Estimating the Relation of Big Data on Business Model Innovation: A qualitative research.

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Disclaimer

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Abstract

Gaining interdisciplinary attention across academia, the concept of Big Data also finds application in the business world. Realizing the potential of the trend, this research considers the impact of Big Data with a strategic perspective and by focusing on the following research question: *How can data and data-driven decisions lead to business model innovation*? Challenging the assumption that Big Data even has the potential to impact business models, this research firstly elaborates on the construct of business models and business model patterns. Subsequently, the Big Data concept is defined, by focusing on its unstructured and fast-moving nature. Considering the broad influence Big Data might have on business models, a qualitative research design is esteemed appropriate to answer the research question: The analyses of semi-structured interviews with experts give insights about complex relations in the field of Big Data. For this research 13 participants contributed their opinions on Big Data, among others, they identify current methods and illustrate data visions for the future. One of the main findings of this research is that Big Data still imposes problems on managers, most of them are of analytical, technical or cultural nature. At the same time, the agents that suffer from insufficient data analytics, are invested to generate a data strategy that will facilitate data management. This research defines that data objects must be prioritized due to their utility, by means of data valuation. Associating a monetary value with data objects helps managers to commit to their decisions in data management. Furthermore, this research reveals that Big Data integration improves operations at various levels. In an incremental instance, businesses can reduce costs or differentiate their product and service portfolio through Big Data integration. Furthermore, Big Data finds applications on a strategic level: This research detects that Big Data possesses the proficiency to facilitate all business model dimensions and even to create innovation. Concluding, this master thesis contributes to the research field of Strategy & Innovation as it increases the theoretical understanding of Big Data and its integration in strategic decision making. It considers several related topics to assess the capability of data, by including the notions of data monetization and experience data. Furthermore, this thesis discloses novel case studies, which give evidence of the status quo of data integration across industries. By deriving propositions, this study serves as a valuable guideline for further research on data management and business model innovation.

Keywords: Big Data, Business Model, Business Model Innovation, Data Monetization

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1. Introduction

Artificial Intelligence and Machine Learning are dominating topics in the current scientific discussions. Especially, moral issues received increased societal attention, as the decisions taken in this regard will become a guideline on how society chooses to assign responsibility along with legal consequences. Autonomous driving is one of many examples in which control is automatically given to technology, following a predefined course of action (Dignum, 2018). In addition to society, businesses are affected by technological improvements using robotics, Machine Learning, and sensors to boost performance (Wright & Schultz, 2018). These enhancements are facilitated by the concept of Big Data. Promising insights into virtually all business areas, Big Data is becoming an omnipresent topic. Once managers learn how to integrate data, the analytics capabilities can be used to benchmark past evolvements, predict future behavior and detect patterns. Businesses learn to exploit unstructured data such as social media data and thereby fast-forward their digitalization efforts. According to Sanders (2016), companies like Amazon perfected Big Data deployment in their processes and even managed to focus their whole business model around data. For other players, new technologies prove to be more costly and difficult to implement because they engage in a fragmented integration of data and as a consequence, cannot fully leverage the benefits of a data-driven decision culture (Sanders, 2016). Despite the fact that various technologies evolved that build on Big Data, it also poses a new set of challenges and potential obstacles: The identification of appropriate technology to satisfy business requirements (Oussous, Benjelloun, Ait Lahcen, & Belfkih, 2018). Creating a business case, this study identifies problems that managers face with Big Data. Furthermore, this research paper determines a roadmap, outlining critical steps managers must follow to integrate data in their decision making and give data a purpose. Ultimately, the goal is to assess whether and how corporations can develop the ability to utilize data in a way that will result in business model innovation. Using a qualitative research design, this thesis builds on the theoretical assumptions of academia. Testing the underlying concepts, interviews with industry experts are conducted to assess the status quo. Further expanding the existing literature, theories are developed using insights from representatives of various industries. In order to achieve its objective of theory developing, this paper is structured in the following way: In the next chapter, the prevailing literature is summarized, and sub-questions are derived that will support answering the overarching research question. The third chapter describes the methodology which is followed by the assessment of the findings from the interviews in chapter four. In the fifth section of this paper, propositions will clarify the results and prepare the stage for future research. Complementing this research, limitations that alleviate the findings are presented in chapter six. The introduction of prospective research is illustrated in the final section of this study. Summarizing the scope of this master thesis, the following research question will be answered in the course of this paper:

How can data and data-driven decisions lead to business model innovation?

