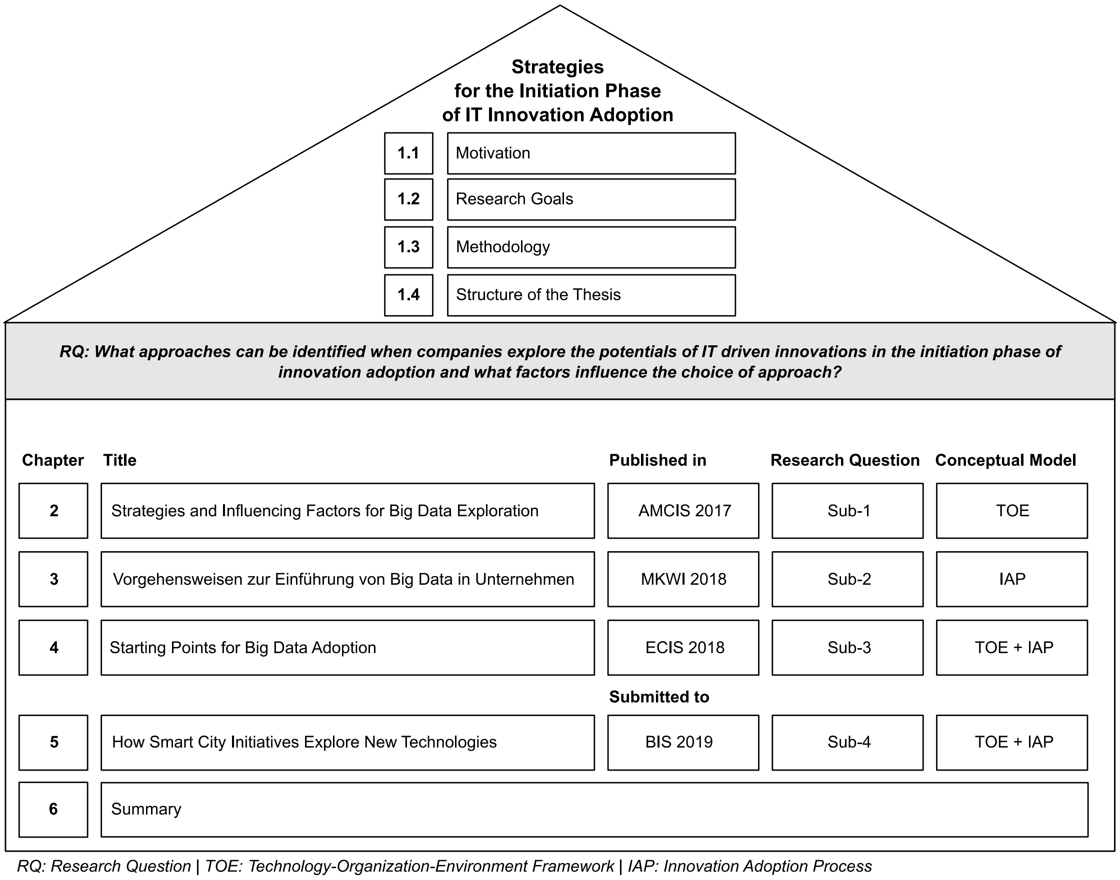

Figure 1.5 Structure of the thesis

Chapter 2 focuses on the general adoption of big data in companies. It introduces the case companies and examines their general drivers and influencing factors for big data adoption. The current literature for big data adoption is reviewed and compared with the results of the study. This chapter also briefly introduce two different strategies for big data adoption and provides the basis for the next chapters.

Sub-1: *What factors influence and drive companies within the initiation phase of big data adoption?*

Chapter 3 concentrates on the adoption process for big data in companies and examines the previously identified strategies in detail. The analysis of the multiple case study reveal that three different approaches for big data adoption in the initiation phase of innovation adoption exist.

Sub-2: *Which generic approaches can be identified when companies explore the potentials of big data in the initiation phase of innovation adoption?*

Chapter 4 picks up the three different adoption approaches and sheds light on the criteria that affect the decision on which approach to choose for big data adoption. The study analyzes the influence factors from a technological, organizational and environmental perspective and identifies factors that are decisive for decision-making.

Sub-3: *What factors influence the choice of approach?*

Chapter 5 focuses on the generalizability of the previous results. Therefore, a second multiple case study was conducted focusing on smart city initiatives and their adoption activities for smart services. In consequence, this chapter describes the identified approaches for the initiation phase of smart services adoption and the decision-relevant criteria for these approaches.

Sub-4: *What approaches do smart city initiatives use when they initially explore the potential of new technologies for smart services and which factors influence their choice of approach?*

Chapter 6 summarizes the results of the dissertation and gives an overview of the practical and theoretical contribution of this thesis.

2 Strategies and Influencing Factors for Big Data Exploration

Christian Bremser, Gunther Piller and Franz Rothlauf

Abstract

Many enterprises feel the need to explore the possibilities big data may provide for their business. However, they hesitate to apply big data, as they are unsure how to successfully identify new opportunities. We analyze in a multiple case study how companies start to investigate big data applications. Based on these case studies, we find two generic strategies companies tend to follow. These strategies focus either on the search for potential business opportunities or on the need to develop technology infrastructure. In order to understand the strategy selection, we utilize the Technology-Organization-Environment (TOE) framework. Our findings are twofold. First, we identify factors that influence the choice of strategy. Second, we identify the factors that influence the initiation phase of big data adoption within a chosen strategy.

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2.1 Introduction

Big data promises new data driven services to improve products, services or processes of companies from all industries (see e.g. (Jukić et al., 2015; Sivarajah et al., 2017)). Although many enterprises feel the need to explore the possibilities big data provides for their business, they hesitate to apply big data as they are unsure how to start and how to successfully identify new business opportunities. These questions concern many companies. For example, a research from Gartner reports that 82% of companies are still experimenting with big data, developing strategies or gathering knowledge (Kart, 2015). Only 14% have put big data projects into production. Apparently, the productive use of big data technologies is still low, compared to the interest in the topic. Therefore studies of big data adoption are interesting and important.

Innovation adoption is often described by three major phases (Damanpour & Schneider, 2006; Rogers, 2003): initiation, adoption and implementation. Along this path new technologies have to overcome several hurdles before being used productively. For technology driven innovations, like big data, the starting phase, where enterprises search for valuable use cases and applications leveraging new possibilities, poses a first serious obstacle. This initial step towards a successful adoption is the focus of our research.

This paper studies several cases on how companies start exploring big data. In particular we utilize the Technology-Organization-Environment (TOE) framework (Tornatzky, Fleischer, & Chakrabarti, 1990) to investigate the initiation phase of big data adoption. Based on the reported case studies, we find two generic strategies that are pursued by organizations. These strategies focus either on the search for potential business opportunities or on the need to develop technology infrastructure. The use of the TOE helps to understand these strategies and their determinants: We first identify and classify factors that influence the choice of strategy. Second, we recognize factors with major influence on the initiation phase of big data adoption within a chosen strategy.

Our results are based on a multiple case study. Our main information sources are in-depth expert interviews with key-informants. For the explanation of our results we use the TOE (Tornatzky et al., 1990) adapted from existing big data adoption studies (Agrawal, 2015; Malaka & Brown, 2015; Nam, Kang, & Kim, 2015).

This report is organized as follows: Current research on big data adoption is summarized in the next section. In section 2.3, we sketch our conceptual model based on TOE and existing big data adoption models. Our research design is introduced in section 2.4. The results of our cases are described and discussed in the last sections of this paper.

2.2 Current Research on Big Data Adoption

In accordance with many other definitions, the TechAmerica Foundation (2012) states "big data is a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information." Obviously, there are ambiguities about limits on the three Vs –

volume, variety and velocity – that define big data. However, for every company a "three-V tipping point" exists beyond which traditional data management and analysis technologies become inadequate for deriving intelligence within a sufficient period of time. This tipping point poses a threshold beyond which firms start dealing with big data and examine the value of new technologies compared with their present implementations (Gandomi & Haider, 2015).

Regardless of the ambiguities about the onset of big data, researchers and business people agree that big data has the potential to answer new and complex analytical questions and provides information insight that would have been concealed by conventional analysis methods (Boyd & Crawford, 2012). In order to unlock this potential, companies have to acquire big data resources and develop capabilities to leverage their possibilities (Mikalef et al., 2016). The literature defines three key typologies of big data capabilities (see e.g. (Akter et al., 2016)): management capabilities (e.g. data governance), technology capabilities (e.g. integrating and operating Hadoop components) and talent capabilities (e.g. data science knowledge).

The introduction of innovations in companies – such as big data – which eventually leads to the development and deployment of corresponding capabilities, is described by innovation adoption processes. These can in general be divided into three typical phases: initiation, adoption (decision) and implementation (see e.g. (Damanpour & Schneider, 2006; Rogers, 2003; Zmud, 1982)). During the initiation phase companies become aware of an innovation, consider its use for a recognized need and propose its adoption. In the adoption phase proposed ideas are evaluated from technical, financial and strategic perspectives. Then an adoption decision is taken, which includes the allocation of resources for the implementation and assimilation of an accepted solution. All preparations for its productive use are then carried out during the implementation phase.

Currently, the adoption of big data is discussed extensively by software vendors and IT consultancies. However, scientific research is still scarce. Nam et al. (2015) investigates the key factors that influence big data adoption in the three innovation phases. For this purpose the TOE framework has been used (Tornatzky et al., 1990). It describes the impact of technological, organizational and environmental aspects on organizational decision making with respect to technology innovations. Nam et al. (2015) explore in particular the influence of direct and indirect benefits, financial readiness, information system (IS) competence as well as industrial and government pressure. As main results they find, that the initiation phase of the innovation process is positively affected most by IS competence. Industry pressure and perceived direct benefits also seem to be important, however with smaller impact. The adoption phase is driven by industry pressure while the implementation stage is mostly influenced by IS competence and financial readiness. Different approaches to big data adoption and their relation to TOE aspects have not been investigated.

The TOE was also utilized by Malaka and Brown (2015), who studied the adoption of big data analytics within the telecommunication industry in South Africa. They identified major challenges and mapped them to the three perspectives of the TOE. Technological challenges found were data integration, data privacy, return on investment, data quality, cost, data integrity, performance and scalability. Major challenges from an organizational perspective were ownership and control, skills shortages, business focus and prioritization, training, organizational silos and unclear processes. From the environmental context no major challenges were highlighted. Organizational aspects were recognized as the major inhibitors to adoption. An examination of the different phases of the adoption process has not been pursued.

The approach of Agrawal (2015) is quite similar. He used the TOE to explore the high-level determinants that influence the adoption of big data analytics in emerging economies. The innovation process was considered in its entirety, without distinguishing different phases. As a result the six variables complexity, compatibility, regulatory support, organizational size, competition intensity and environmental uncertainty were found to be significant determinants. Of those regulatory support and complexity were inhibitors and most influential, all other factors were facilitators of adoption.

Similar factors influencing big data adoption have been found recently also in a content analysis based on research publications in the business intelligence and analytics literature by Sun et al. (2016).

Chen et al. (2015) used a multiple case study to obtain a more detailed view on big data adoption processes and corresponding influencing factors. As a result, they describe several steps within the three phases of the innovation adoption process from Rogers (2003). TOE, Diffusion of Innovation (DOI) (Rogers, 2003) and IT Fashion Theory (Wang, 2010) were used as sources for influence factors. From DOI, which describes the process of spreading an IT innovation among the members of a social system, one obtains relative advantage, compatibility, complexity, observability and trialability as important attributes. The IT Fashion Theory on the other hand provides aspects that highlight the social settings of emerging IT trends. In particular, it includes the influence of fashion-setters like consultants and technology analysts. Chen et al. (2015) extend the aspects of these theories by including organizational, environmental, social variables as well psychological factors. They found that relative advantage is a necessary but not sufficient condition for big data adoption. As a central result, they uncovered a so called “Deployment Gap” and a “Limbo Stage”, where companies continuously experiment for a long time with big data technologies and do not proceed to deployment despite the intent to adopt. While this research sheds light on the later stages of big data adoption, details and strategies for its starting phase have not been explored.

In comparison to existing studies our research focuses on the initial phase of big data adoption. We investigate the strategies companies use to approach big data and the factors influencing their choice. With respect to the innovation adoption processes, we explore in particular the initiation phase. It includes the identification of potential application areas and use cases. If – at the end of this phase – the intention to adopt a specific big data use case is high, organizations propose its adoption. They then proceed with a thorough evaluation, including e.g. prototyping, and implementation activities. These later steps are studied, e.g., in Chen et al. (2015) and not focus of this paper.

2.3 Conceptual Framework

The goal of this research is to identify how companies approach big data, what strategy they use, and whether there are factors that have a significant impact on their choice of strategy. For this purpose, we use the TOE framework (Tornatzky et al., 1990). It describes the main factors influencing the adoption of technology innovations. These factors are clustered into three dimensions: technology, organization and environment.

The technology dimension encompasses the characteristics of available technologies which are relevant to a company. The organizational dimension covers company attributes, such as size, formal and informal linking structures, competencies and the amount of slack resources. The company's environment and its influence are described in the environmental dimension. It includes competitors, industry specifics and governmental regulation. The main strength of the TOE framework is its adaptability and the freedom to vary the factors or measures for each new research context (Baker, 2012). As a consequence the TOE is extensively used in adoption research (for examples see e.g. (Baker, 2012; Oliveira & Martins, 2011)). Central to most of these studies is the identification and classification of factors that influence the adoption of a certain technology as well as their interplay. The TOE has also been applied to big data adoption as summarized in the previous section. The corresponding results for influencing factors are shown in Table 2.1. As already mentioned, they have been related to the entire adoption process.

Dimension	Malaka, Brown (2015)	Agrawal (2015)	Nam et al. (2015)
Environment	- Industry/market competition - Vendor reliance - Data security & privacy	- Environmental uncertainty - Competition intensity - Regulatory support	- Perceived industry pressure - Perceived government pressure
Technology	- Time and cost - Data integration - Veracity - Performance & scalability	- Complexity - Compatibility - Relative advantage	- Perceived direct benefit - Perceived indirect benefit
Organization	- Ownership and control - Skill shortage - Communication processes	- Technological resource competency - Organizational size - Absorptive capacity	- Perceived financial readiness - Perceived IS competence

Table 2.1 Influencing factors of big data adoption studies

For our investigation of the initiation phase of big data adoption and the corresponding strategies and influence factors, we use the TOE as a conceptual framework, including the factors from Table 2.1 as a starting point. The goal of our study is twofold: First, we identify the factors which drive the strategy companies currently use to approach the potentials of big data. Second, we recognize the factors with major influence on the initiation phase of big data adoption within a chosen strategy.

2.4 Research Design

Phenomena around big data adoption are complex and certainly not well understood so far, thus a case study approach is suitable (Yin, 2003). We chose a multiple case design to support the generalizability of results (Dubé & Paré, 2003; Yin, 2003).

Our main information sources are in-depth expert interviews with key-informants (Bagozzi, Yi, & Phillips, 1991). Interviewees were heads of business and IT divisions, chief architects and chief strategist. In addition to the interviews, we collected available public and corporate information about big data initiatives of participating companies.

The expert interviews were semi-structured. The interviews covered all dimensions of the TOE described in the previous section. We kept our questions open to allow interviewees freely to speak. The first part contains general questions about the role and responsibility of the interviewee, the current strategic and tactical challenges of the company and their influence upon dealing with new possibilities of big data. The second part of our questions concentrates on the current use of data, methods and technologies for data-driven decision making as well as corresponding organizational structures and processes. For example, we asked about the relevance of data and data-driven decision making in different organizations and inquired which kind of analytical applications were in use currently. The third and most extensive set of questions was directed upon "why" and "how" organizations explore the potentials of big data. These questions concerned the trigger of big data initiatives, their focus and their organizational setup. Also we inquired the process for the evaluation of big data potentials and the criteria applied therein.

The selection of cases follows a literal replication logic (Dubé & Paré, 2003) to ensure comparable organizational and technological contexts. We have investigated cases from ten companies. Our focus was on large companies with more than 10,000 employees with their headquarters in Germany and operating internationally. Pure internet companies were excluded. To obtain insights into sector-specific variations, the cases cover different types of industries, including transportation, banking, insurance, manufacturing, pharma, retail and utilities.

Every interview lasted approximately 90 minutes. The interviews were recorded and transcribed. The data collection started in June 2016 and stretched over a period of seven months. Shortly after each interview, the main points and key findings were recapitulated in a contact summary sheet. The interviews were then analyzed and coded. We used first-level coding (Miles, Huberman, & Saldana, 2013) to identify in particular all statements related to company's procedures for big data exploration, the goals of their initial activities and corresponding influence factors. The collected company documents and information were used to triangulate our findings. Furthermore, we established a case study database to minimize errors and biases (Yin, 2003) and stored all information about the data collection process, the data itself and the case study results into the database. According to Yin (2003), this helps to provide the same results on repeated trials.

2.5 Results from Case Studies

An overview of the analyzed cases is given in Table 2.2. The companies operate in B2B as well as in B2C segments. The interviewees had roles in business and IT.