1.1 Contribution to Academia

This paper is based upon two pillars, namely research about business models and data as an asset. Throughout the master thesis, the two topics are merged to generate a new perspective, which is evaluated by interview partners. Following the analyses of the interviews, propositions are developed which should enable future research. All in all, the contribution to academia is threefold:

The existing literature about Big Data is tested and extended by propositions about proficient data management.

The topic of data monetization and its ability to transform the business model is assessed, and new cases to exemplify the impact are discovered.

The ability of data to create business model innovation is illustrated by six real-life examples. Propositions are formed to evaluate the applicability of data on all business model dimensions.

2. Literature Review

Placing this thesis into context, the following section elaborates on the understanding of business models, business model patterns, business model innovation as well as the relevance of data. Within the second part of this chapter, the sub-questions of this research are presented.

2.1 Business Models

2.1.1 Business Model Concept and Business Model Patterns

Creating a milestone in the business model literature, Zott, Amit, and Massa (2011) established business models as a strategic concept. Throughout the academic world, there are opposing views about the exact definition and scope of the concept. Most definitions are placed in a strategic context, concerning e-commerce, or the way businesses integrate innovation and technology (Dijkman, Sprenkels, Peeters, & Janssen, 2015; Wirtz, Schilke, & Ullrich, 2010). Following the inventor's reasoning, business models generally describe how a focal firm conducts activities to fulfill the customer's requirements, sometimes with details about the specific industry (Zott & Amit, 2013). This research orients itself on the business model structure developed by Teece (2010): The three elements necessary for each business model are *value creation, value delivery, and value capture*. The first characteristic describes the benefit for the customer or the added value for the targeted group. *Value delivery* refers to the channel or approach that the customer is engaged in, namely how he or she receives the product or service. And third, *value capture* represents the added value for the company, either financially or non-monetary (Teece, 2010).

Evaluating the existing business model helps managers to draw connections between internal processes and external influences, including the customer. Especially the technique of visualizing will forge a picture how the dimensions *value creation, value delivery* and, *value capture* interact, and how mutual dependencies are created (Baden-Fuller & Mangematin, 2013). Besides, a company with its number of business units can have multiple active business models, for example by targeting different customer groups. At the same time, a business unit can be exemplified as one specific taxonomy or pattern to showcase how a process is arranged. To structure the existing taxonomies more elaborately, scholars have developed patterns that represent similar cases and point out the underlying features. An example of a business model pattern is the idea of 'Freemium': Spotify, Skype, and LinkedIn are using the concept to offer customers a basic version of the service for free, while they charge a premium for a more elaborate and enhanced version (Gassmann, Frankenberger, & Csik, 2014). As there were numerous taxonomies defined across academia, Remane, Hanelt, Tesch, and Kolbe tried to consolidate the research in 2017. The authors aggregated 182 patterns. Today, due to an increasing prominence of the internet, new business models emerge: Digital business model patterns are characterized by their appearance on the internet (Bock & Wiener, 2017), while others consider the sharing economy (Foss & Saebi, 2017), the circular economy (Lüdeke-Freund, Gold, & Bocken, 2019), or the Internet of Things (Dijkman, Sprenkels, Peeters, & Janssen, 2015). Understanding the ramifications of a business model helps to identify the underlying principles, the core activities that are required to introduce the model, and the potential outcomes. Comparing preceding cases in which the model was utilized can assist to find the one that promises the desired outcome (Chatterjee, 2013). Baden-Fuller and Morgan (2010) imagine business modeling as a recipe for success. "[Business Models] embody some general principles (of cooking: baking, roasting, frying etc, and cooking times and temperature, etc.) as well as particular details of the ingredients and their assembly for specific dishes" (Baden-Fuller and Morgan, 2010). However, not everyone is capable to follow a recipe structurally and often the venture does not turn out the way as expected, still, it can lead to successful recreations of the original idea. The business model patterns can help in that regard as ''Classification is necessary in order to understand innovation because only then we can appreciate what is meant by new'' (Baden-Fuller & Haefliger, 2013, p. 420).

Commonly, there are three reasons managers evaluate their current business model and its feasibility: External pressure, a specific objective, and pursuit for innovation (Figure 1). The evaluation can be a response to external influences, for instance, a shift in a target group or a new competitor on the market. Lüttgens and Diener (2016) draw on the concept of Porter's Five Forces (The Five Competitive Forces That Shape Strategy, 2008), in which the author considers the size of existing threats. The threats include 'rivalry among existing competitors', 'threat of new entrants', 'bargaining power of suppliers and buyers' and last 'the threat of substitutes'. Using business model patterns, Lüttgens and Diener (2016) developed a guide to shield the business from any of the five threats. Creating a framework that links business model patterns to the threats will allow the user to respond to the external threats and minimizes its impact. In the research of Lüttgnes and Diener (2016), the evaluation of the business model is used as a reaction to a situation, however, it can also be used in a proactive manner. Pursuing a specific goal, scholars suggest that there are patterns that promise specific opportunities. For example, Streuer, Tesch, Grammer, Lang, and Kolbe (2016) suggest that some patterns are more likely to drive profit than others: In 'Self-Service', the supplier offers the product in a way that the customer can purchase the item without any personal involvement in a self-serving manner. As labor costs are minimized, a higher level of profit level can be achieved. Other patterns are more applicable for retailers or merchants: A 'Multi-sided Platform' displays various benefits for retailers, especially if the retailer is able to create a digitalized system (Weking, Hein, Böhm, & Krcmar, 2019). Next to the patterns, the evaluation of the business model structure is firstly theoretical and there are constraints why the introduction of a business model can have unexpected effects and desired outcomes cannot be guaranteed: One of the limitations is the technological capability of a firm (Chesbrough, 2010), which will be elaborated on in chapter 2.1.3. The mismatch of business models and firm capabilities is why most of the tools to quantify the business model shift have not yet been accepted in the literature (Groesser & Jovy, 2016). As already suggested, managers can have a clear purpose in mind when evaluating the incumbent business model, however, it can also be a source of creativity to develop something completely new. McGrath (2010) found that especially in uncertain environments, the 'discovery-driven' perspective of business modeling can generate more creative ideas than conventional approaches. Being able and willing to experiment will lead to better models in a shorter timeframe (McGrath, 2010). Due to its experimental and imaginative nature, the business model evaluation is especially helpful, as it takes out the limitation of the imaginary process (Cosenz & Noto, 2018). Predictions and potential future implications are more difficult to estimate in volatile environments and periods (Schrauder, Kock, Baccarella, & Voigt, 2018). Since business model evaluations can help generating innovative results, they can become a source of competitive advantage (Foss & Saebi, 2017).

Business Model Evaluation		
External Influences	Goal-Orientation	Search for Innovation