#	Industry	Number of employees	Business segment	Role of Interviewee
1	Transport	>50,000	B2C, B2B	Head of Domain Architecture
2	Banking	>50,000	B2C, B2B	Head of IT Architecture
3	Insurance	>10,000	B2C, B2B	Head of Group strategy
4	Manufacturing Vehicle	>50,000	B2B	IS Chief-Architect
5	Retail Trade	>50,000	B2C	Head of Business Intelligence
6	Utilities	>50,000	B2C, B2B	Chief Digital IT Strategist
7	Manufacturing Vehicle	>50,000	B2B	Head of Analytics Lab
8	Manufacturing Apparel	>50,000	B2C	Head of Data Analytics Lab
9	Manufacturing CPG	>10,000	B2C	Head of Marketing & Analytics
10	Manufacturing Chemicals	>10,000	B2B	Head of BI Architecture

Table 2.2 Companies participating in analysis

The results of our cases are based on a twofold analysis and are summarized in Table 2.3 and 2.4. First, we conducted a within-case analysis to extract aspects which were mentioned as main factors influencing the current big data activities of companies. These are listed as case characteristics. We also extracted information regarding big data activities and goals during the initiation phase, when firms initially explore big data potentials. These are also included in Table 2.3 and 2.4. After we conducted the within-case analysis, we used a cross-case analysis to search for similarities and differences or patterns in the cases. While conducting this analysis, two different strategies for approaching big data potentials became apparent:

Business first (Table 2.3): Organizations in this category explore big data potentials entirely from a business perspective. They search for use cases with high expected business value. These use cases span from possible improvements of existing processes to entirely new business services or business models. Investigations of the required effort for corresponding implementations into the productive IT landscape are postponed to a later stage. For example in case 1 the transportation company established innovation units staffed mainly with people from business departments to search for promising use cases with high business value. Studies of constraints from a technical or data management perspective were excluded in this phase.

#	Case Characteristics	Explorative Big Data Activities & Goals
1	- strong competition from low cost players, falling prices and volatile commodity markets - big data as part of digital strategy, management support, dedicated resources, e.g. innovation units, data labs - expected benefits in process optimizations and new business services for travelers - complexity is not considered during the initiation phase	establish innovation units; fast validation of business cases for ideas in lab environment; focus on process optimizations and new business services
6	- deregulated market and energy transition causes uncertainties - data-driven company is long-term goal and big data initiatives are driven by top management - benefits are expected for customer retention and through new digital products, e.g. for smart meters - high BI maturity and the availability of IS resources supports the development of new data-driven products	search for digital product ideas; agile and fast product development in data labs; data-driven validation of products in market
8	- big data is placed as a mega trend by top management - operational efficiency is seen as key challenge in a highly competitive global fashion market; its improvement is focus of first activities - BI maturity is high - high perceived complexity of available technologies and lack of external available knowledge	establish lab environment, develop big data show cases for organization; focus on operational efficiency
9	- market is characterized by aggressive trade groups firing up competition and economic uncertainties, e.g. brexit votum - integrated and harmonized data architecture exists - benefits are expected in particular in the area of promotional efficiency - new technologies are explored through external providers	integrate additional data sources; expand data hub; strengthen promotional efficiency

Table 2.3 Overview of cases using business first

Platform building (Table 2.4): These organizations initially focus on an identification of key activities for the development of a future-oriented big data platform and not on the search for particular business applications. Their goal is to lower the barrier for a later implementation of big data use cases. Specific application scenarios do not yet exist, but are expected to come up eventually. For example in case 2 a company from the banking industry started to meet existing requirements without relation to big data use cases through an implementation of new big data technologies. They introduced Hadoop components for a standard storage system and improved data integration capabilities. Both will help future big data use cases – so their assumption.

#	Case Characteristics	Explorative Big Data Activities & Goals
2	- cost pressure through low interest rates, new competitors (e.g. fintechs), strong regulatory measures - regulatory requirements block IT resources - new technologies (e.g. blockchain), changing customer expectation - transformation of business model and new digital strategy - missing central data warehouse and issues in data quality - benefits are seen in e.g. optimized risk management, fraud detection	realize existing requirements with new technologies; systematic development of a data lake; improve data integration and lower barrier for big data use cases
3	- new technologies (e.g. autonomous driving) and ongoing low-interest rates attack existing business - potential conflicts between new data services and anticipated customer privacy - missing top management support, missing digital strategy and complexity of available technologies block use case exploration although financial readiness is given - IT resources are fully utilized by ongoing operations	set up working groups; explore requirements from straw men use cases for organization, data and technologies; identification of key activities to prepare platform
4	- competitors from emerging markets causes cost pressure, decreasing profit margins - fragmented data architecture and large number of systems lead to hurdles in organizational performance management - new top management emphasizes data-driven decision-making - benefits like process optimization are expected but the complexity of big data technologies is perceived as high, therefore basic data management & BI tasks are addressed first	rise BI maturity; set up data lab to test feasibility of performance KPIs; improve operational efficiency
5	- non-traditional competitors like Amazon increase competition in a market with low profit margins - data is seen as an asset, BI maturity is high - big data is seen as just another set of technologies - complexity challenges of new technologies is outsourced - no obvious big data use cases with additional benefits	continuous exploration of new technologies; optimize business processes and improve understanding of customer
7	- regulatory measures, e.g. driving safety and emission reduction - data is distributed over different production sites and systems - big data is perceived as complex, therefore data lab focuses on approaching analytics and developing decision documents for the management - big data is part of a formulated strategy	establish lab environment; explore requirements for big data; harmonize data & increase efficiency of operational processes
10	- increasing regulatory measures in human healthcare causes cost pressure and drive the utilization of IT - global market is consolidating as a result of strong competition - a digital strategy has been recently launched - self-service BI is widely used, BI maturity is high - data governance in big data environments is perceived as complex, therefore a systematic exploration of technologies appears appropriate	explore technological and organizational requirements of big data; systematic development of a data lake; exploration of new data based revenue streams

Table 2.4 Overview of cases using platform building

2.6 Discussion

Following the TOE framework we collect all influencing factors from the investigated cases and assign them to the different TOE dimensions. The result is shown in Table 2.5, including brief comments and explanations. As compared to previous applications of TOE to big data (Agrawal, 2015; Malaka & Brown, 2015; Nam et al., 2015) a company's strategy or support by top management was found as an additional influencing factor (see e.g. cases 3, 6, 8) within the organizational dimension of TOE. This aspect was also recognized for BI adoption (see e.g. (Hung et al., 2016)).

Technology	Organization	Environment
- benefits (value for business processes and models) - compatibility (fit to existing technologies, processes or culture) - complexity (many components with multiple ways to combine and use)	- IS competence (competence of IT usage and IT management in an organization) - financial readiness (availability of financial resources) - strategic readiness (big data is part of strategy, supported by top management)	- competitive pressure (new competitors, disruptive business models) - environmental uncertainty (volatile markets, changing customer expectations) - regulatory measures (energy transition, emission reduction, finance regulatory)

Table 2.5 Overview of TOE categories

Table 2.6 shows the factors which had the main influence on a company's choice of strategy for approaching big data – i.e. business first or platform building. Here the environment dimension as well as benefits and compatibility from the technology dimension are absent. Factors in the environment dimension and potential benefits of big data technologies always motivated investigations of their potentials, but where not acting differently for both strategies. Also compatibility aspects did not affect the strategy choice.

#	complexity	IS competence	financial readiness	strategic readiness
1		▲	▲	▲
6		▲	▲	▲
8			▲	▲
9			▲	
2		▲	▲	
3	▲			▲
4	▲	▲	▲	
5		▲		
7	▲	▲	▲	
10		▲	▲	

Table 2.6 Major influence factors

We found that organizations choose business first as strategy, when at least financial readiness is given. It empowers them either to establish own lab environments for the investigation of use cases, or to engage external partners to do so. IS competences for big data and strategic readiness also support this strategy. For example, the management of the manufacturing company in case 8 placed big data as a megatrend and formulated a corresponding strategy. Their financial readiness allowed them to establish a lab environment and to allocate IS resources. Another example is the manufacturing company in case 9. Here no appropriate internal IS resources were available. However financial readiness enabled the organization to search for use cases and to commission external partners to carry out proof of concept projects.

Contrary to business first, companies who follow platform building are typically influenced by a lack of financial readiness. In our cases, this was mostly caused by cost pressure through strong competition or high regulatory measures. Regulatory measures also led to an increase of corresponding IT demands and a strong utilization of IT resources. These factors prevented organizations to establish lab environments for big data or to commission external partners. Case 2 and 10 are typical examples.

Companies choosing platform building as their strategy also perceive the complexity of big data often as high and have lack of needed IS competencies. In case 4 and 7, a shortage of IS competences was signaled by a low BI maturity. Building up basic IS capabilities for big data, e.g. for data integration, is often done by straw men use cases (see e.g. case 3). These are industry-typical use cases (e.g. fraud detection in financial industry), which are leveraged to capture and analyze essential big data requirements. Missing top management support, as in case 3, also increases the preference for platform building.

Besides the identification of factors that drive the strategy how companies approach the potentials of big data, we were able to recognize factors in the TOE with major influence on the initiation phase of big data adoption within a chosen strategy.

We found that organizations following the strategy business first were mainly driven by expected benefits – the influencing factor within technology dimension of TOE. Their search for use cases fully focuses on potential business benefits of big data use cases and their underlying technology. Possible challenges with respect to compatibility, when e.g. integrating a new big data application into existing IT systems, are investigated after a clear indication of business value. They are evaluated when the organization propose a use case for adoption – i.e. after the initiation phase of technology innovation adoption.

Organizations following the strategy platform building focus on building a big data platform that can serve eventually upcoming use cases. The most relevant TOE factors for these efforts are: IS competence, complexity and financial readiness. Developing big data capabilities will enhance IS competence and will reduce complexity. As a consequence, the cost for a future evaluation and introduction of big data use cases become more favorable with respect to a given level of financial readiness.

2.7 Summary

In this paper we have investigated through an analysis of ten cases how companies start exploring big data potentials. We found that companies use two strategies to approach big data adoption. They either focus on use cases with a high potential business case, or on developing capabilities for future big data platforms. The choice of strategy can be described by external and internal influence factors within the technology, organization and environment dimensions of the TOE framework.

In particular we found that the organizational dimension of the TOE has a major influence on the choice of strategy. The availability of IS competence, financial and strategic readiness determine whether organizations choose business first or platform building. A perceived complexity of the technology dimension supports this choice.

Within a chosen strategy, we were able to observe that organizations are either driven by the technology, or by the organization dimension of the TOE. The technology dimension and its benefit aspect could be identified as main driver within the strategy business first. Organizations following this strategy are searching for use cases with high business value. We also found that organizations following platform building are driven by the organizational dimension of the TOE. They make efforts to establish IS competences and reduce the complexity of big data technologies. In this way they lower the hurdle for an eventual adoption of big data applications.

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3 Vorgehensweisen zur Einführung von Big Data in Unternehmen

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Abstract

Im Zuge einer fortschreitenden Digitalisierung versprechen sich viele Unternehmen durch die Einführung von Big-Data-Technologien neue Möglichkeiten, Daten geschäftswirksam einzusetzen. Allerdings nutzen nur wenige Firmen Big-Data-Anwendungen produktiv, trotz ihres vermuteten hohen Potenzials. Auf welche Art und Weise Unternehmen die Möglichkeiten von Big Data untersuchen, ist die zentrale Fragestellung der vorliegenden Arbeit. Im Rahmen einer multiplen Fallstudie werden drei verschiedene Vorgehensweisen identifiziert. Unternehmen konzentrieren sich zuerst entweder auf rein betriebswirtschaftliche Aspekte, oder auf einen systematischen Aufbau einer Big-Data-Technologie- und Datenplattform. Als theoretische Basis dient die Innovationsadoptionsforschung.

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3.1 Einführung

Die mit Big Data verbundenen Nutzenpotenziale und Herausforderungen sind im Zeitalter einer immer schneller fortschreitenden Digitalisierung ein wichtiges Thema für Unternehmen aller Branchen. Big Data verspricht neue datengetriebene Services, um Prozesse zu verbessern sowie innovative Produkte und Geschäftsmodelle zu ermöglichen (Sivarajah et al., 2017). Vor diesem Hintergrund investiert eine steigende Zahl von Unternehmen in Big Data, verbunden mit der Hoffnung, sich Wettbewerbsvorteile sichern zu können (Constantiou & Kallinikos, 2015). Dennoch scheinen Unternehmen Schwierigkeiten bei der produktiven Einführung von Big-Data-Anwendungen zu haben. Einer Gartner Studie zur Folge haben nur 14% der Unternehmen Big-Data-Anwendungen im produktiven Betrieb (Kart, 2015). Untersuchungen, die die Einführung von Big-Data-Anwendungen begleiten sind somit wichtig und von wissenschaftlichem und praktischem Interesse.

Die Einführung von technologischen Innovationen wird in der wissenschaftlichen Literatur durch die Innovationsadoption beschrieben. Der Prozess der Innovationsadoption erstreckt sich typischerweise über zwei Phasen (Rogers, 2003): Initiierung und Implementierung. Innerhalb dieser Phasen müssen neue Technologien zahlreiche Hürden überwinden. Für technologiegetriebene Innovationen, wie Big Data (Nam, Kang, & Kim, 2015), stellt die Initiierungsphase, in der Unternehmen nach wertvollen Anwendungsfällen für bestimmte Big-Data-Technologien suchen, eine erste Hürde dar. Um diesen initialen Schritt in Richtung produktiver Implementierung zu untersuchen, geht die vorliegende Arbeit folgender Forschungsfrage nach:

Welche generischen Vorgehensweisen lassen sich in der Initiierungsphase bei Unternehmen, die Big-Data-Anwendungen einführen, identifizieren?

Trotz einer hohen Relevanz, existieren bisher keine spezifischen Studien zur Initiierungsphase der Big-Data-Adoption. Aktuelle Arbeiten untersuchen vornehmlich allgemeine Einflussfaktoren und Hürden bei der Implementierung von Big-Data-Technologien. Im Gegensatz hierzu analysiert dieser Beitrag derzeitige Vorgehensweisen bei der Untersuchung von neuen Potenzialen. Hierfür wurde eine multiple Fallstudie mit zehn Großunternehmen durchgeführt. Als theoretische Ausgangsbasis wird der organisationale Adoptionsprozess von Rogers (2003) verwendet.

In einer fortschreitend digitalen Welt sind Unternehmen unter anderem dazu aufgefordert, sich aktiv mit neuen Technologien, ihren Möglichkeiten für Geschäftsprozesse und ihren Konsequenzen für die Unternehmens-IT auseinanderzusetzen. In dieser Arbeit wird gezeigt, wie dies im Bereich von Big Data derzeit geschieht.

Kapitel 3.2 nimmt Bezug zum aktuellen Stand der Forschung. In Kapitel 3.3 wird das konzeptionelle Modell und in Kapitel 3.4 das Forschungsdesign vorgestellt. Kapitel 3.5 präsentiert die Daten der Fallstudien. Eine Diskussion der Ergebnisse in Kapitel 3.6 und eine Zusammenfassung der Arbeit in Kapitel 3.7 schließen die Arbeit ab.

3.2 Stand der Forschung

Big Data wird von der TechAmerica Foundation (2012) definiert als „a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information." Aus der Definition wird offensichtlich, dass es sich bei Big Data um ein Bündel neuer technologischer und methodischer Möglichkeiten handelt, die es erlauben große, komplexe und schnell wachsende Datenbestände zu verarbeiten (z.B. In-Memory Datenverarbeitung, NoSQL Datenbanken). Big Data Analytics steht hierbei für verschiedene Techniken, die es erlauben, Wissen aus Big Data zu extrahieren (LaValle et al., 2011). Unternehmen wollen diese Möglichkeiten nutzen und versprechen sich vielseitige Vorteile durch die Einführung von konkreten Big-Data-Anwendungen (siehe dazu z.B. (Davenport, Barth, & Bean, 2012; Kiron, Prentice, & Ferguson, 2014; LaValle et al., 2011)).

Die Einführung von technologischen Innovationen wird in der wissenschaftlichen Literatur durch die Innovationsadoption beschrieben. Diese stellt zum einen die Einflussfaktoren auf die Entscheidungsfindung innerhalb des Einführungsprozesses dar (Rogers, 2003). Zum anderen beschreibt sie den Prozess, den Innovation von ihrer ersten Wahrnehmung in Unternehmen bis zu ihrem produktiven Einsatz durchlaufen (Fichman, 2000). Vorangegangene Arbeiten im Kontext der Big-Data-Adoption fokussieren überwiegend die Untersuchung allgemeiner Einflussfaktoren auf den Adoptionsprozess mittels Technology-Organization-Environment Framework (TOE) (siehe hierzu z.B. (Agrawal, 2015; Malaka & Brown, 2015; Sun et al., 2016)). Das TOE unterteilt diese Einflussfaktoren hinsichtlich ihrer technologischen, organisatorischen und umweltbedingten Aspekte (Tornatzky, Fleischer, & Chakrabarti, 1990). Als Ergebnis wird gezeigt, dass Herausforderungen im technologischen Bereich in der Einhaltung von Datenschutz und in der Datenintegration liegen. Organisatorische Aspekte, wie u.a. fehlendes analytisches Können oder unklare Prozesse und Priorisierung von Anwendungsfällen sind weitere Hemmnisse bei der Einführung von Big Data. Positiv wird die Adoption hingegen von Unternehmensgröße und Wettbewerbsintensität beeinflusst.

Nam et al. (2015) untersuchen in ihrer Forschungsarbeit die Veränderung der Einflussfaktoren innerhalb des Adoptionsprozesses. Als Ergebnis weisen Nam et al. nach, dass vorhandene IS-Kompetenz den Beginn des Adoptionsprozesses positiv beeinflusst, während Wettbewerbsintensität und finanzielle Bereitschaft die erfolgreiche Implementierung von Anwendungsfällen maßgeblich fördern.

In Bremser et al. (2017) wird im Rahmen von TOE gezeigt, welche Faktoren die Herangehensweise von Unternehmen an Big-Data-Potenziale beeinflussen. IS-Kompetenz, wahrgenommene Komplexität der Big-Data-Technologien, sowie finanzielle und strategische Bereitschaft von Unternehmen wurden als wesentliche Einflussgrößen identifiziert.