Figure 1: Arguments for Business Model Evaluation

2.1.2 Business Model Innovation

Following the experimental approach in business modeling, the recombination of elements can result in innovative business models in which customers receive a differentiated value proposition. When evaluating ideas, open innovation and acceptance of suggestions from outside the firm boundaries can yield even more possibilities in business model evaluation (Downs & Velamuri, 2018). Defining the scope of the activity, the evaluation is not restricted to a managerial level but can occur at single business units of a company, and also in a functional or operational setting. Next to structural changes, all potentially involved stakeholders need to be reconsidered in addition to their roles in the new business model (Spieth, Schneckenberg, & Ricart, 2014). One topic, in which all characteristics of the business model must be reassessed, is sustainability. A sustainability-driven venture must place external stakeholders at the focus of the venture to develop an environmentally friendly solution, which must also be feasible in practical implementation (Bocken, Short, Rana, & Evans, 2013; Carayannis, Sindakis, & Walter, 2015; Del Baldo & Baldarelli, 2017). Managers have to evaluate the target group along with the ecological offering, appropriate delivery method, and revenue generation. The creation of a completely new business model can be considered innovative, as it changes all business model dimensions – but can it only be considered 'innovative' if the whole model is turned around? Some authors argue that at least two of the characteristics have to change in order to be considered innovative (Gassmann, Frankenberger, & Csik, 2014). Nevertheless, this paper follows the recommendation of Foss and Saebi (2017), namely that *any* change that is fundamental to the business model can be considered innovative. The authors reviewed 150 articles with regard to business model innovation and concluded that innovation should be defined as "designed, novel, and nontrivial change[s] to the key elements of a firm's BM [Business Model] and/or the architecture linking these elements'' (Foss & Saebi, 2017, p. 216).

2.1.3 The Role of Technology - Digitalization

According to Chesbrough (2010), technology plays a vital role in businesses and determines the failure or success of a company. An even more interesting relationship is that business model choice moderates the impact of technology on firm performance. Deciding on a business model that builds on firm capabilities is crucial to facilitate success. According to Baden-Fuller and Haefliger (2013), a heterogeneous group should be involved in business model evaluation, including representatives of the IT. While IT developers will understand technical requirements and boundaries, they might underestimate customer expectations, which the business side should be able to evaluate more adequately. Furthermore, the choice of technology can be its own source of innovation: Offerings that were traditionally delivered analog reach a bigger target group through a digital version. Thereby, *value delivery* is altered through digitalization. An example of this phenomenon is Airbnb since the company has turned the hospitality industry upside down by leveraging technology (Souto, 2015). Digitizing processes even has the potential to change other dimensions of the business model, namely *value creation* and *value capture*. Automated processes create benefits for both customers and businesses, as the value chain is optimized, and processes are faster (Rachinger, Rauter, Müller, Vorraber, & Schirgi, 2019). Woerner and Wixom (2015) suggest that company outlines can change through digitalization, as the operations are more and more connected digitally and linked to other partners in the eco-system, resulting in a correlated network of stakeholders. Through digitalization, companies build more touchpoints with customers and improve the level of communication. Digitalization impacts all business model characteristics, as illustrated in Figure 2, and can ultimately lead to business model transformation.

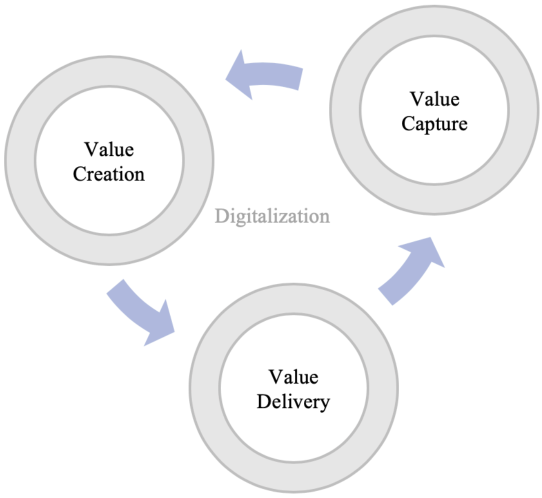

Figure 2: Digitalization impacts all business model dimensions

In academic research, there is a gap of additional identified variables that have the potential to trigger innovation in business models (Foss & Saebi, 2017). To fill this research gap, this master thesis identifies the impact of data as potential driving factor. Recognizing the significance of data, and more particular, Big Data, one first has to understand the scope of the concept and types of data implied. In the next passage, the concept of data is elaborated followed by sub-questions