Eine Untersuchung des Big-Data-Adoptionsprozess gibt es bisher nur von Chen et al. (2015). Diese nutzen eine multiple Fallstudie, um die Implementierungsphase zu beschreiben und Faktoren zu validieren, die diese beeinflussen. Die Faktoren dieser Untersuchung entstammen dem TOE (Tornatzky et al., 1990), der Diffusionstheorie (Rogers, 2003) und der IT Fashion

Theorie (Wang, 2010). Die Diffusionstheorie beschreibt die Ausbreitung einer Innovation innerhalb eines sozialen Systems und die Faktoren, die diese beeinflussen (Rogers, 2003). Die IT Fashion Theorie betrachtet soziale Aspekte im Rahmen der Innovationadoption, wie z.B. der Einfluss von Berater und Analysten (Wang, 2010). Nach Chen et al. (2015) umfasst die Implementierungsphase tiefgreifende organisatorische Veränderungen, die für eine produktive Implementierung von Big-Data-Anwendungen notwendig sind. Als Ergebnis präsentieren sie eine „Limbo Stage", in der Unternehmen, trotz positiver Absicht Big-Data-Anwendungen produktiv einzuführen, nicht über das Testen von Anwendungsfällen hinauskommen.

Die Darstellung der aktuellen Forschungsergebnisse zeigt, dass die Einflussfaktoren auf den Adoptionsprozess bereits umfangreich betrachtet wurden. Eine Untersuchung des Adoptionsprozess erfolgte durch Chen et al. (2015), jedoch fokussierte dieser die Implementierungsphase. Es ist damit festzuhalten, dass für die Initiierungsphase trotz ihrer hohen Relevanz keine wissenschaftliche Untersuchung existiert.

3.3 Konzeptionelles Modell

Um die Forschungslücke zu adressieren und die Einführung von Big-Data-Anwendungen zu untersuchen, wird in dieser Arbeit der Adoptionsprozess von Rogers als theoretische Ausgangsbasis verwendet (Rogers, 2003). Der Prozess der Innovationsadoption kann nach Rogers (2003) in die Phasen Initiierung und Implementierung unterteilt werden, wobei beide Phasen durch eine Adoptionsentscheidung getrennt sind. Die Initiierungsphase besteht aus den Stufen Agenda-Setting und Matching und ist Basis des konzeptionellen Modells.

Das Agenda-Setting wird ausgelöst durch ein organisationales Problem oder durch die Wahrnehmung einer Innovation. Das organisationale Problem äußert sich durch eine wahrgenommene Leistungslücke, welche Resultat interner Ineffizienz oder veränderter Umweltbedingungen ist (Damanpour & Schneider, 2006). Die Wahrnehmung einer Innovation erfolgt durch kontinuierliches Scannen der Unternehmensumwelt (z.B. das Beobachten von Wettbewerbern oder technologische Entwicklungen). Beides löst in Unternehmen das Bedürfnis nach der Einführung einer Innovation aus. Innerhalb der Agenda-Setting-Stufe werden daher die unternehmerischen Reaktionsmöglichkeiten abgewogen, wie beispielsweise auf die Verfügbarkeit neuer Technologien reagiert werden kann.

Die Matching-Stufe umfasst Aktivitäten, die prüfen, ob die identifizierte Innovation geeignet ist, die organisationalen Bedürfnisse zu erfüllen und deren Einführung im Kontext der jeweiligen Unternehmenssituation sinnvoll ist. Typischerweise befassen sich einige Mitglieder einer Organisationseinheit intensiv mit den Funktionen dieser Innovation, um eine Empfehlung bezüglich der produktiven Einführung abgeben zu können. Fällt diese Prognose positiv aus, wird im Adoptionsprozess die Implementierungsphase angestoßen. Diese setzt sich aus den Stufen „Redefining", „Clarifying" und „Routinizing" zusammen und umfasst alle Aktivitäten und Entscheidungen, die dazu nötig sind, die Innovation produktiv zu nutzen. Die vorliegende Forschungsarbeit konzentriert sich auf die Initiierungsphase des Adoptionsprozess. Die

Implementierungsphase ist nicht Gegenstand dieser Arbeit und wird von Chen et al. (2015) untersucht.

3.4 Forschungsdesign

Die Erforschung der Big-Data-Adoption in Unternehmen stellt ein komplexes Forschungsfeld dar. Aus diesem Grund wurden Fallstudien als geeignetes Mittel zur Analyse dieses komplexen Phänomens erachtet (Dubé & Paré, 2003; Yin, 2003). Die Hauptinformationsquellen waren Experteninterviews mit Schlüssel-Informanten. Die Teilnehmer umfassten Führungskräfte aus Business und IT-Einheiten, sowie Chef-Architekten und Chef-Strategen. Alle Interviewteilnehmer waren verantwortlich für die jeweiligen Big-Data-Initiativen in ihren Unternehmen.

Im Sinne einer stringenten Umsetzung des Forschungsdesigns wurden vier etablierte Gütekriterien zugrunde gelegt (Yin, 2003): externe Validität, interne Validität, Konstruktvalidität und Reliabilität.

Die externe Validität fokussiert die Generalisierbarkeit der Ergebnisse. Diese wird durch das Replizieren der Fallstudien sichergestellt. Im Kontext der Big-Data-Adoption wurde entschieden, eine multiple Fallstudie durchzuführen. Die Auswahl der Fallstudien erfolgte hierbei nach der „literal“ Replikationslogik (Dubé & Paré, 2003). Zur Sicherstellung eines vergleichbaren organisatorischen und technologischen Kontexts wurde daher bei der Auswahl der Fallstudien explizit auf reine Internetunternehmen verzichtet und der Big-Data-Bezug mittels wissenschaftlicher Taxonomien geprüft (siehe z.B. (Kune et al., 2016)). Die Big-Data-Taxonomien stellen ein Klassifikationsschema dar und zeigen auf, welche Technologien, Methoden und Daten typischerweise im Kontext von Big Data verwendet werden.

Um die interne Validität sicherzustellen, wurde der Interviewleitfaden auf Basis des konzeptionellen Models, das in Kapitel 3.3 beschrieben wurde, aufgebaut. Die Experteninterviews waren semi-strukturiert und die Fragen bewusst offengehalten, um den Teilnehmern die Möglichkeit zu geben, frei zu sprechen. Der Interviewleitfaden baute sich wie folgt auf: Der erste Teil enthielt generelle Fragen über Rolle und Verantwortung des Interviewteilnehmers, sowie die aktuellen strategischen und taktischen Herausforderungen des Unternehmens und deren Einfluss auf den Umgang mit Big Data. Der zweite Teil der Fragen konzentrierte sich auf den aktuellen Einsatz von Daten, Methoden und Technologien zur datengetriebenen Entscheidungsfindung, sowie die entsprechend notwendigen Organisationsstrukturen und Prozesse. Zum Beispiel wurde nach der derzeitigen Relevanz von Daten im Entscheidungsfindungsprozess in verschiedenen Organisationen innerhalb der Unternehmen gefragt. Der dritte und umfangreichste Teil der Fragen richtete sich nach dem „warum“ und „wie“ Unternehmen im Kontext der Big-Data-Adoption vorgehen und erste Potenziale von Big-Data-Anwendungen finden. Dies umfasste den Auslöser solcher Big-Data-Initiativen, deren Fokus und organisatorische Einbindung, sowie den Prozess zur Identifikation und Evaluation von Big-Data-Einsatzszenarien.

Um Konstruktvalidität sicherzustellen, schlägt Yin (2003) unter anderem Triangulation vor. Innerhalb der Fallstudien wurden daher unterschiedliche Datenquellen herangezogen. Neben den Interviews wurden öffentliche und - sofern verfügbar - interne Dokumente über Big-Data-Initiativen und Strategien der jeweiligen Unternehmen verwendet. Des Weiteren wurden Interviews mit Unternehmensberatungen und Software-Anbietern durchgeführt, die auf die Adoption von Big Data spezialisiert sind und bereits mit Unternehmen aus entsprechenden Branchen zusammengearbeitet haben.

Die Reliabilität der Fallstudien wurde sichergestellt, indem eine Fallstudien Datenbank eingerichtet wurde. Dort wurden Daten zum Datenerfassungsprozess, Fallstudienprotokolle, die Daten selbst, wie z.B. Transkripte und Fallstudienresultate abgelegt. Nach Yin (2003) wird damit sichergestellt, dass außenstehende Dritte bei Durchführung der Studie zu gleichen Ergebnissen kommen können.

Die Datenerhebung erfolgt im Zeitraum von Juni 2016 und erstreckte sich über einen Zeitraum von sieben Monaten. Jedes Interview dauerte im Durchschnitt 90 Minuten und wurde vor Ort oder per Telefonkonferenz durchgeführt. Die Gespräche wurden aufgezeichnet und im Anschluss transkribiert. Nach jedem Interview wurde ein „Contact-Summary-Sheet“ (Miles, Huberman, & Saldana, 2013) angefertigt, welches erste Eindrücke und Hauptinhalte des Interviews rekapitulierte.

Tabelle 3.1 präsentiert einen Überblick über die Teilnehmer der Fallstudie. Der Fokus der Fallstudienauswahl liegt auf Unternehmen, die mehr als 10.000 Mitarbeiter aufweisen und deren Unternehmenszentrale in Deutschland ist. Die untersuchten Unternehmen operieren sowohl im Business-to-Consumer- als auch im Business-to-Business-Segment. Die Interviewteilnehmer stammen aus IT und Fachbereichen und verantworten in ihrem jeweiligen Unternehmen Big-Data-Initiativen.

#	Branche	Beschäftigte	Geschäftsfeld	Rolle des Teilnehmers
1	Transport	>50.000	B2C, B2B	Head Domain Architecture
2	Banken	>50.000	B2C, B2B	Head IT Architecture
3	Versicherungen	>10.000	B2C, B2B	Head Group Strategy
4	Schienenfahrzeugbau	>50.000	B2B	IS Chief-Architect
5	Einzelhandel	>50.000	B2C	Head Business Intelligence
6	Energie	>50.000	B2C, B2B	Chief Digital IT Strategist
7	Automobilindustrie	>50.000	B2B	Head Analytics Lab
8	Bekleidungshersteller	>50.000	B2C	Head Data Analytics Lab
9	Konsumgüterproduktion	>10.000	B2C	Head Marketing & Analytics
10	Pharmaindustrie	>10.000	B2B	Head BI Architecture

Table 3.1 Teilnehmende Unternehmen

Die Ergebnisse der Fallstudien wurden anhand eines zweistufigen Verfahrens extrahiert. Im ersten Schritt wurde eine Within-Case-Analyse durchgeführt und alle charakteristischen Inhalte, die sich auf das Agenda-Setting und Matching beziehen, extrahiert (Yin, 2003). Die Darstellung der Phasen erfolgt in Kapitel 3.5 anhand der Prozessdefinition von Hammer und Champy (2003), wonach ein Prozess Input, Aktivitäten und Ergebnis umfasst. Im zweiten Schritt wurde eine Cross-Case-Analyse durchgeführt und die Fallstudien miteinander verglichen. Das Resultat dieses Vergleichs wird in Kapitel 3.6 diskutiert.

3.5 Ergebnisse der Fallstudien

Auslöser für ein Unternehmen sich mit den Möglichkeiten einer technologischen Innovation zu befassen ist nach Rogers eine Leistungslücke der Firma oder das Wahrnehmen neuer Möglichkeiten (Rogers, 2003). Im Fall technologiegetriebener Innovationen wird in der dann gestarteten Agenda-Setting-Phase geprüft, wie das Unternehmen auf die Verfügbarkeit neuer Technologien reagieren soll (Rogers, 2003). Resultat ist eine sogenannte Agenda, die das Ziel der nächsten Schritte im Adoptionsprozess festlegt.

In der nachfolgenden Matching-Phase wird untersucht, inwieweit eine Innovation dazu genutzt werden könnte, unternehmerische Bedürfnisse zu adressieren. Kann für einen konkreten Anwendungsfall eine erfolgversprechende Prognose abgegeben werden, wird dieser zur Implementierung vorgeschlagen (Rogers, 2003). Tabelle 3.2 zeigt eine Übersicht der Agenda-Setting- und Matching-Phase.

Bei allen Teilnehmern der Fallstudie wurde der Adoptionsprozess für Big Data durch das Senior Management angestoßen. Ausschlaggebend war bei allen Unternehmen die Wahrnehmung des Hypes um Big Data und nicht die Suche nach Möglichkeiten zur Lösung bestehender interner Anforderungen. Ein Interviewteilnehmer der Fallstudie 8 beschrieb dies beispielsweise wie folgt:

„es war unserer damaliger CIO [...], der gesagt hat, Big Data ist ein Megatrend, den will ich auf keinen Fall verpassen [...].“

Agenda-Setting	
Input	Performance Gap oder Wahrnehmung einer Innovation
Aktivität	Betrachtung unternehmerischer Reaktionsmöglichkeiten
Resultat	Agenda: Legt das unternehmensspezifische Ziel der nächsten Aktivitäten im Adoptionsprozess fest
Matching	
Input	Agenda
Aktivität	Erprobung, in wieweit unternehmerische Bedürfnisse mit Hilfe einer Innovation adressiert werden können
Resultat	Entscheidungsvorlage für die mögliche Implementierung eines Anwendungsfalls

Table 3.2 Agenda-Setting und Matching nach Rogers (2003)

Die langfristigen Ziele, die sich Unternehmen mit Big Data erhofften, spannten die gesamte Bandbreite, von einer Optimierung bestehender Geschäftsprozesse, bis zu Services für gänzlich neue Geschäftsmöglichkeiten, auf. Ein Zitat aus Fallstudie 5 belegt dies:

„[Wir hoffen Big Data] entweder zur Rationalisierung [nutzen zu können] oder auch zu anderen Wertschöpfungsmöglichkeiten, die jetzt nicht unbedingt was mit Rationalisierung zu tun haben, sondern wo wirklich neue Felder hinzukommen.“

Um die jeweilige Stoßrichtung der nächsten Big-Data-Aktivitäten festzulegen, wurde das Thema in allen Unternehmen im Senior Management besprochen. Als Resultat wurden erste Ziele und hierfür notwendige Schritte festgelegt. So wurden Verantwortliche für Big-Data-Initiativen und Ressourcen für Projektteams benannt. Tabelle 3.3 zeigt die kurzfristigen Ziele als Agenda der jeweiligen Big-Data-Initiative.

#	Fallspezifische Ziele
1	Portfolio für innovative datengetriebene Produkte, Services, Geschäftsmodelle
2	Möglichkeiten technologische Hürden für künftige Big-Data-Anwendungsfälle kostenneutral zu minimieren
3	Roadmap für einen systematischen Aufbau unternehmensinterner Fähigkeiten Big-Data-Technologien zu nutzen und Daten geeignet bereitzustellen
4	Konsistente Datenbasis für unternehmensweite Analysen, initial zur Identifikation von Effizienzsteigerungspotenzialen innerhalb bestehender Wertschöpfungsketten
5	Möglichkeiten eines zukunftsorientierten Ausbaus der Daten- und Technologieplattform für analytische Anwendungen
6	Portfolio innovativer digitaler Produkte für öffentliche, gewerbliche und private Kunden
7	Liste mit notwendigen Grundlagen bezüglich Technologien und Organisationen für zukünftige datenbasierte Produktinnovationen sowie eine konsistente Datenbasis
8	Potenziale für innovative Produkte und Verbesserungen der Prozesse entlang bestehender Wertschöpfungsketten
9	Möglichkeiten von Datenanalysen zur Effizienzsteigerung bestehender Prozessen mit Schwerpunkt Marketing & Vertrieb
10	Datenbasis aus bestehenden und neuen Daten für zukünftige Datenservices

Table 3.3 Agenda der Interviewteilnehmer

Wie Tabelle 3.3 zeigt, war es Ziel einiger Unternehmen (Fälle 1, 6, 8, 9) sich unmittelbar mit möglichen Anwendungsfällen zu befassen. Für den Rest der Unternehmen (Fälle 2, 3, 4, 5, 7, 10) stand vorerst die Schaffung einer guten technologischen Ausgangsbasis und Datengrundlage im Vordergrund.

Ihrer Agenda folgend, haben die befragten Unternehmen ihre Aktivitäten in der Matching-Phase unterschiedlich ausgerichtet. Die wichtigsten Aktivitäten der untersuchten Fälle werden in Tabelle 3.4 dargestellt. Für ihre Ausführung wurde ein jeweils passender organisatorischer Rahmen festgelegt. Die gewählten Organisationsformen variieren zwischen Arbeitskreisen, eigenständigen Einheiten innerhalb der IT oder aus der Unternehmensorganisation gelöste Laborumgebungen.