2.2 The Concept of Data

Using data is one of the foundational elements of people's perception of the world. It builds our history and lets people conclude the past. Thanks to data, people have a collective understanding of the world (Jones, 2019), nevertheless, it can be construed in different ways (Boisot & Canals, 2004). Working with data is anything but a new concept, it is simply our assessment and working habits that adjusted over the years. According to Boisot and Canals (2014), the value of data can be considered from a business perspective - but to create a more accurate picture, the source and intended usage of the data must be incorporated. Data must be reviewed situationally and in context of its application. Also, data is not equivalent to information and knowledge, instead, work-intensive processes are required to translate knowledge from data files and to find relevant insights. The general concept of data was expanded by the rise of Big Data, especially by the characteristics of accessibility and omnipresence (Jones, 2019). Among scholars, there are different perceptions regarding the scope of Big Data, hence, the following sequence will explain the concept by starting with a quote from Najafabadi et al. (2015), who explain the meaning of Big Data:

> *Big Data generally refers to data that exceeds the typical storage, processing, and computing capacity of conventional databases and data analysis techniques. As a resource, Big Data requires tools and methods that can be applied to analyze and extract patterns from large-scale data. The rise of Big Data has been caused by increased data storage capabilities, increased computational processing power, and availability of increased volumes of data, which give organization more data than they have computing resources and technologies to process. (p.6)*

The definition of Big Data is vigorously debated in academic research, nevertheless, there is an understanding that is constructed out of five Vs: *Volume, Velocity, Variety, Veracity,* and *Value*. Volume refers to the fact that Big Data databases are massive and appear in a large quantity. Second, *Velocity* represents the unstructured nature of user-generated information, e.g. from social media, created at a high rate. Third, the information bundles are not in the same format, but in different *varieties* and from different sources. The information might be encoded within pictures, text or voice messages. On another dimension, data can either be internally or externally sourced. As a reference, internal data are existing data or readily available data that are generated from own channels. On the other hand, acquired data, social media data, free data from a website or even customer provided data, like feedback, are extracted from external sources. All these characteristics are embedded in the term *Variety* (Brownlow, Zaki, Neely, & Urmetzer, 2015; Hartmann, Zaki, Feldmann, & Neely, 2016). The fourth characteristic *Veracity* refers to the quality of the information provided, its truthfulness and authenticity (Grover & Kar, 2017). The last dimension *Value* is based on the benefit of the information. The following Figure 3 sums up the main features of the dimensions. As Big Data is an extension of data, the terms 'data' and 'Big Data' are henceforth considered synonyms.

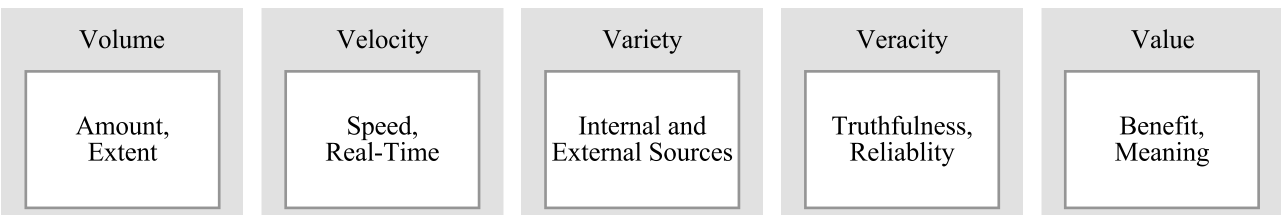

Figure 3: The 5V of Big Data

When the question of importance between the dimensions arises, scholars demonstrate contradicting views. Disregarding the latest dimension of *Value*, as it is context-dependent, Ghasemaghaei and Calic (2019) have shown that *Velocity, Variety,* and *Veracity* improve innovation competency. Contrarily, simply having more volume of data does not seem to foster innovation in a company. Data-initiated projects, however, are mostly driven by data *Variety* due to the accessibility of more sources and resulting credibility (Bean, 2016). Focusing on the *Velocity* and influence on agility of a company, the study of Dykes (2017) suggests that the speed of data is crucial to stand up to competitors, like Amazon, which builds their business around agile decision making. Generating a comprehensive overview, Ranjan (2019) determined which of the different Vs is most decisive in a given industry. Generally, the examples show that there is mixed understanding in the literature, as to which part of Big Data is the most influential. Most often, the value is determined by the context or intended use.