	Fallspezifische Aktivitäten
1	- Suche nach neuen, potenziellen datengetriebenen Produkten und Kundenservices - Bewertung der Anwendungsfälle hinsichtlich ihres betriebswirtschaftlichen Mehrwerts - Validierung von Prototypen in ausgewählten Marktsegmenten
2	- Analyse bestehender Anforderungen in Hinblick auf Möglichkeiten Big-Data-Technologien einzusetzen - Suche nach Gelegenheiten bestehende IT-Bausteine kostenneutral durch Big-Data-Technologien zu substituieren (z.B. Hadoop File System statt Oracle Cluster)
3	- Standortbestimmung über derzeit vorhandene Big-Data-Fähigkeiten und Lücken mittels branchentypischer Anwendungsfälle - Entwurf einer Roadmap um fehlende Fähigkeiten zu entwickeln, mit Fokus auf Big-Data-Technologien und Datenmanagement
4	- Identifikation von Schwachstellen in der Datenarchitektur - Definition von Performance-KPIs für funktionsübergreifender Geschäftsprozesse - Planung eines Cloud Data Lakes zur unternehmensweiten Bereitstellung eines konsistenten Datenbestands
5	- Kontinuierliche Evaluation von technologischen Innovationen zum Ausbau der zentralen Datenplattform - Identifikation und Integration weiterer Datenquellen für zukünftige Anwendungsfälle
6	- Suche nach neuen datengetrieben Kundenservices im B2C- und B2B-Segmet - Beurteilung der Betriebswirtschaftlichkeit der Anwendungen als Proof of Concept (PoC) innerhalb einer zeitlich abgegrenzten Testphase in ausgewählten Marktsegmenten
7	- Reduktion der Datensilos und Erstellen einer zentrale Datenbasis - Explorative Umsetzung branchentypischer Anwendungsfälle in einer Laborumgebung - Evaluierung von typischen Big-Data-Anforderungen hinsichtlich notwendiger technologischer und organisatorischer Auswirkungen
8	- Suche nach Anwendungsfällen in Fachbereichen mit Fokus auf potenzielle Wachstumsfelder und Kundennutzen - Aufbau eines Labors zur explorativen Datenanalyse, Einstellung von Data Scientists und Data Engineers - Identifikation von Leuchtturm Use Cases und Umsetzung als PoC in Laborumgebung
9	- Identifikation neuer Potenziale für datengetriebene personalisierte Kundenservices in Marketing und Vertrieb - Durch konkrete Anwendungsfälle getriebene Erweiterung der unternehmensweiten Datenplattform mit zunehmender Integration externer Daten, z.B. Mediadaten
10	- Aufbau eines Data Lakes in einer Cloud Infrastruktur, Integration der Unternehmensdaten - Entwurf und Implementierung von Prozessen zur Datengovernance - Bereitstellung von Data Scientist zur Untersuchung künftiger Big-Data-Anwendungsfälle

Table 3.4 Wesentliche Aktivitäten der Matching-Phase

Ziel der Matching-Phase ist eine Entscheidungsvorlage, um beschließen zu können, ob ein konkreter Big-Data-Anwendungsfall produktiv implementiert werden soll oder nicht. Wie Tabelle 3.4 zeigt, befassen sich einige Unternehmen (Fälle 2, 3, 4, 5, 7, 10) in Übereinstimmung mit ihrer Agenda zuerst mit dem Aufbau einer Datenplattform und der Entwicklung von Fähigkeiten mit Big-Data-Technologien umzugehen. Untersuchungen konkreter unternehmensspezifischer Anwendungsfälle werden von diesen Firmen erst im Anschluss an diese Vorarbeiten geplant. Unternehmen (Fälle 1, 6, 8, 9), die mögliche Anwendungsfällte prototypisch umsetzen und evaluieren, nehmen diese bei einer positiven Adoptionsentscheidung in ein Projekt- oder Innovationsportfolio auf. Dort konkurrieren sie dann mit anderen Unternehmensprojekten um Ressourcen zur produktiven Implementierung.

3.6 Diskussion

Ein Vergleich der Fallstudien zeigt, dass drei unterschiedliche Vorgehensweisen identifiziert werden können. In Abbildung 3.1 werden diese schematisch dargestellt.

Die erste Vorgehensweise (Business First) fokussiert ausschließlich auf betriebswirtschaftliche Aspekte. Unternehmen suchen nach Anwendungsfällen mit einem hohen geschäftlichen Mehrwert. Sowohl eine Optimierung bestehender Geschäftsprozesse als auch die Bereitstellung neuer Produkte und Service werden untersucht. Dies wird durch ein Zitat aus Fallstudie 1 greifbar:

„[...] das eine ist das existierende Geschäft dem Markt anzupassen [...], also existierende Prozesse zu verbessern [...]. Daneben gibt es das zweite Thema, neue Prozesse zu erfinden oder neue Geschäftsmodelle – tatsächlich Innovationen – anzugehen.“

Eine technische Bewertung der Anwendungsfälle hinsichtlich ihrer Integration in bestehende IT-Landschaften erfolgt in der Initiierungsphase nicht. Dies belegt unter anderem ein Zitat aus der Fallstudie 6:

„Die Integrierbarkeit ist dabei anfangs tatsächlich nachrangig [...]. Wenn wir ein Produkt erfolgreich an den Markt gebracht haben, das auf der grünen Wiese entstanden ist, dann will man natürlich irgendwann auch eine Integration durchführen.“

Typischerweise werden bei diesem Vorgehen Big Data Use Cases als eigenständige IT-Systeme mit den jeweils notwendigen Big-Data-Technologien (BD-Tech.) und Daten in einer Laborumgebung umgesetzt und dann mit ausgewählten Marktteilnehmern getestet. Ist diese Phase erfolgreich, wird der Use Case zur produktiven Implementierung vorgeschlagen. Beispielsweise wird in Fallstudie 6 gesagt:

„[Ziel ist es, Use Cases in] 6-12 Monaten mit mehreren tausenden vielleicht auch einigen zehntausend Kunden [...] im echten Einsatz zu verproben. Und dann gibt's die Entscheidung, go or no-go“.

Bei einer positiven Entscheidung wird eine Anwendung erstmals als eigenständiges IT-System weiter betrieben, um sie dann Schritt-für-Schritt in eine bestehende IT-Landschaft einzufügen. Unternehmen mit dieser Vorgehensweise finden sich in Fallstudie 1, 6, 8 und 9.

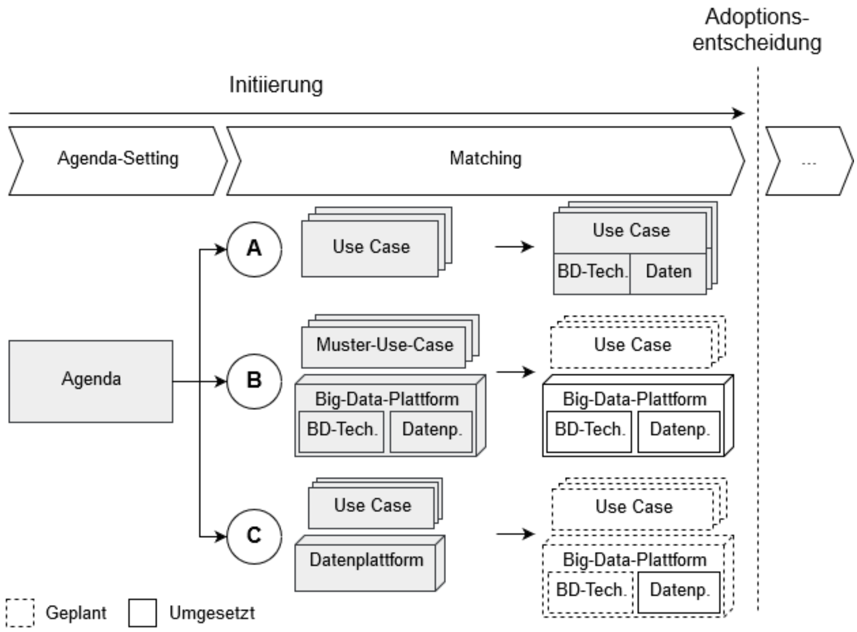

Figure 3.1 Vorgehensweisen zur Analyse von Big-Data-Potenzialen: A) Business First, B) Platform Building, C) Data Integration

Die zweite Vorgehensweise (Platform Building) zielt auf den Aufbau einer Technologie- und Datenplattform (Datenp.) für Big Data ab. Dieser Aufbau orientiert sich oft an Anforderungen aus branchentypischen Muster-Use-Cases. Zudem werden auch bestehende Anforderungen an die IT genutzt, um neue Technologien einzuführen, wie z.B. in Fallstudie 2:

„[…] es ist Strategie, [...] für Sachen, die wir verpflichtend machen müssen, auf neue Technologien zu setzen, um damit [...] die Hürde für weniger gut kalkulierbare Use Cases […] klein zu machen.“

Unternehmen mit dieser Vorgehensweise wollen unter anderem aufgrund von finanziellen Restriktionen die monetären Aufwände für zukünftige Anwendungsfälle möglichst gering halten. Daher werden, wie z.B. in Fallstudie 2, bestehende Data-Management-Technologien sukzessive durch Big-Data-Technologien substituiert. Nicht den Anschluss an aktuelle Entwicklungen zu verlieren, obgleich Fachbereiche noch keine überzeugenden Big-Data-Anwendungsfälle identifiziert haben, ist eine weitere beobachtete Motivation für Platform Building, wie z.B. in Fallstudie 5:

„In Memory Technik, [...] das wird die nächsten 10 Jahren in allen Bereichen Einzug halten. Dann kann ich investieren ohne konkrete Nutzung schon direkt vor Augen zu haben“.

Die aus diesem Vorgehen resultierende Big-Data-Plattform bildet die Grundlage für eine nachfolgend geplante Identifikation und Bewertung von Big Data Use Cases. Dieser Vorgehensweise folgen die Fallstudien 2, 3, 5 und 7.

Vornehmliches Ziel der dritten Vorgehensweise (Data Integration) ist die Bereitstellung einer konsistenten Datenbasis für zukünftige Analysen. Sie wird als elementare Grundlage für alle weiteren Entwicklungen im Themenbereich Big Data angesehen. So wird in Fallstudie 10 betont:

„…das ist unser Ansatz [...], wir wollen dieses Enterprise Data Repository aufbauen, [...] Schritt für Schritt alle Daten dort hineinbringen und verwalten, monitoren und ein semantisches Netzwerk darüber aufbauen“.

Die geschaffene Datenplattform soll dann erstmals in Use Cases mit traditionellen Analysen für unternehmensweite Fragestellungen verwendet werden. Ist dies erfolgreich, will man sich mit Big-Data-Anwendungsfällen und -Technologien auseinandersetzen. Die Fallstudien 4 und 10 fallen in diese Klasse.

3.7 Zusammenfassung und Ausblick

In dieser Arbeit wurde untersucht, wie sich Unternehmen den Möglichkeiten von Big Data nähern, um letztendlich über die Implementierung und Einführung neuer Anwendungen zu entscheiden. Theoretischer Rahmen war der Adoptionsprozess von Rogers (2003), dessen erste Phasen Agenda Setting und Matching in einer multiplen Fallstudie detailliert beleuchtet wurden. Als Ergebnis konnten drei unterschiedliche Vorgehensweisen identifiziert werden. Unternehmen konzentrieren sich zuerst entweder auf rein betriebswirtschaftliche Aspekte, oder auf einen systematischen Aufbau einer Big-Data-Technologie- und Datenplattform.

Als nächster Schritt soll im Detail untersucht werden, welche Einflussgrößen für diese unterschiedlichen Strategien verantwortlich sind und welche Vor- und Nachteile mit ihnen verbunden sind. Die hieraus gewonnenen Erkenntnisse sollen dann zur Konstruktion eines Methodenbaukastens zur Identifikation und Bewertung potenzieller Big-Data-Anwendungsfälle genutzt werden.

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4 Starting Points for Big Data Adoption

Christian Bremser

Abstract

As part of an advancing digitalization, many enterprises feel the need to explore the possibilities big data may provide for their business. However, only a few companies use big data applications productively, despite its high expected potential. How companies examine the possibilities of big data, is therefore a highly interesting and relevant question. Based on a multiple case study we identify three different approaches and factors that influence the choice of approach: Companies either initially focus entirely on business aspects, or on a systematic build-up of a big data technology and data platform. Innovation adoption research is used as a theoretical basis.

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4.1 Introduction

The potential benefits and challenges associated with big data are an important topic for companies in all industries. Big data promises new data-driven services to improve processes and enable innovative products and business models (Sivarajah et al., 2017). Against this background, a growing number of companies are investing in big data looking for competitive advantages (Constantiou & Kallinikos, 2015). Nevertheless, companies seem to have difficulties with the productive implementation of big data applications. According to a Gartner study, only 14% of enterprises have put big data projects into production (Kart, 2015). Therefore research on the adoption of big data applications is important and of scientific and practical interest.

The introduction of new technologies is described by innovation adoption theories. The process of innovation adoption typically involves two phases (Rogers, 2003): initiation and implementation. Within these phases, new technologies have to overcome several hurdles before being used productively, i.e. being integrated into an existing IT landscape and deployed at full-scale (Fichman, 2000). For technology-driven innovations, like big data (Nam, Kang, & Kim, 2015), the initiation phase, where companies search for valuable use cases for different big data technologies, poses a first serious obstacle. This initial step towards the exploration of big data potentials is the focus of our study. In particular we address the following research question:

What approaches can be identified when companies explore the potentials of big data in the initiation phase of innovation adoption and what factors influence the choice of approach?

Despite its high relevance, there are no specific studies on the initiation phase of big data adoption. Current research mainly investigates general influencing factors and hurdles during the implementation of big data technologies. In contrast, this paper analyses current approaches for the exploration of new big data potentials in the initiation phase and factors that influence the choice of approach. For this purpose, a multiple case study with ten companies from different industries was conducted. The organizational adoption process of Rogers (2003) in combination with the Technology-Organization-Environment framework (TOE) (Tornatzky, Fleischer, & Chakrabarti, 1990) has been used as a theoretical starting point.

This report is organized as follows: The current research on big data adoption is summarized in the next section. Section 4.3 presents our conceptual framework. Section 4.4 introduces the research design. Section 4.5 presents the findings from our cases. A discussion of the results in section 4.6 and a summary of the main points in section 4.7 complete this work.

4.2 Current Research on Big Data Adoption

Big data is defined by the TechAmerica Foundation (2012) as "a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information." Obviously, big data is a bundle of new technological and methodological possibilities that allow to process and analyze large, complex and rapidly growing data sets (e.g. stream analytics, in-memory data processing, NoSQL databases). In this respect, companies are challenged to identify the technologies and methodologies which are most beneficial to them. This distinguishes big data from the adoption of previous technology trends, such as ERP or CRM, where individual technologies and use cases were considered.

Enterprises want to take advantage of the opportunities big data success stories promise and expect a wide range of benefits through the introduction of big data applications (see, for example, (Brown, Chui, & Manyika, 2011; Davenport, Barth, & Bean, 2012; Kiron, Prentice, & Ferguson, 2014)). In order to unlock this potential, companies have to acquire big data resources and develop capabilities to leverage their possibilities (Mikalef et al., 2016). The literature defines three key typologies of big data capabilities (see e.g. (Akter et al., 2016)): management capabilities (e.g. data governance), technology capabilities (e.g. integrating and operating Hadoop components) and talent capabilities (e.g. data science knowledge).

The development and deployment of corresponding capabilities starts with the introduction of technology innovations (Mikalef et al., 2017). Latter can be described by innovation adoption theory. On the one hand, this theory covers the identification of factors that influence the decision-making process of innovation adoption (Rogers, 2003). On the other hand, it describes the process which innovations have to go through, ranging from an initial awareness in companies to its productive use (Fichman, 2000).

Previous work in the context of big data adoption mainly focuses on the investigation of general influencing factors through the TOE (see, for example, (Agrawal, 2015; Malaka & Brown, 2015; Sun et al., 2016)). The TOE describes the impact of technological, organizational and environmental aspects on organizational decision-making with respect to technology innovations (Tornatzky et al., 1990). As a result, it has been shown that the protection and integration of data are considered as important technological challenges (Agrawal, 2015; Malaka & Brown, 2015; Sun et al., 2016). Organizational aspects, such as unclear processes, lack of analytical skills or indistinct prioritization of use cases are further obstacles to the successful adoption of big data. However, the adoption is most often positively influenced by company size and competition intensity. Nam et al. (2015) have investigated the change of influencing factors during the adoption process. As a result, they show that existing IS competence has a positive impact in the beginning of the adoption process, while competitive intensity and financial readiness significantly support the successful implementation of big data. Bremser et al. (2017) have used the TOE to identify factors that drive the approaches companies use to explore big data potentials. IS competence, perceived complexity of the big data technologies, as well as the financial and strategic readiness of companies were found to have major impact.

So far an investigation of the big data adoption process has been carried out only by Chen et al. (2015). They use a multiple case study to describe the implementation phase and corresponding influencing factors. For this purpose, they build upon TOE (Tornatzky et al., 1990), diffusion of innovation (Rogers, 2003) and the IT fashion theory (Wang, 2010). The diffusion theory describes the spreading of an innovation among members of a social system (Rogers, 2003). The IT fashion theory highlight the social settings of emerging IT trends, e.g. the influence of consultants and technology analysts (Wang, 2010). According to Chen et al. the implementation phase involves far-reaching organizational changes that are necessary for the productive implementation of big data applications. As a result, they present a "limbo stage", where companies continuously experiment with big data technologies for a long time and do not proceed to deployment, despite their intent to adopt.

In comparison to existing studies our research focuses on the initial phase of big data adoption. We investigate the approaches companies use in the initiation phase and factors that influence their choice of approach.

4.3 Conceptual Framework

For our study, we use the innovation adoption process of Rogers (2003) and the TOE framework (Tornatzky et al., 1990).

According to Rogers (2003), the process of innovation adoption is described by two major phases: initiation and implementation, with both phases being separated by an adoption decision. The initiation phase consists of the stages agenda-setting and matching. The agenda-setting is triggered by an organizational problem or by the perception of an innovation. Both force companies to weigh up possible reactions and evaluate the potentials of an innovation. This evaluation is typically undertaken in the matching stage, where organizational members explore the capabilities of an innovation to predict its potential for specific application scenarios. If advantages are expected, the implementation phase is triggered and all activities and decisions necessary to put the innovation into production are carried out. The decision on how to evaluate the potentials of an innovation is determined by an agenda which results from the agenda-setting (Rogers, 2003). To investigate the factors that influence this decision, the TOE provides a good theoretical foundation.

The TOE describes the factors influencing the adoption of technology innovations. These factors are clustered into three dimensions: technology, organization and environment (Tornatzky et al., 1990). The technology dimension encompasses the characteristics of available technologies which are relevant to a company. The organizational dimension covers company attributes, such as size, formal and informal linking structures, competencies and the amount of slack resources. The company's environment and its influence are described in the environmental dimension. It includes competitors, industry specifics and governmental regulation.

In conclusion, the conceptual framework used in this research combines the innovation adoption process of Rogers (2003) with the TOE (Tornatzky et al., 1990), as shown in figure 4.1.

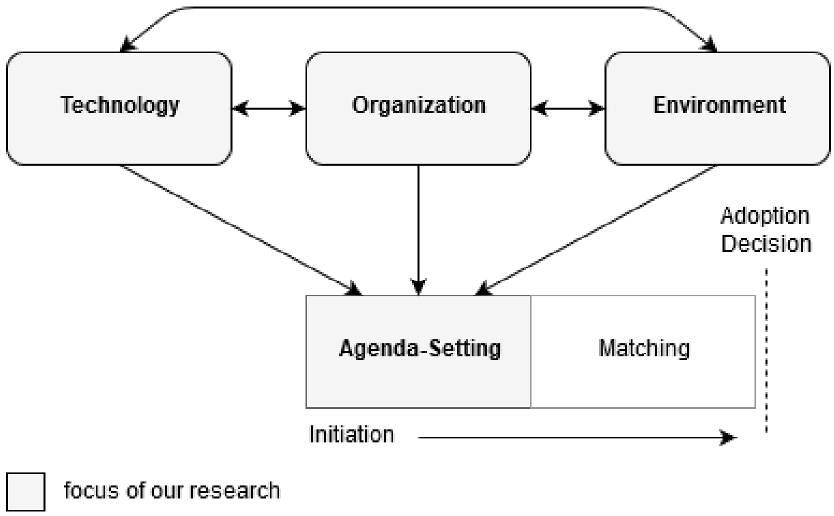

Figure 4.1 Conceptual framework

4.4 Research Design

Phenomena around big data adoption are complex and certainly not well understood so far. For this reason, a case study approach is suitable (Dubé & Paré, 2003; Yin, 2003). Our main information sources are in-depth expert interviews with key-informants. Interviewees were heads of business and IT divisions, chief architects and chief strategist.

In the sense of a strict implementation of the research design, four established quality criteria were used (Yin, 2003): external validity, internal validity, construct validity and reliability. The external validity focusses on the generalizability of the results. This is ensured by replicating the case studies. In the context of big data adoption, it was decided to conduct a multiple case study. The case studies were selected according to the "literal replication logic" (Dubé & Paré, 2003). In order to ensure a comparable organizational and technological context pure internet companies were excluded and traditional companies with existing IT infrastructure and application landscapes were in focus. In addition, the reference of selected cases to big data has been validated by scientific big data taxonomies (see, e.g. (Kune et al., 2016)). They represent a classification scheme for technologies, methods and data typically used in the context of big data.

In order to ensure internal validity, an interview guide was developed on the basis of the conceptual framework described in section 3 of this paper. The expert interviews were semi-structured and we kept our questions open to allow interviewees freely to speak. The first part contained general questions about the role and responsibility of the interviewee, the current strategic and tactical challenges of the company and their influence upon dealing with new possibilities of big data. The second part of our questions concentrated on the current use of data, methods and technologies for data-driven decision making as well as corresponding organizational structures and processes. For example, we asked about the relevance of data and data-driven decision making in different organizations and inquired which kind of analytical applications were currently in use. The third and most extensive set of questions was directed upon “why” and “how” organizations explore the potentials of big data. These questions concerned the trigger of big data initiatives, their focus and their organizational setup. Also we inquired the process for the evaluation of big data potentials and the criteria applied therein.

Yin (2003) suggests triangulation to ensure construct validity. Within the case studies, different data sources were therefore used. In addition to the key-informant interviews, public and - if available - internal documents of big data initiatives and strategies of the investigated companies were analyzed. Furthermore, interviews with other organizational members, consultants and software vendors specialized on big data adoption were conducted.

In order to minimize errors and biases, the reliability of the case study analysis was ensured by establishing a case study database. There, we stored all information about the data collection process, the data itself and the case study results. According to Yin (2003), this helps to provide the same results in repeated trials.

The data collection started in June 2016 and stretched over a period of seven months. Each interview lasted approximately 90 minutes and was conducted on site or by telephone conference. The conversations were recorded and transcribed. Shortly after each interview, the main points and key findings were recapitulated in a contact summary sheet (Miles, Huberman, & Saldana, 2013). The interviews were then analyzed and coded. We used first-level coding (Miles et al., 2013) to identify in particular all statements related to company’s procedures for the initiation phase of big data adoption.

Table 4.1 presents an overview of the participants of the case study. In the case selection, we focused on companies with more than 10,000 employees and headquarters in Germany. The investigated companies operate in business-to-consumer as well as in business-to-business segments and have successfully launched first big data initiatives. The interviewees were responsible for big data activities within their organizations and had roles in business and IT.

#	industry	number of employees	business segment	role of interviewee
1	Transport	>50,000	B2C, B2B	Head of Domain Architecture
2	Banking	>50,000	B2C, B2B	Head of IT Architecture
3	Insurance	>10,000	B2C, B2B	Head of Group strategy
4	Manufacturing Vehicle	>50,000	B2B	IS Chief-Architect
5	Retail Trade	>50,000	B2C	Head of Business Intelligence
6	Utilities	>50,000	B2C, B2B	Chief Digital IT Strategist
7	Manufacturing Vehicle	>50,000	B2B	Head of Analytics Lab
8	Manufacturing Apparel	>50,000	B2C	Head of Data Analytics Lab
9	Manufacturing CPG	>10,000	B2C	Head of Marketing & Analytics
10	Manufacturing Chemicals	>10,000	B2B	Head of BI Architecture

Table 4.1 Participating companies

The analysis of these cases was carried out in a twofold way. First, we have used a within-case analysis (Yin, 2003) to extract all characteristic content and influencing factors related to the agenda-setting of individual cases. In the second step, a cross-case analysis (Yin, 2003) was conducted and the cases were compared to each other. The results of these analyses are shown in chapter 4.5 and discussed in chapter 4.6.

4.5 Results from Case Studies

Having identified the importance of the initiation phase of the big data adoption process, we now analyze this phase in detail, based on the evidence from our ten cases. In section 5.1 we outline the different approaches companies chose, while the factors that influence this choice are discussed in section 5.2.

4.5.1 The Initiation of the Innovation Adoption Process

The agenda-setting is, according to Rogers (2003), triggered by a performance gap or the perception of new possibilities. Both triggers force enterprises to consider the potentials of an innovation. In the case of technology-driven innovations, like big data, companies examine how they would leverage new technologies. Within agenda-setting a so-called agenda is defined determining the goals for the next steps in the adoption process.

Our analysis shows that in all cases, the hype surrounding big data was decisive to the initiation of the big data adoption process. An interviewee from case 8 described this as follows:

"It was our former CIO [...], who said that big data is a megatrend, which we definitely should not miss."

Pushed by the hype, companies hope to open up valuable possibilities through big data that range from improvements of existing business processes to entirely new business services or business models. This is confirmed by a quote from case 5:

"... [we hope to use big data] either for rationalization or for other value-creation opportunities, which are not necessarily connected to rationalization, but where really new fields are opened up."

Due to the manifold expectations, the topic was discussed at senior management level in all companies. There, next activities were defined and first big data initiatives were launched. Project teams were staffed and first objectives were set. Although expectations of long term benefits were similar in all cases, short term goals of big data initiatives differ.

In the cases 1, 6, 8 and 9, senior management asked for big data application scenarios. A quote from case 1 confirms this:

“In the business departments, innovation workshops or design thinking, or other methods are used to create a portfolio of ideas and use cases.”

Table 4.2 details the goals of the respective big data initiatives.

1	Portfolio for innovative data-driven products, services, business models
6	Portfolio of innovative digital products for public, commercial and private customers
8	Potentials for innovative products and process optimizations along existing value chains
9	Possibilities of data analyses to increase the efficiency of existing processes with focus on marketing and sales

Table 4.2 Goals of companies searching for business potentials

In the cases 2, 3, 5 and 7, the search for a good technological starting point was in the centre of first activities. Table 4.3 shows the respective goals.

2	Possibilities for a cost-neutral reduction of technological hurdles for future big data applications
3	Roadmap for a systematic development of internal capabilities to use big data technologies and to provide data appropriately
5	Opportunities for a future-oriented development of a data and technology platform for analytical applications
7	List of requirements with respect to technologies and organizations for future data-driven product innovations as well as a consistent data base

Table 4.3 Goals of companies looking for a technological starting point

In the remaining cases, the set-up of a central and company-wide data basis was in focus as summarized in table 4.4 and illustrated by a quote from case 10:

„That's our goal, to have a central data basis in the company, which I can use for data science and analytical use cases."

4	Consistent data basis for company-wide analyses, initially for the identification of potential efficiency enhancements within the existing value chain
10	Data basis out of existing and new data for future data-driven services

Table 4.4 Goals of companies aiming for a central data basis

The different agendas that have been presented complete the agenda-setting stage and initiate the subsequent matching stage. Based on different agendas, companies carried out three distinct approaches: Business First, Platform Building and Data Integration.

In the approach Business First, enterprises explore big data potentials entirely from a business perspective. They search for use cases with high expected business value. Companies with this approach can be found in cases 1, 6, 8 and 9. The search for use cases is typically carried out by the business departments using methods like design thinking. The interviewee from case 6 confirms this:

"What we are currently using as a methodology for developing products, but also for optimizing processes, is design thinking. Here, we try to identify "need-driven", what does the customer really need for products."

The proposals from the business departments are then developed in lab environments as prototypes or proof of concepts. Subsequently, the prototypes are tested in market segments to evaluate their business potentials. For example, case 6 states:

"[the goal is to] test use cases in 6-12 months with several thousands, maybe even ten thousands of customers in real use. And then there's the decision: go or no-go."

If the evaluation is positive, a use case is proposed for adoption and the implementation phase of the innovation adoption process is started.

In case 2, 3, 5 and 7, the Platform Building approach aims upon the development of a technology and data platform for big data. Typically industry-specific application scenarios are used as an orientation to establish corresponding capabilities (e.g. implement big data technologies; integrate new data sources). Also existing business demands are utilized to introduce new technologies, for example in case 2:

"... it is the strategy [...] to use new technologies for existing demands that we are obliged to do, in order to [...] reduce the hurdle for hardly-calculable [big data] use cases."

The objective of the Data Integration approach is to provide a consistent basis of data for future analyses (case 4, 10). For instance, case 10 emphasizes:

"... this is our approach [...], we want to build up an enterprise data repository, [...] step by step, to integrate and organize all data there, to build a semantic network."

The platform resulting from the Data Integration approach is first used for traditional analyses and can be seen as an antecedent of the Platform Building approach. If the analyses proof successful, the integration of big data technologies is considered as a next step. In both, Platform Building and Data Integration, the created platform forms the basis for the subsequent identification and evaluation of big data use cases.

4.5.2 Influencing Factors

Based on our analysis, different factors that influence the choice of approach could be identified. Companies following the approach Business First look for new revenue opportunities, typically driven by a strong competition and market uncertainties. The transformation towards an increasingly data-driven business is seen as a strategic task. This is emphasized, e.g. by case 6:

"It was recognized that we will have to become a data-driven company in order to secure our long-term existence in the market."

In order to gain a better understanding of customers and drive the development of new products and services, big data is seen as the most important prerequisite. The unique role of big data is emphasized, e.g. by a quote from case 6:

"Big data is indeed an excessively used term, but for us it is the most important driver for the development of new products"

High financial readiness and substantial senior management support typically enable this approach. For example, the CIO of case 8 placed big data as a megatrend and established corresponding management goals to ensure management support. Their financial readiness allowed them to establish a lab environment and to allocate IS resources. Another example is the company in case 9. Here no appropriate internal IS resources were available. However financial readiness enabled the organization to search for use cases and to commission external partners to carry out proof of concept projects:

"Our IT is a profit centre. They do not expose employees to innovative topics [..] Therefore, I have to hire Accenture or any other consultancy; we pay the double day rate, but can realize our use cases in half of the time."

Table 4.5 shows the decisive influencing factors and example statements for the decision to Business First during agenda-setting.

#	case specific influence factors	example statements
1	- strong competition from low cost players - digital strategy supports big data activities - data and analytics plays an important role in service development - good financial situation allows the build-up of dedicated resources, e.g. innovation units, data labs	*“To deal with low-cost competitors, we have to focus on data and analytics, in order to generate further business and offer new data-driven services.”*
6	- transformation towards a data-driven company - changes in energy market causes uncertainties for established business model - expected benefits from new digital services, e.g. smart meters seem promising	*“It was recognized that we must become a data-driven company in order to secure our long-term existence in the market. So we have to develop new products, improve internal and external processes and to do the whole thing data-driven.”*
8	- changing customer expectation - expected unique role of big data in customer understanding - growth-orientated business strategy - the build-up of data analytics team and the recruitment of data scientists is enabled through a good financial situation	*"The consumer expects an ever more individualized and personal address. [..] he expects individualized products and brand messages. And you can only get closer to that if you really know the customer and his behavior. [..] this is only possible with big data."*
9	- market is characterized by aggressive trade groups firing up competition - economic uncertainties, e.g. brexit votum - integrated and harmonized data architecture exists - financial resources enable the procurement of external specialists - appointment of a digital transformation officer	*“We have an incredibly aggressive competition. There are 'local beauties' that are getting stronger and stronger. [..] Besides, we can’t reach people with our classic ads anymore. So we have to be very smart, think about how we advertise and how we can use big data to measure our promotional efficiency.”*

Table 4.5 Influence factors and corresponding statements for Business First

Firms that chose Platform Building or Data Integration are less innovation driven. Some of them are exposed to high cost pressure and did not have additional financial resources at hand to address new topics (case 2, 4 and 10). Instead, they were focusing on internal efficiency and process automation, as stated by case 4:

“In our industry the market segment for highly innovative products is a very limited one [..] So the main focus should be internal efficiency in order to make cost-attractive offers for our standard products.”

Additionally, we identified companies (case 3, 5 and 7) that, despite their financial readiness, did not see a need to identify concrete big data use cases yet. A lack of strategic orientation towards digitalization and no obviously attractive big data use cases were typical reasons for this behavior. However, also in these cases senior management expects big data becoming increasingly relevant. To prepare for the future they therefore decided in the agenda-setting for a systematic build-up of big data capabilities. This is emphasized by a statement from case 7:

"We do not necessarily need to solve the autonomous driving. [..] Our goal is to provide the technical possibilities that this can work in future."

Table 4.6 shows the different influencing factors and corresponding statements for Platform Building.

#	case specific influence factors	example statement
2	- cost pressure through low interest rates and strong regulatory measures - digital transformation strategy - use case-driven implementation of big data is seen as risky	*"In banks, income does no longer come from interest rates. [..] So we have to work on our costs by automating back-office processes, [..] collecting and analysing more data. [..] Big data can surely enable that"*
3	- healthy financial position - digitalization efforts are restrained and not pursued by all management levels - no obvious benefits from big data - focus on traditional measures for business development	*"At the moment we are using traditional measures, e.g. portfolio pruning, premium adjustment and process improvement. Perspectively, however, we must initiate new initiatives and open up new business opportunities. Big data is one of the possibilities we need to consider and see if it will create new business opportunities."*
5	- big data is seen as just another set of technologies - BI maturity is high and data are seen as an asset - no obvious big data use cases with additional benefits	*"[..] we solve issues infrastructural and not application-related. [..] we basically want to analyze and evaluate everything and therefore, we have created a central data platform which we are now systematically developing."*
7	- financial resources enable the construction of dedicated resources, e.g. a big data lab - digitalization strategy is being developed - benefits from big data are expected but use cases are not obvious	*"We appointed a Digital Transformation Officer this year in August. The digitalization strategy is also being developed at the moment. So, we are still in a discovery phase [..]"*

Table 4.6 Influence factors and corresponding statements for Platform Building

For the approach Data Integration we have observed that companies perceive the integration efforts for big data technologies as high. A fragmented data architecture was the main reason for this, as case 10 confirms:

"One major question in context of big data is how we actually use data. Today our data is stored in various applications. [..] So the problem is, ultimately, if I want to establish a digital business, then we need data in access [..] the different data interfaces make it difficult."

Influencing factors and corresponding example statements for Data Integration are summarized in Table 4.7.

#	case specific influence factors	example statement
4	- competitors from emerging markets cause cost pressure and decreasing profit margins - fragmented data architecture and large number of systems lead to hurdles for performance management - benefits from e.g., process optimization are expected, but the complexity of data integration and harmonization is perceived as high	*“We still have many business areas whose data sources have not yet been harmonized in a data warehouse. Therefore we have a huge challenge in data preparation first"*
10	- fragmented application and data architecture - transformation towards a data-driven company - increasing regulatory measures in human healthcare causes cost pressure and drives the utilization of IT - data governance in big data environments is perceived as complex	*“At the moment, I’m leading a cooperate-wide initiative that focus on how we can use big data to enable the transformation towards a data-driven business”*

Table 4.7 Influence factors and corresponding statements for Data Integration

4.6 Discussion

Based on the evidence from our ten cases, this study shows how companies proceed in the initiation phase of the big data adoption. During agenda-setting senior management defines the goals of the first activities in the adoption process. As a result, we found agendas describing three different approaches companies use to approach the potentials of big data: Business First, Platform Building and Data Integration. A comparison shows that Business First focuses on the identification of business potentials and initially neglects integration challenges for new technologies and data sources. This is in contrast to Platform Building and Data Integration. There, the integration of technologies and data is of primary interest and seen as a necessary step towards the successful adoption of big data. Only after that, use cases with high potential value are searched for.

Agenda-setting is the key stage in the innovation adoption process, as it determines all the following steps in the initiation phase. In order to understand the decision-making in this stage, we followed the TOE framework and collected all influencing factors from the investigated cases (table 4.5, 4.6 and 4.7). We then abstracted and assigned them to the different TOE dimensions. Table 4.8 shows the result.