2.2.1 Pitfalls and Challenges

There are numerous benefits of integrating Big Data and its five Vs in decision making, however, they impose unfavorable influences on managers, too. According to Katal, Wazid, and Goudar (2013), the main issue for managers is the volume of data and the speed at which it is being produced. Often, agents are overwhelmed by structurally handling the data streams. Representing another problem, some data files are difficult to extract because they are trapped in company silos: In contained spaces, data files are stored and processes manually, meaning that they are not automatically usable for research (Brown, Chui, & Manyika, 2011). Hence, data analysts employ a high level of effort in searching data files and transforming them to generate a complete and representative business picture. Next to data completeness, data quality and integrity are just as challenging. As reported by Davenport and Patil (2012), finding the right methods of processing, cleansing and preparing data is crucial to make data available for usage. Specializing in data management, data scientists can be engaged to assume the responsibility to convert data into assets. Next to data management, developing algorithms to automate processes and visualizing data are two of the core abilities of data scientists (Davenport & Patil, 2012). Analyzing Big Data files has to be done credibly and reliably: Scientists have to engage in the interpretation in a very structured way to not misinterpret the findings (Merendino et al., 2018). Considering that data scientists distinguish the beneficial data elements from the rest and turn heterogeneous data into an understandable set of information (Najafabadi et al., 2015; Brown, Chui, & Manyika, 2011), they carry a high level of responsibility in the decision making. At the same time, information technology is evolving and simplifying the data scientists' tasks. However, it is crucial to invest in human capital and education to enable staff to operate computers and accelerate Machine Learning (Provost & Fawcett, 2013). According to a Gartner research, companies were increasingly investing in technologies in 2014 (Gartner, 2014). Nonetheless, in 2016, more resources were allocated to human resources, specifically in training to manage Big Data technologies (Gartner, 2016). Data that is presented in an automated and comprehensible way can enable managers to make their decisions data-driven. Implementing a data-driven decision culture yields various benefits, such as automated processes. Throughout the implementation cultural aspects must be considered. By implementing automation stakeholder interests might be neglected, leading to increased job satisfaction among employees. To ease the situation, managers must be careful and inclusive in their communication (Davenport, Barth, & Bean, 2012). Even though Big Data considerations have been around for some years now, many established companies still suffer from issues associated with Big Data. Building on theory developed by Katal, Wazid, and Goudar (2013), the first sub-question of this research estimates, whether the problems associated with Big Data have changed over time.

SQ 2.1 Which hurdles do companies have to overcome when integrating data in their decision making?

2.2.2 Strategic Value

If managers want to implement a data-driven culture they must do so in a proactive way: It requires a cultural mindset change and a high level of managerial commitment (Brock & Khan, 2017; Tabesh, Mousavidin, & Hasani, 2019). In line with the research of Dallemule and Davenport (2017), data must exclusively be used from reliable sources, and managers must try to find a complete and accurate picture of the situation from a data perspective. The strategic development of a company-wide data strategy supports this agenda and unifies efforts to integrate data in decision making. An aligned system is part of the data strategy, as it ensures that information is stored at the right place and is communicated through appropriate and reliable channels (Liang, You, & Liu, 2010). Hartmann, Zaki, Feldmann, and Neely (2016) have shown that new types of data sourced from channels like social media are evolving and provide additional opportunities for data amplification, considering all businesses, start-ups and corporations alike. Hence, one should contemplate expanding the data strategy by the inclusion of external information (Sorescu, 2017). Even open data or publicly-available information can be helpful to expand customer knowledge (Lakomaa & Kallberg, 2013). While the integration of more data sources seems to be helpful to estimate accuracy, the volume alone does not seem beneficial. Instead, managers should collect data files that are relevant and linked to the desired outcome, rather than simply collecting all available information (Marr, 2017). The second question of this research aims to define a guideline that supports managers in creating a data strategy, which ultimately leads to a data-driven culture.

SQ 2.2 How can companies prioritize their efforts to create a data strategy?