Technology	Organization	Environment
- expected unique benefits (it is expected that the use of big data supersedes other business development measures [+] or not [-]) - perceived complexity (effort and risk for the use of big data are perceived as high [+] or low [-])	- innovation driven (the business strategy is innovation orientated, e.g. first mover [+] or not [-]) - digital strategy (big data or digitalization is part of the strategy and supported by all management levels [+] or not [-]) - financial readiness (sufficient financial resources [+] or not [-]) - maturity of data architecture (harmonized [+] vs. fragmented data architecture [-])	- IS fashion (big data is perceived to be important for the industry [+] or not [-]) - regulatory measures (industry is under strong regulatory pressure [+] or not [-]) - market uncertainties (market is volatile [+] or not [-]) - competitive pressure (competitive pressure is high [+] or moderate [-])

Table 4.8 Abstracted influencing factors assigned to TOE dimensions

Table 4.9 visualize the factors which had influence on a company's choice of approach. We found that companies decide for Business First, when their business strategy is innovation driven, a digital strategy exists and big data is expected to supersede other measures for business development. Financial readiness empowers them either to establish own lab environments for the investigation of use cases, or to engage external partners to do so.

Companies who follow Platform Building are typically less innovation driven, focusing initially other measures for business development. A missing digital strategy also supports the decision. In case 2, the decision towards Platform Building is driven by a low financial readiness, although unique benefits from big data are expected. This decision is supported by the perception that a use-case-based approach seems risky.

Firms in Data Integration expect unique benefits from big data to the transformation towards a data-driven company. However, a low maturity of data architecture forces them to address basic data management tasks first. Due to a fragmented application and data landscape the efforts for big data are perceived as high. A low financial hinders them to reduce the perceived complexity by e.g. procuring external specialist knowledge.

Additionally, we found IS fashion as a general trigger of the adoption process in all observed companies which reflects the hype that surrounds big data. Other factors from the environment dimension mostly influence aspects within the organization dimension. In our cases, for example, strong competition or high regulatory measures caused cost pressure and a low financial readiness in case 2, 4 or 10.

	Business First				Platform Building				Data Integration	
	1	6	8	9	2	3	5	7	4	10
expected unique benefits	+	+	+	+	+	-	-	-	+	+
perceived complexity	-	-	-	-	+	-	-	-	+	+
innovation driven	+	+	+	+	-	-	-	-	-	-
digital strategy	+	+	+	+	+	-	-	-	+	+
financial readiness	+	+	+	+	-	+	-	+	-	-
data architecture	+	+	+	+	+	+	+	+	-	-
IS fashion	+	+	+	+	+	+	+	+	+	+
regulatory measures	-	+	-	-	+	+	-	-	-	+
market uncertainties	-	+	+	+	+	-	-	-	-	-
competitive pressure	+	-	+	+	+	-	+	-	+	-

Table 4.9 Approaches and corresponding influencing factors

4.7 Summary

In this paper we have investigated through an analysis of ten cases how companies start exploring big data potentials. We could identify three different approaches for the initiation phase of big data adoption: Business First, Platform Building and Data Integration. Which of them to take is decided by senior management during the agenda-setting stage of the innovation adoption process. This choice is influenced by external and internal factors, which could be assigned to the technology, organization and environment dimensions of the TOE.

In particular we found that the technology and organization dimension are most relevant during decision-making. Especially financial readiness, expected unique benefits and the maturity of a companies' data architecture are major influencing factors in agenda-setting.

The theoretical and practical contributions of this research are as follows: While many studies use TOE for technology adoption decisions, we combine it with the process of innovation adoption and describe decision-making in the agenda-setting stage. Our study shows that the innovation adoption process and TOE can successfully be used to describe and understand the exploration of technological innovations with high diversity. The study further contributes to understand how companies behave in the era of digitalization, where technological innovations are surrounded by hype while company specific application scenarios are still unclear.

From a practical point of view, companies can compare their big data activities with the different approaches and drivers identified in this paper, to possibly re-consider their way of action. Providing a method for the identification of suitable platform capabilities and big data use cases is planned as a next step in our research agenda. The corresponding design-oriented approach will benefit from the insights gained in this study.

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5 How Smart City Initiatives Explore New Technologies

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Abstract

The concept of smart city is considered as a new paradigm of urban development. Information and communication technologies are expected to transform cities into smart cities and improve the citizens' quality of life. However, smart city initiatives still have difficulties to leverage value from technology opportunities. How smart city initiatives examine the possibilities of new technologies is therefore a highly interesting question. Based on a multiple case study we identify two different approaches and factors that influence the choice of approach: Cities either initially focus on use cases solving urban challenges, or on a systematic build-up of a technological platform for future use cases. Innovation adoption research is used as a theoretical basis.

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5.1 Introduction

According to the latest UN forecast, 70 percent of the world's population will live in cities by 2050 (United Nations, 2018). This means that 2.5 billion people will move to urban areas in the next 30 years. Problems such as housing scarcity, overloaded infrastructures and CO2 pollution caused by public transport will continue to worsen as the number of city inhabitants increases. In recent years, numerous smart city initiatives have been launched to tackle these problems (Zelt, 2017). Their aim is to leverage developments in digitalization to create new solutions for improving the efficiency of urban services and the quality of citizens' life (Neirotti et al., 2014). The politicians' conviction that technology can contribute to make the city a more liveable and sustainable place is also reflected in the figures of funding programmes. The EU is providing €718 million for smart, green and integrated transport innovations as part of the European Horizon 2020 programme (European Commission, 2018). Such high funding also attract the private sector. Multinational information technology (IT) companies such as IBM or Cisco have discovered the smart city market as a growth driver for their business. These companies offer a variety of integrated solutions for different smart city scenarios (e.g. IBM's Intelligent Waste Management Platform (IBM, 2015)). Collaborations between private and public sectors have also led to criticism of the smart city concept. Brown (2014), Söderström et al. (2014) and Schaffers et al. (2011) criticize them as inefficient and driven by IT vendors. The inefficiency is also criticized by the European Commission (2016) which stated in a working paper, that "city planners, administrators, citizens, entrepreneurs and all other stakeholders must reconsider the way they have approached urban services" to gain value from technology opportunities. Also Anttiroiko, Valkama and Bailey (2014) state that the public sector has difficulty exploiting the value from new technologies. Despite these findings, there have been few attempts in science to understand how smart city initiatives leverage value of new technologies.

The introduction of new technologies is described by innovation adoption theories. The process of innovation adoption typically involves two phases (Rogers, 2003): initiation and implementation. Within these phases, new technologies have to overcome several hurdles before being used productively, i.e. being integrated into an existing IT landscape and deployed at full-scale (Fichman, 2000). For technology innovations, the initiation phase, where organizations search for ways to use a new technology, poses a first serious obstacle (Curry et al., 2016). This initial step towards the exploration of technology potentials is the focus of our study. In particular we formulate the following research question:

What approaches do smart city initiatives use when they initially explore the potential of new technologies for smart services and which factors influence their choice of approach?

To address our research questions, a multiple case study with eight smart city initiatives was conducted. The organizational adoption process (Rogers, 2003) in combination with the Technology-Organization-Environment framework (TOE) (Tornatzky, Fleischer, & Chakrabarti, 1990) has been used as a theoretical foundation. The TOE describes the impact of technological, organizational and environmental aspects on organizational decision-making with respect to technology innovations (Tornatzky et al., 1990).

This paper is organized as follows: The current research on technology adoption research in smart city is summarized in the next section. Section 5.3 presents our conceptual framework. Section 5.4 introduces the research design. Section 5.5 presents the findings from our smart city cases. A discussion of the results in section 5.6 and a summary of the main points in section 5.7 complete this work.

5.2 Current Research

The term "Smart City" has been widely used in academia, consultancies and governments. Nevertheless, there is still a lot of confusion on what it really means to be a "smart" city (Angelidou, 2017; Caragliu, Bo, & Nijkamp, 2009; Nam & Pardo, 2011). According to Anthopoulos, Janssen and Weerakkody (2016) a smart city is an innovative city that uses information and communication technology to improve citizens' quality of life and the efficiency of urban services. To meet these goals, smart cities need to introduce new technologies and realize smart services that address the concerns and needs of citizens (Anthopoulos et al., 2016; Pourzolfaghar & Helfert, 2017).

Smart services are considered as core element of a smart city and understood as an outcome of innovation (Anthopoulos et al., 2016). The term summarizes the services that a smart city delivers to its stakeholders by the use of the city's intangible resources (e.g. people, knowledge, methods) and tangible resources, in particular information systems, data, and corresponding technologies (Angelidou, 2017; Anthopoulos et al., 2016; ITU-T Focus Group on Smart Sustainable Cities, 2014).

Previous work in the context of technology adoption in smart cities is still scarce and focuses primarily on influencing factors. These are either investigated for the general adoption of the smart city concept or for the adoption of a specific technological solution. For example, Neirotti et al. (2014) used in an empirical analysis a sample of 70 cities to investigate context variables that support the adoption of the smart city concept. As a result, they show that economic development and structural urban variables (e.g. demographic density, city area) drive the initiation of smart city programs in urban areas. Nam and Pardo (2011) and Caragliu et al. (2009) argue that a successful adoption of the smart city concept depends on investments in human and social capital, investments in modern and traditional infrastructure and the participation of citizens. Batubara, Ubacht and Janssen (2018) use the TOE to describe main challenges in the adoption of blockchain technologies in smart cities. As a result, it has been shown that a lack of legal and regulatory support and new governance models are considered as main barriers of blockchain adoption.

So far an investigation of the technology adoption process in smart cities has only been carried out by van Winden and van den Buuse (2017). They used a multiple case study to investigate the implementation phase of smart city projects. Based on twelve smart city initiatives they identify three types of full-scale deployments in smart city projects: roll-out, expansion, and replication. They also identify corresponding influencing factors, e.g. upscaling in the implementation stage is often hindered by an absence of knowledge transfer, a lack of funding and missing standards such as data models or IT systems.

In comparison to existing studies, our research focuses on the initial phase of innovation adoption. We investigate how cities initially explore the potential of new technologies for smart services and factors that influence their choice of approach.

5.3 Conceptual Model

For our study, we use the innovation adoption process (Rogers, 2003) and the TOE framework (Tornatzky et al., 1990).

According to Rogers (2003), the process of innovation adoption is described by two major phases: initiation and implementation, with both phases being separated by an adoption decision. The initiation phase consists of the stages agenda-setting and matching. The agenda-setting is triggered by an organizational problem or by the perception of an innovation. Both force organizations to weigh up possible reactions and evaluate the potentials of an innovation. This evaluation is typically undertaken in the matching stage, where organizational members explore the capabilities of an innovation to predict its potential for specific application scenarios. If advantages are expected, the implementation phase is triggered and all activities and decisions necessary to put the innovation into production are carried out. The decision on how to evaluate the potentials of an innovation is determined by an agenda which results from the agenda-setting (Rogers, 2003).

To investigate the factors that influence this decision, the TOE provides a good theoretical foundation. The TOE describes the factors influencing the adoption of technology innovations. These factors are clustered into three dimensions: technology, organization and environment (Tornatzky et al., 1990). The technology dimension encompasses the characteristics of available technologies which are relevant to an organization. The organizational dimension covers organizational attributes, such as size, formal and informal linking structures, competencies and the amount of slack resources. The organization's environment and its influence are described in the environmental dimension. It includes competitors, industry specifics and regulation. As a very generic framework, the TOE is extensively used in adoption research (for examples see e.g. (Baker, 2012; Oliveira & Martins, 2011)) and can be adapted to different research contexts in a straightforward way (Baker, 2012). For our research the technological dimension reflects attributes describing existing and new technologies that are relevant for a smart city. The organization dimension covers organizational aspects of the city and its smart city initiative. The environment dimension describes the influence of the multiple stakeholders that surround a smart city.

In conclusion, the conceptual framework used in this research combines the innovation adoption process (Rogers, 2003) with the TOE (Tornatzky et al., 1990), as shown in figure 5.1.

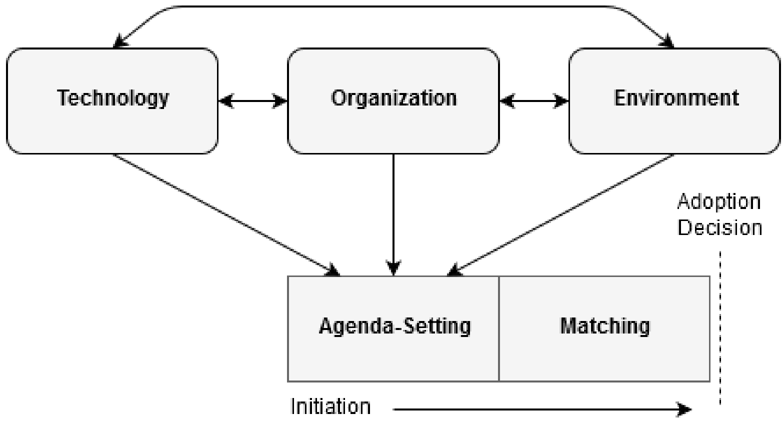

Figure 5.1 Conceptual framework

5.4 Research Design

This study uses a qualitative research methodology because we have little understanding of how cities explore the potential of new technologies for smart services and why they choose certain strategies. A qualitative approach allows us to obtain detailed descriptions of adoption behavior. For our research purpose, we choose a case study method. This method is especially appropriate whenever research deals with "how" and "why" questions and facilitates analyses of contemporary phenomena in a real word context (Benbasat, Goldstein, & Mead, 1987; Darke, Shanks, & Broadbent, 1998; Dubé & Paré, 2003; Yin, 2003). Our main information sources are in-depth expert interviews with key-informants (i.e. smart city representatives) and public documents from smart city initiatives.

In the sense of a strict implementation of the research design, four established quality criteria were used (Yin, 2003): external validity, internal validity, construct validity and reliability. The external validity focusses on the generalizability of the results. This is ensured by replicating the case studies. Therefore we selected a multiple case study design following the "literal replication logic". The literal replication logic ensures an analytical generalization by selecting cases from a similar contextual background to predict similar results (Dubé & Paré, 2003; Yin, 2003). In order to ensure a comparable organizational and technological context, we followed the smart city conceptualization of Angelidou (2014) and selected existing major European cities with matured infrastructure. In addition, the selected cities and corresponding smart city initiatives have been validated by the smart city framework of Giffinger (2007), which consists of six main components (smart economy, smart people, smart governance, smart mobility, smart environment, and smart living). Against this background, we selected only cities which are active in at least two categories.

Table 5.1 shows the cases under study.

#	City	Inhabitants of urban area	Role of Interviewee
1	Amsterdam	>2.3 Mio.	Program ambassador
2	Barcelona	>5.3 Mio.	Catalan smart city coordinator
3	Dublin	>1.9 Mio.	Smart city coordinator
4	Cologne	>2.1 Mio.	Smart city project manager
5	Copenhagen	>1.3 Mio.	Head of IT
6	Berlin	>4.1 Mio.	Policy advisor smart city
7	Vienna	>1.7 Mio	Expert for urban innovation
8	Zurich	>1.6 Mio	Deputy director urban development

Table 5.1 Participants of case study

Following Eisenhardt (1989), an a priori specification of constructs helps researchers to shape the initial design of theory-building research. In order to ensure internal validity, we followed this argumentation and developed the interview guideline on the basis of the conceptual framework described in section 3 of this paper. The expert interviews were semi-structured and we kept our questions open to allow interviewees freely to speak. The first part contained general questions about the role and responsibility of the interviewee and the general goals of the smart city initiative. The remaining part of the interview guide was structured analogously to the conceptual model. The second part of our questions concentrated on activities related to agenda-setting. For example, we asked how specific needs for technology innovations are recognized, how they are prioritized and whether specific objectives for technology adoption exist. We also asked about factors that have influenced the first decisions about dealing with new technologies. Hereby we covered in particular the TOE dimension of our conceptual model. The third and most extensive set of questions was directed upon the matching stage. We focused on "why" and "how" the initiatives explore the potentials of new technologies. These questions concerned, e.g. the methods and challenges during the identification of technology opportunities, the evaluation of technology potentials and the criteria applied therein.

Yin (2003) suggests triangulation to ensure construct validity. Within the case studies, different data sources were therefore used. In addition to the key-informant interviews the rich body of public documents of smart city initiatives was analyzed to validate the information retrieved from the key-informant interviews. Table 5.2 provides an overview of case information sources.

Data source	Description
Interviews with smart city representatives	13 interviews were conducted
Publicly available documents from members of the smart city initiative	151 technology adoption related press articles, blog entries, white papers, annual reports and conference presentations were screened

Table 5.2 Main information sources

In order to minimize errors and biases, the reliability of the case study analysis was ensured by establishing a case study database. There, we stored all information about the data collection process, the data itself and the case study results. According to Yin (2003), this helps to provide the same results in repeated trials and makes the data available for independent inspections.

The data collection started in February 2018 and stretched over a period of five months. The conversations were recorded and transcribed. Shortly after each interview, the main points and key findings were recapitulated in a contact summary sheet (Miles, Huberman, & Saldana, 2013).

The analysis of the cases was carried out in a twofold way. First, we have used a within-case analysis (Yin, 2003) to extract all characteristic content (i.e. trigger of the process, activities in agenda-setting and matching) and influencing factors related to the agenda-setting of individual cases. For this purpose, we followed the deductive content analysis method (Mayring, 2008) and used first-level coding (Miles et al., 2013) supported by the software f4analyse. In the second step, a cross-case analysis (Yin, 2003) was conducted and the cases were compared to each other. The results of these analyses are shown in chapter 5.5 and discussed in chapter 5.6.

5.5 Results from Cases

Based on the evidence from our cases, we now describe our observations about the initiation phase of technology adoption. In section 5.5.1 we outline the different approaches cities chose, while the factors that influence this choice are presented in section 5.5.2.

5.5.1 The Initiation of the Innovation Adoption Process

Agenda-setting is, according to Rogers (2003), triggered by a performance gap or the perception of new possibilities. Both triggers force organizations to consider the potentials of an innovation. In the era of digitalization, cities launch smart city initiatives and examine how they would leverage new technologies for smart services. Within agenda-setting a so-called agenda is defined determining the goals for the next steps in the adoption process.

5.5.1.1. Agenda-Setting

Our analysis shows that in all smart city initiatives the combination of urban challenges (such as CO2 congestion, scarcity of housing or energy management), availability of funding and high hopes on technology innovations were decisive for the start with technology exploration for smart services. For example, this is confirmed in case 6:

"[..] Berlin is facing major challenges such as rapid population growth, strict climate targets and social housing. At the same time, technological innovations are playing an increasingly important role in political discussions. On the one hand, this is due to the new opportunities and its societal relevance. On the other hand, there is a multitude of new funding opportunities available [..]. Ultimately, it is the interaction of several factors." (Interview)

Within the smart city initiatives, the exploration and assessment of new technologies was perceived as a constant and important task. A quote from case 8 emphasizes this:

"In order to get cities on the way to smart cities, it is necessary to focus on meaningful and economic use cases and to constantly deal with the potential of new technologies." (Interview)

In discussions with the smart city initiatives, however, it quickly became apparent that there are different ways in which cities start to explore the potential value of new technologies.

In cases 1, 4, 7 and 8, the city administration asked the respective smart city initiative to collect possible use cases first. The focus of these use cases should be on solving urban problems. It was argued that technology creates value whenever it solves a problem. This is confirmed, for example, by a quote from case 7:

"In Vienna, a demand-oriented approach [for the introduction of new technologies] is chosen. If a problem requires a new solution, the appropriate means are sought to develop a suitable solution - these of course often include digital or technological components." (Interview)

This attitude is also reflected in the goals of the first steps towards technology adoption in smart city initiatives which are summarized in table 5.3.

1	Portfolio of user generated ideas for smart services based on a smart city web portal
4	Portfolio of smart services that recognize the specific needs and challenges of the city
7	Portfolio of technologically driven innovations that are linked to social innovations, and place the needs of people at the centre of this initiative
8	Web portal for smart city stakeholders to connect and foster the creation of innovative ideas for smart services

Table 5.3 Goals for first steps of technology adoption in smart city initiatives

In the cases 2, 3, 5 and 6 the search for a good technological foundation was in the center of first activities. It was considered important to deal with the technology first to facilitate a subsequent identification of use cases by a then available data and technology platform. Table 4 shows the respective goals.

2	Developed technological infrastructure and open access to city's data to accelerate innovation and digital economy
3	Digital master plan for the adoption of new technologies
5	Big data platform to enable advanced analytics in city context for future smart services
6	Link existing technologies to create new solutions and connect innovative technologies with existing infrastructures

Table 5.4 Goals for first steps of technology adoption in smart city initiatives

The different goals that have been presented complete the agenda-setting stage and initiate the subsequent matching stage.

5.5.1.2. Matching-Stage

According to Rogers (2003), organizational members explore the capabilities of an innovation in this stage. Therefore, cities follow two different approaches based on their agendas: A need driven and technology driven approach.

The need driven approach focusses on the development of a portfolio of potential applications solving smart city challenges. Identified use cases are evaluated on how they contribute to the superordinate smart city goals (e.g. CO2 reduction through improvements in public mobility). If this is verifiable, corresponding technologies are implemented and the application is tested as a prototype. Typical examples for a need driven approach can be found in case 1, 4, 7 and 8.

In case 1, the initiative launched a central web portal to connect different stakeholders, receive user-initiated project proposals (e.g. ideas, how new technologies can be used to solve challenges) and attract people to launch projects as pilots. Connected stakeholders were e.g.: the city itself, private companies (e.g. Dutch telecommunication provider, Dutch post), representatives from academia and society. The smart city team assesses the project proposals. If the assessment proof successful, the project proposals are conducted as pilots in designated city areas (e.g. the Utrechtsestraat in Amsterdam city centre). The lessons learned from the pilots are then used for refinements and a further evaluation whether the goals could be achieved (e.g. people accept the technology, CO2 pollution could be reduced). In case of a positive evaluation result, the implementation of the use case is triggered and it is rolled out to other urban areas or scaled up to the whole city.

The city in case 4 started with a similar approach. Creativity methods like design thinking were used to identify citizen’s needs and corresponding smart services. The assessment of possible use cases is then conducted by a public-private partnership between the city and RheinEnergie Cologne. Criterions for the evaluation are measurable effects on the general smart city goals and a positive cost-benefit relation. If an evaluation proves to be successful, appropriate technologies were identified, pilots implemented and tested. This is confirmed by a statement from case 4:

“Use cases are tested and implemented locally within a limited geographical area within the city. If the applicability proves to be successful, a continuation is actively supported and the use case is rolled out to other areas of the city.” (Interview)

In the technology driven approach, cities initially invest in cyber-physical systems (i.e. combination of computational components with mechanical and electronic parts) and develop platforms that integrates different new technologies for data acquisition, integration and storage. These platform capabilities are then advertised and communicated to attract private organizations (e.g. companies, start-ups, local communities) to drive the identification and exploration of use cases, e.g. through hackathons. This approach often concentrates on certain domains of a smart city (e.g. smart transportation, smart energy). Cases 2, 3, 5 and 6 reflect this strategy.

In case 2, the city started with a massive expansion of the fibre optic infrastructure and initiated public private partnerships with private companies. These partnerships helped to deploy an internet of things (IoT) platform (i.a. installing 19,500 smart meters) and connect 90% of the households to the city's fibre optic network. Based on the public private partnerships the smart city initiative developed a central data platform, where different data sources were gathered and integrated. This data and technological platform is seen as a facilitator for the future identification and implementation of innovative use cases and the city's transformation to a smart city. This is confirmed by a quote from case 2:

"We understood that internet and new technologies were a unique and incredible opportunity to transform Barcelona [..] However, technology should not be seen as a goal in itself. Technology is simply a facilitator." (Public Documents)

The initial provisioning of data and technology was followed by the redesign of an old industrial district to shape a place, where start-ups can use the implemented technologies, analyze the generated data and identify and test potential applications.

In case 6, the connection of innovative technologies with existing infrastructure was one goal of the city's first efforts. Requirements for infrastructure projects were therefore utilized to anchor new technologies in the city's infrastructure. It was expected that these new technologies would open up data sources that could be of value for a later identification of smart services. A quote from case 6 emphasizes this:

"We had recently tendered new toilet houses. These are also potential carriers of new technologies. They can be equipped with a transmitter and a sensor [..] generate data of which we perhaps do not know yet what they could be used for. But that may be of great value in the future." (Interview)

5.5.2 Influencing Factors

Based on our analysis, different factors that influence the choice of approach could be identified. Cities following a need driven approach see citizens and private companies as a driver for innovations. A statement from case 1 confirms this:

"I think at the moment we see that you need leadership from the public sector, but real innovation comes from the private sector" (Public Documents)

This choice is supported by the perceived need of empowering citizens and local start-ups to raise their participation in city development. A platform where citizens can submit their ideas and vote on others' proposals for smart services should meet this need. For example, in case 1, the city is calling innovators and start-ups for ideas to solve specific challenges of the city. An online platform visualizes the progress of the proposal and stages an idea has to go through. A team of public and private smart city stakeholders decides whether an idea passes a stage.

A missing dedicated smart city budget could also be identified as an enabler of this approach. For example, in case 4 the need driven approach is seen as a way to tackle societal challenges. By addressing these challenges, the smart city initiative hopes to receive EU funds from the Horizon 2020 funding program. This is confirmed by the statement:

"Financing projects is a constant challenge as Cologne does not have a smart city budget [..] Therefore, the mediation of funds from EU projects is often necessary." (Interview)

A summary of the case specific influencing factors is presented in table 5.5.

#	case specific main influence factors	sample statement
1	- innovative smart services are expected as unique facilitator for sustainable economic development - empowerment of citizens and local start-ups is perceived as important for the identification of potential smart services - transparency in political decision on project proposals is perceived as important to increase citizen's engagement	*"Co-creating and co-developing urban solutions requires involvement and empowerment of citizens in the innovation process. This should enhance [..] accepted solutions that work and create value for all involved parties, including citizens." (Public Documents)*
4	- no dedicated smart city budget; dependence on third party funds - expectation of economic returns by solving city's challenges with smart services - coordination and communication of different projects within the city is perceived as important to identify synergies and valuable smart services	*"Smart city Cologne is at the same time a coordination and communication platform for various projects for climate protection, energy and transport change and improved energy efficiency." (Interview)*
7	- empowerment of the private sector is perceived as important for identification of use cases - single focus on smart city technologies is expected to neglect citizen participation and exacerbate the digital divide - initial identification of lighthouse use cases is expected to attract further capital	*"Technology is only used where necessary, not wherever possible." (Interview)*
8	- existing technology infrastructure is perceived as sufficient for current digitalization efforts - synergies for new smart services are expected by the coordination of municipal companies that are already working on their own digitalization projects - public and private companies are perceived as innovators	*"By comparison, the [technology] infrastructure in Switzerland and here in the city of Zurich is already well developed and will be further optimized." (Interview)*

Table 5.5 Influencing factors for the need driven approach

A technology driven approach could be found, when cities see implemented technologies as the most important step, before the identification of smart services. This is confirmed by a statement from case 5:

"If we build a state-of-the-art digital infrastructure, we can build solutions for tomorrow." (Public Documents)

Expectations of economic growth and new jobs underpin this choice. This is highlighted in case 2, for example. The city established an IoT infrastructure and made all collected data publicly available. In this way, the smart city initiative hopes to attract private companies, which in turn create new jobs and contribute to economic growth.

Table 6 summarize the case specific influencing factors.

#	case specific main influence factors	sample statement
2	- welfare of citizens is expected to increase due to an open and modern technology platform - new technologies are intended to make business processes of public administration more accessible, efficient, effective and transparent - synergies are expected by standardized information sharing within the city's companies	*"Through investment in IoT for urban systems, Barcelona [will achieve] a wide array of benefits. From reduced congestion and lower emissions, to cost savings on water and power [..]" (Public Documents)*
3	- modern technology infrastructure is seen as a unique prerequisite for solving urban problems - new technologies are intended to increase the efficiency of the city's overall management - job creation is expected	*"[Our technology and data] platform should lead to improved economic development by speeding up the advancement of services based on data[..]" (Public Documents)*
5	- availability of data is perceived as a unique starting point for developing smart services - modern technology platform is perceived as key for later smart city developments - new businesses and a highly skilled workforce are expected to be attracted by a modern technology platform	*"The City Data Exchange for Copenhagen is a solution for making public and private data accessible so that the data can help power innovation [..]If we combine data from the private sector and data from the city then it is expected that we can make new solutions and new products out of it." (Interview)*
6	- data and information are perceived as essential resources of an information society - technology innovations are perceived as complex but perceived as unique opportunity for the future development of the city - coordination of digitalization activities in public companies within the city is perceived as important in order to guide the development of city wide technology and data platform	*"We have a supervisory board function in the federal state companies. This means that we can actively discuss and shape guidelines for project contracting."(Interview)*

Table 5.6 Influencing factors for the platform driven approach

5.6 Discussion

Based on the evidence from our cases, this study shows how smart city initiatives proceed in the initiation phase of the adoption of new technologies. During agenda-setting the city's management defines the goals of the first activities in the adoption process. As a result, we found agendas describing two different approaches smart cities initiatives use to exploit the value of new technologies: A need driven and a technology driven approach. The need driven approach focuses initially on the identification of valuable use cases for new technologies to solve urban challenges. After that, appropriate technologies were used for prototyping and testing. This is in contrast to the technology driven approach. There, the systematic implementation of new technologies is of primary interest. These technologies are considered as the basis for a subsequent identification and implementation of use cases.

Agenda-setting is the key stage in the innovation adoption process, as it determines all following steps in the initiation phase. In order to understand the decision-making in this stage, we followed the TOE framework and collected the influencing factors from the investigated cases (table 5.5 and 5.6). We then abstracted and assigned them to the appropriate TOE dimensions. Table 5.7 shows the result.

Technology	Organization	Environment
- perceived complexity (the use of new technologies is perceived as complex [+] or not [-]) - technology landscape (existing technology landscape is perceived as sufficient [+] or not [-]) - information exchange (standardized information exchange is perceived as essential [+] or not [-]) - unique benefits (it is expected that the use of new technologies supersedes other measures for solving urban problems [+] or not [-])	- financial readiness (dedicated smart city budget is substantial [+] or limited [-]) - perceived role of private sector (it is expected that innovative use cases come from private sector [+] or not [-]) - perceived role of initiative (smart city initiative is primarily seen as coordination platform [+] or not [-]) - economic returns (direct economic (e.g. job creation) returns are expected [+] or not [-])	- information systems (IS) fashion (the use of new technologies is perceived as important [+] or not [-]) - citizen's involvement (raise citizen's involvement is a primarily goal [+] or not [-])

Table 5.7 Abstracted influencing factors assigned to TOE dimensions

Table 5.8 visualize the factors which had influence on a city's choice of approach. We found that cities with a need driven approach typically expect that innovative application scenarios come from private sector. Against this background, the initiatives aim to empower citizens and encourage them to participate more actively. This is also reflected by their governance model. It considers the smart city initiative primarily as a central organisation for the coordination of projects between public and private sector.

Initiatives that follow a technology driven approach perceive a standardized information exchange as a driver for innovations from public and private companies. Implemented modern technologies are seen as unique opportunity to increase efficiency of urban services and attract private companies as well as start-ups. The initiatives hope that these companies will in turn create new local jobs and identify and provide smart services.

Additionally, we found IS fashion as a general trigger of the adoption process in all observed initiatives as it reflects the hype that surrounds technology innovations such as blockchain or big data. At the same time, these new technologies are perceived as complex. A frequent argument for the perceived complexity was a lack of IT know-how in public institutions and limited financial resources that impedes the acquisition of external knowledge. Furthermore, most of the interviewed initiatives perceived their financial readiness as low and reported that they are highly dependent on regional, national or international funding schemes. The existing technology landscape was also perceived as insufficient for future requirements in the majority of cases.

	need driven				**technology driven**			
	1	**4**	**7**	**8**	**2**	**3**	**5**	**6**
perceived complexity	+	+	+	+	+	+	+	+
technology landscape	-	-	+	+	-	-	-	-
information exchange	-	-	-	-	+	+	+	+
unique benefits	+	-	-	-	+	+	+	+
financial readiness	+	-	-	-	+	-	+	-
perceived role of private sector	+	+	+	+	+	-	-	+
perceived role of initiative	+	+	+	+	+	-	-	+
economic returns	-	+	+	-	+	+	+	+
IS fashion	+	+	+	+	+	+	+	+
citizen’s involvement	+	+	+	+	-	-	-	-

Table 5.8 Approaches and corresponding influencing factors

5.7 Summary

In this paper we have investigated through an analysis of eight cases how smart city initiatives start exploiting potentials of new technologies.

We could identify two different approaches for the initiation phase of technology innovation adoption: a need and technology driven approach. In the agenda-setting phase of the innovation adoption process, the city administration decides which approach to take. This choice is influenced by external and internal factors, which could be assigned to the technology, organization and environment dimensions of the TOE. In particular we found that the perceived importance of standardized information exchange, expected unique benefits of new technologies and citizen’s involvement are most relevant during decision-making in the agenda-setting.

The theoretical and practical contributions of this research are as follows: Our study shows that the innovation adoption process and TOE can successfully be used to describe and understand the exploration of new technologies in smart cities. The study further contributes new factors to the existing IS adoption literature and provides a starting point for further quantitative and qualitative adoption research. From a practical point of view, cities initiating a smart city program can compare their planned activities with the different approaches and drivers identified in this paper, to possibly re-consider their way of action. Providing a method for the identification of use cases for smart services is planned as a next step in our research agenda. The corresponding design-oriented approach will benefit from the insights gained in this study.

We are sensible that our study faces limitations which should be addressed in future research: A possible restriction may result from the point in time of observation. We investigated how smart city initiatives start to adopt new technologies. During our research we have observed that the approaches of cities change over time and can coexist as the initiative progresses. A longitudinal study could help to describe and understand these changes.

Our identified approaches also open the door for further research: On the one hand, a detailed analysis of the processes within the different approaches could help to provide smart cities a suitable method for the successful identification, evaluation and adoption of smart services. On the other hand, the choice of approach and the impact on the success of smart service implementation could be investigated in order to provide recommendations for practitioners on what approach they should take.

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6 Summary

6.1 Results

The research results of this dissertation are presented according to the four research papers. In order to structure the results, the research question of each scholarly contribution was taken up again and placed before the results summary from the individual chapters.

Sub-1: What factors influence and drive companies within the initiation phase of big data adoption?

The big data adoption process was triggered in all observed cases by the perception of the hype surrounding big data. None of the interviewed companies was confronted with acute problems in data management; instead, big data was a dominant topic at top management level, driven by the medial presence and the perception that big data will become an existential industry issue for future competition. The top managers installed therefore big data initiatives to examine the company specific potentials of big data. Within these initiatives, two initial drivers for the adoption of big data became apparent in the analysis of the cases:

- expected direct benefits
- IS capabilities for big data

Companies that were driven by the expected direct benefits of big data aimed in their first steps on a fast realization of business potentials. For example, companies founded innovation units and staffed them with people from business departments and data scientist to search for promising big data use cases with high business value. These activities were typically enabled by a strategic readiness and supported by the top management. A further identified influence was the high financial readiness of these companies. Available financial resources empowered them to either establish own innovation units for the investigation of use cases or to engage external partners to do so.

Companies driven by IS capabilities for big data focused initially on an identification of key activities for the development of a future-oriented big data platform. For example, a case company evaluated industry-typical big data use cases (e.g. artificial intelligence based approach for fraud detection in financial industry) to derive requirements for their own big data initiative. IS competence, perceived complexity and financial readiness were identified as most influential for these companies. A lack of IS competences, signaled for example by a low business intelligence maturity, forced companies to address basic data management tasks first and increased the perception that big data topics are complex. Cost pressure through a strong competition in industry or high regulatory measures caused a low financial readiness, which in turn prevented these organizations to establish lab environments for big data or to commission external partners.