2.2.3 Opportunities

Data analytics provides benefits on all levels: On an operational level, for example, managers use data to compare their decisions with past behavior and evaluate whether the approach yielded the expected results. On a high managerial level, however, data insights can create an even stronger impact (Dallemule & Davenport, 2017). There is a strong connection between strategy and access to data. A focus on IT capabilities can lead to a stronger positioning in the market (Liang, You, & Liu, 2010), and lead to innovations in business (Mazzei & Noble, 2017). As soon as managers are capable to interpret the data in a meaningful way, they can reap the benefits of their efforts. For instance, data is used to improve flexibility and agility in systems or to reduce risk in decision making (Grover & Kar, 2017). Once the hurdles of data management are lowered, performance and operational measures improve. This intuition is reasoned by the fact that Big Data yields better foundations to make predictions (McAfee & Brynjolfsson, 2012). To realize the potential of Big Data, it is important to understand that it is supporting decisions in three ways (Watson, 2014): descriptive, predictive and exploratory. Descriptively, or backward-looking, it helps people to make sense of the past. The predictive power of data will support managers in their assessment of the future and suggests paths to follow. Last, exploratory or discovery-driven insights will reveal relationships among variables or trends. Dallemule and Davenport (2017) argue that the latter, namely that the potential to see new connections is a more valuable capability than rationalizing processes due to Big Data insights: On a long-term basis, the capability to innovate is much more valuable than the ability to marginally reduce bottlenecks. According to Hartmann, Zaki, Feldmann, and Neely (2016), these are the two main applications in which data can be useful for companies, namely the streamlining of processes and secondly product or service innovation. The answer to the third sub-question of this thesis will determine in which dimension companies are currently placing their focus concerning data. Furthermore, it will elaborate on the ability to use data as an asset against new entrants and whether it is used more to improve cost efficiency or product or service differentiation.

SQ 2.3 In which areas can well-established companies harness the power of data?

2.2.4 Data impacting the Business Model

Including the concept of business modeling, one clear way to substantially change the business model through data is by data monetization. To explain data monetization, the following example by Brown, Chui, and Manyika (2011) is presented: A transportation company, which collects extensive amounts of data on global shipments, shifts its business model to focus on data. Initially, data was used to optimize internal planning but as the managers realized the value of their data collection, they used the opportunity to sell their knowledge to suppliers. The suppliers then used the information to improve their forecasting and communicated the information back to the transportation company. In this way the transportation company focalized data throughout their whole business model. The managers changed the *value creation*, as their original suppliers became primary customers, the *value delivery* as they reported to customers on a frequent basis, and lastly the *value capture*, as they received a previously untapped stream of cash flow. In this example, the whole business model was replaced. To govern the sale of data, a dedicated group of people is necessary, often a spin-off is created to differentiate between the core business and data monetization unit (Woerner & Wixom, 2015). Data monetization, or data repurposing, receives more attention among scholars (Hartmann, Zaki, Feldmann, & Neely, 2016; Brownlow, Zaki, Neely, & Urmetzer, 2015; Wixom & Ross, 2017), however, it comes with limitations: Firstly, it is a difficult endeavor to turn data into insights that are beneficial for another entity, especially considering the necessary level of trust between the parties of the exchange (Najjar & Kettinger, 2013). Secondly, there are legal boundaries that limit the strength of the idea. Hence, the next question of this paper tries to answer the feasibility of data monetization.

SQ 2.4 What are the limitations of using data monetization to innovate the business model?