Table 6.1 shows the identified influencing factors with a brief description and assigned to the TOE dimensions.

Technology	Organization	Environment
- benefits (value for business processes and models) - compatibility (fit to existing technologies, processes or culture) - complexity (many components with multiple ways to combine and use)	- IS competence (competence of IT usage and IT management in an organization) - financial readiness (availability of financial resources) - strategic readiness (big data is part of strategy, supported by top management)	- competitive pressure (new competitors, disruptive business models) - environmental uncertainty (volatile markets, changing customer expectations) - regulatory measures (energy transition, emission reduction, finance regulatory)

Table 6.1 Identified influencing factors for the initiation phase

Sub-2: Which generic approaches can be identified when companies explore the potentials of big data in the initiation phase of innovation adoption?

In order to determine the direction of the first big data activities, the topic was discussed at senior management level and short-term goals set. The short-term goals aimed either at the search for potential big data use cases or at the creation of a good technological starting point. Following these short-term goals, the investigated companies carried out three different approaches within the initiation phase of big data adoption:

- Business First
- Platform Building
- Data Integration

The first approach (Business First) focuses entirely on a business perspective. Companies in this category search for use cases with high expected business value. These use cases span from possible improvements of existing processes to entirely new business services or business models. A technical evaluation of the use cases with regard to their possible integration into existing IT landscapes is not carried out during the initiation phase. Typically, big data use cases are developed as stand-alone IT systems with necessary big data technologies and data in a laboratory environment. Developed prototypes are then tested with selected market participants. If this phase is successful, the use cases are suggested for productive implementation. In case of a positive decision, applications will initially operate as independent IT systems, being then integrated step by step into existing IT landscapes.

The second approach (Platform Building) aims upon the development of a technology and data platform for big data. For this purpose requirements derived from industry-specific use cases are analyzed for orientation. In addition, existing business demands were used to introduce new technologies. Companies with this approach want to keep the monetary expenses for future use cases as low as possible - mostly due to financial restrictions. Therefore existing data management technologies are successively substituted by big data technologies. To keep pace with current developments - although business departments have not identified convincing big data use cases yet - is another observed motivation for platform building. The big data platform resulting from this approach forms the basis for the subsequent identification and evaluation of big data use cases.

The primary objective of the third approach (Data Integration) is to provide a consistent basis of data for future analyses. Consistent and integrated data are considered as a fundamental basis for all further developments in the area of big data. In the cases following this approach, the created data platform is first used for traditional analyses. If they proof successful, companies plan to deal with big data use cases and technologies. The Data Integration approach can therefore also be seen as an antecedent to the Platform Builder approach.

Sub-3: What factors influence the choice of approach?

Companies following the approach Business First look for new revenue opportunities are typically driven by a strong competition and market uncertainties. The transformation towards an increasingly data-driven business is seen as a strategic task. In order to gain a better understanding of customers and drive the development of new products and services, big data is seen as the most important prerequisite. High financial readiness and substantial senior management support typically enable this approach.

Firms that chose Platform Building or Data Integration are less innovation driven. Some of them are exposed to high cost pressure and did not have additional financial resources at hand to address new topics. Instead, they were focusing on internal efficiency and process automation. Additionally, companies could be identified that, despite their financial readiness, did not see a need to identify concrete big data use cases yet. A lack of strategic orientation towards digitalization and no obviously attractive big data use cases were typical reasons for this behavior. However, also in these cases senior management expects big data becoming increasingly relevant. To prepare for the future they therefore decided in the agenda-setting for a systematic build-up of big data capabilities.

Companies in the approach Data Integration perceive the integration efforts for big data technologies as high. A fragmented data and information systems architecture was the main reason for this.

The identified factors and a brief description of their interpretation are provided in table 6.2.

Technology	Organization	Environment
- expected unique benefits (it is expected that the use of big data supersedes other business development measures [+] or not [-]) - perceived complexity (effort and risk for the use of big data are perceived as high [+] or low [-])	- innovation driven (the business strategy is innovation orientated, e.g. first mover [+] or not [-]) - digital strategy (big data or digitalization is part of the strategy and supported by all management levels [+] or not [-]) - financial readiness (sufficient financial resources [+] or not [-]) - maturity of data architecture (harmonized [+] vs. fragmented data architecture [-])	- IS fashion (big data is perceived to be important for the industry [+] or not [-]) - regulatory measures (industry is under strong regulatory pressure [+] or not [-]) - market uncertainties (market is volatile [+] or not [-]) - competitive pressure (competitive pressure is high [+] or moderate [-])

Table 6.2 Identified influencing factors in chapter 4

How these factors influence the choice of approach is shown in table 6.3. In order to facilitate the interpretation of the results in this table, an exemplary reading of the factor “expected unique benefits” is provided next.

Expected unique benefits was one of the decisive influencing factors for the decision to a certain approach. In table 6.3, all companies received a “+” for expected unique benefits when they stated that they expected unique advantages from big data and preferred big data to other business development measures. For example, the utility company in case 6 explained that big data allowed them to optimize plant maintenance by using image recognition to identify potential damage to power lines or to predict the likelihood of plant failure. These insights would have been concealed by traditional data analysis, so the argumentation of the case company. In contrast, the insurance company in case 3. The company argued that big data is a relevant issue, but that it has not yet been possible to recognize a significant added value compared to other business development measures. Therefore, case 3 received a “-“.

By looking at all cases and their characteristics per influencing factor, it was possible to develop table 6.3. The grouping of the cases according to their approach enabled the identification of factors that were decisive for the decision to a certain approach. After conducting these steps, the expected unique benefits from big data, an innovation driven business strategy, the financial readiness of the company and the maturity of the data architecture could be identified as most relevant criteria.

	Business First				Platform Building				Data Integration	
case number	***1***	***6***	***8***	***9***	***2***	***3***	***5***	***7***	***4***	***10***
expected unique benefits	+	+	+	+	+	-	-	-	+	+
perceived complexity	-	-	-	-	+	-	-	-	+	+
innovation driven	+	+	+	+	-	-	-	-	-	-
digital strategy	+	+	+	+	+	-	-	-	+	+
financial readiness	+	+	+	+	-	+	-	+	-	-
data architecture	+	+	+	+	+	+	+	+	-	-
IS fashion	+	+	+	+	+	+	+	+	+	+
regulatory measures	-	+	-	-	+	+	-	-	-	+
market uncertainties	-	+	+	+	+	-	-	-	-	-
competitive pressure	+	-	+	+	+	-	+	-	+	-

Table 6.3 Results from chapter 4

Sub-4: What approaches do smart city initiatives use when they initially explore the potential of new technologies for smart services and which factors influence their choice of approach?

The analysis of the eight observed smart city cases showed that the adoption of new technologies for smart services is triggered by a combination of urban challenges, availability of funding programs and high expectations on technology innovations. The strategic direction for the smart city initiative is set by the city's management (e.g. mayor, city council) and results in short-term goals for the smart services adoption. These short-term goals focus either on solving urban problems and serving concrete citizen needs or on the search for a good technological foundation for a subsequent identification of potential smart services. As a result, two different approaches for exploring the value of new technologies are carried out by the smart city initiatives:

- need driven
- technology driven

In the need driven approach, smart city initiatives explore technological potentials from a stakeholder-need perspective. They initially focus on the collection of potential smart services solving city challenges (e.g. through virtual collaboration platforms, design thinking projects). Identified use cases are then evaluated on how they contribute to the superordinate smart city goals (e.g. CO2 reduction through improvements in public mobility). If this is verifiable, corresponding technologies are implemented prototypically and the application is tested in dedicated areas.

In the technology driven approach, cities initially concentrate on certain smart city domains (e.g. smart transportation, smart energy). They then invest in cyber-physical systems (i.e. combination of computational components with mechanical and electronic parts) and develop platforms that integrate different new technologies for data acquisition, integration and storage. The resulting platform capabilities are advertised and communicated to attract private organizations (e.g. companies, start-ups, local communities) that are expected to drive the identification and exploration of use cases for smart services, e.g. through hackathons.

Influencing Factors

The analysis revealed that cities with a need driven approach typically expect that innovative smart services come from private sector and only leverage value when concerns and needs of citizens are considered. In order to link innovations with citizens' needs, the collaboration of smart city stakeholder is perceived as highly relevant. The high perceived relevance of collaboration is also reflected in the governance model of these smart city initiatives. It considers them as a central platform for the coordination of projects between public and private sector. The city's goal to increase the involvement of citizens in urban development also supports the choice to a need driven approach. A high perceived complexity of new technologies and a low financial readiness prevents initiatives with a need driven approach from creating innovative smart services on their own and emphasizes the dependency on the private sector as external source for innovations.

Initiatives that follow a technology driven approach perceive a standardized information exchange as a driver for innovations from public and private companies. Implemented modern technologies are seen as unique opportunity to increase efficiency of urban services and attract private companies as well as start-ups. The initiatives hope that these companies will in turn create new local jobs and identify and provide smart services. Despite the technology focus of these smart city initiatives, the existing technology landscape is perceived as insufficient for future requirements. For example, in the case of Dublin, the city stated that new technologies led to improvements, for example in water management (e.g. reduced leakage through automated pressure management). But they also reported that there is still a need to increase the sensor network over the city to improve results.

Additionally, we found IS fashion as a general trigger of the adoption process in all observed initiatives as it reflects the hype that surrounds technology innovations such as blockchain or big data. At the same time, these new technologies are perceived as complex. A frequent argument for the perceived complexity was a lack of IT know-how in public institutions and limited financial resources that impedes the acquisition of external knowledge. Furthermore, most of the interviewed initiatives perceived their financial readiness as low and reported that they are highly dependent on regional, national or international funding schemes.

Table 6.4 summarizes the identified influencing factors and assigns them to the TOE dimensions.

Technology	Organization	Environment
- perceived complexity (the use of new technologies is perceived as complex [+] or not [-]) - technology landscape (existing technology landscape is perceived as sufficient [+] or not [-]) - information exchange (standardized information exchange is perceived as essential [+] or not [-]) - unique benefits (it is expected that the use of new technologies supersedes other measures for solving urban problems [+] or not [-])	- financial readiness (dedicated smart city budget is substantial [+] or limited [-]) - perceived role of private sector (it is expected that innovative use cases come from private sector [+] or not [-]) - perceived role of initiative (smart city initiative is primarily seen as coordination platform [+] or not [-]) - economic returns (direct economic (e.g. job creation) returns are expected [+] or not [-])	- information systems (IS) fashion (the use of new technologies is perceived as important [+] or not [-]) - citizen's involvement (raise citizen's involvement is a primarily goal [+] or not [-])

Table 6.4 Abstracted influencing factors assigned to TOE dimensions

The approaches, cases and corresponding influence factors are shown in table 6.5. Again, a selected example should facilitate reading the table.

Citizen's involvement was identified as one of the discriminatory factors for the strategy decision. In table 6.5, all cities which aimed on raising citizen's involvement in the initiation phase of smart services adoption received an "+". For example, Amsterdam in case 1 stated that the involvement of citizens is a central concern of the smart city initiative. The initiative's assumption is that with a strong citizen participation the transformation to a smart city will succeed. For this reason, the approach to adopting smart service is geared towards a strong interaction between city, citizens and other smart city stakeholders. In contrast, cities with a technology driven approach, initially neglected citizen's involvement and therefore received an "-". For example, Copenhagen in case 5 stated that they see standardized information exchange as the basis for a future society and therefore drive the development of a technological infrastructure for data exchange. The involvement of citizens in the initiation phase is not necessary for this purpose, so their argumentation.

The steps for creating table 6.5 remain the same to the previous description before table 6.3. Based on the analysis of the cases, citizen's involvement, unique benefits of new technologies and standardized information exchange could be identified as decisive criteria.

	need driven				technology driven			
case number	***1***	***4***	***7***	***8***	***2***	***3***	***5***	***6***
perceived complexity	+	+	+	+	+	+	+	+
technology landscape	-	-	+	+	-	-	-	-
information exchange	-	-	-	-	+	+	+	+
unique benefits	+	-	-	-	+	+	+	+
financial readiness	+	-	-	-	+	-	+	-
perceived role of private sector	+	+	+	+	+	-	-	+
perceived role of initiative	+	+	+	+	+	-	-	+
economic returns	-	+	+	-	+	+	+	+
IS fashion	+	+	+	+	+	+	+	+
citizen's involvement	+	+	+	+	-	-	-	-

Table 6.5 Approaches and corresponding influencing factors

6.2 Conclusions

The previous chapter has summarized how organization start with the adoption of IT driven innovations in the era of digitalization using big data and smart services as examples. Practical and theoretical contributions of this dissertation as well as limitations are presented next.

Practical Contribution

From a practical point of view, the three big data adoption approaches identified in this dissertation can be used by companies to position and organize their own activities. Companies may compare their current big data activities with the described approaches and drivers to possibly re-consider their way of action. The same applies to cities and public authorities. The two identified approaches provide a holistic view on how smart city initiatives start the technology adoption for smart services. Cities starting digitalization initiatives can use the identified approaches as orientation and possible starting points. This applied in particular to medium sized cities that are now starting their smart city projects.

Theoretical Contribution

From a theoretical point of view, it could be shown that Rogers' innovation adoption process (Rogers, 2003) and the TOE framework (Tornatzky et al., 1990) can successfully be used to explain the initiation phase of big data and smart services adoption. A comparison of both cases results in two generic approaches: Organizations either start with the identification of use cases and their prototypical implementation or they begin with the integration of IT innovations into their existing IT platform and explore potential use cases later. Figure 6.1 illustrates both approaches.

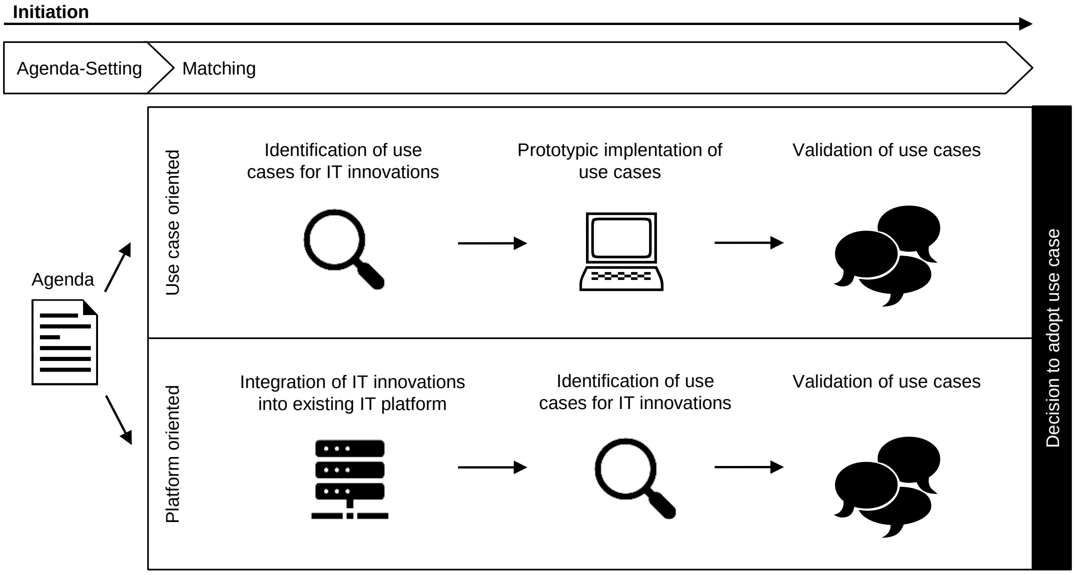

Figure 6.1 General adoption approaches for IT innovations

The analysis of adoption processes in companies and cities also revealed that agenda-setting is the central stage for innovation adoption. The decisions made here determine all further steps in the initiation phase. Thus, an understanding of the influences on this stage is essential. In order to increase understanding, the TOE framework was applied to the agenda-setting stage in the studies of chapters 4 and 5. As a result, different determinants for the decision on a certain approach could be identified. For example, a less innovation driven business strategy was found as a criterion for a platform oriented approach in companies. A high financial readiness, on the other hand, enabled use case oriented activities. Comparing companies and cities results in different decision patterns for a particular approach. For example, the unique benefits of an IT innovation motivated companies to follow a use case oriented approach, while it encouraged cities to follow a platform oriented approach.

In summary, the dissertation provides four important theoretical contributions. First, different paths for approaching an IT innovation within the initiation phase of innovation adoption could be found. Second, the agenda-setting stage is the central stage for innovation adoption approaches, as the decision on a certain approach is made here. Third, the TOE framework is generally applicable, but the influencing factors it describes are domain-specific. Fourth, with the combination of agenda-setting and TOE framework, the dissertation enters a new path in adoption research and provides a framework for researchers to better understand decision-making in entrepreneurial approaches to innovation adoption.

Limitation & Future Research

The dissertation faces limitations which should be addressed in future research: A possible restriction may result from the setting of the case studies.

The big data case study focused on traditional companies based in Germany with more than 10,000 employees. Focusing on companies from Germany might ignore possible cultural or country specific factors that could influence the choice of approach and limits the generalizability of the results. An expansion of the focus on start-ups, e-commerce companies or small and medium sized companies could also provide interesting insights and enrich the picture of possible big data adoption approaches and corresponding influences.

Considerations, as in the big data cases, could also apply to the smart city case study. Concentrating on European cities could exclude important influences that may exist for smart city initiatives outside the European Union. In addition, during research it could be observed that the approaches of cities change over time and can coexist as the initiative progresses. A longitudinal study could help to describe and understand these changes.

The identified approaches also open the door for further research: On the one hand, a detailed analysis of the processes within the different approaches could help to provide organizations a suitable method for the successful identification, evaluation and adoption of big data applications or smart services. On the other hand, the choice of approach and the impact on the success of innovation adoption could be investigated in order to provide recommendations for practitioners on what approach they should take.

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