2.2.5 The Influence of Data on Business Models

Since business model innovation does not necessarily require the whole model to change, it can also only be one part that is influenced (Foss & Saebi, 2017) by data. It is interesting to see at which dimension, *value creation, value delivery,* or *value capture*, data can play a decisive role. As previously mentioned, managers can gain an understanding of their processes by realizing the value of data and changing their *value capture*, for example by introducing an automated system (Najafabadi et al., 2015). One of today's biggest corporates players, Amazon, is showcasing how data can be used to innovate (Mazzei & Noble, 2017): An example of a data-driven innovation is the Dash Button to accelerate the ordering process in a fast and user-friendly way, allowing the company to redefine its *value delivery*. Drawing on customer knowledge, the retailer cannot only determine the best sellers but also the products that are ordered at the highest frequency. Amazon produces the most appropriate Dash Buttons and even translates the orders more efficiently, as the company anticipates a higher level of sales. While the method of *value delivery* changed in this example, the actual product for the customer and revenue generation stays the same. Continuing with the example of Amazon, according to Mazzei and Noble (2017), the company culture at the retailer is truly data-driven, which is mostly due to the CEO: Jeff Bezos encourages employees to leverage *all* available data to perfect customer experience and stay the market leader. For SMEs and 'digital natives' like Amazon the integration of Big Data in business models has a positive impact on firm performance (Bouwman, Nikou, Molina-Castillo, & de Reuver, 2018). At this point, there is rare evidence whether the benefits hold for established corporations, too (Günther, Rezazade Mehrizi, Huysman, & Feldberg, 2017). Searching for evidence to fill the gap in the literature, this research recommends this last sub-question.

SQ 2.5. To what extent can data enable business model innovation and what are current examples?

3. Methodology

Structurally approaching this master thesis, the methodology was developed by a five-step approach: Starting with the planning step, the research question is derived from existing literature together with the sub-questions. Secondly, the preparation step includes the decision about the sampling method, resulting in the development of a semi-structured interview guide. Subsequently, the interviews were conducted. The processing of the data was performed in the third step of this method. In the fourth step, the data elements were analyzed and illustrated. Lastly, the findings were discussed, and managerial implications defined. An overview is presented in Figure 4.

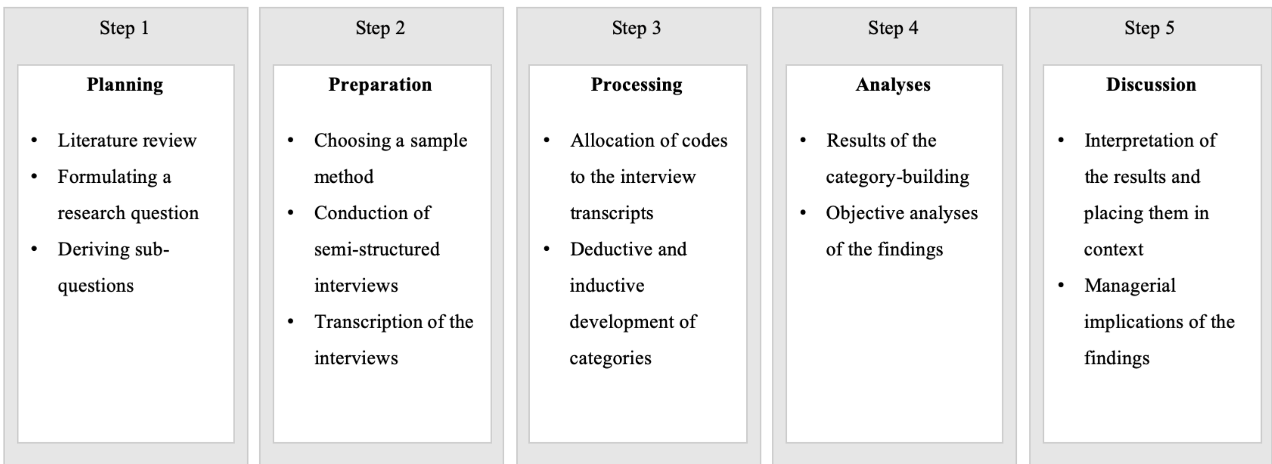

Figure 4: The set-up of this paper's method is determined by the qualitative research guide of Kuckartz (2019)

3.1 Research Method

Following the research question, namely, to understand the implications of using data for business model innovation, a qualitative approach was considered appropriate: This research engages in theory testing and extends the analysis by theory building. In qualitative research, theories of different business disciplines are incorporated, leading to new concepts. In successive studies, the developed propositions can be analyzed in-depth and in a quantitative way (Doz, 2011).

A method that is recognized among qualitative researchers is the Qualitative Content Analysis because of its high level of transparency, reliability, and reproducibility (Kuckartz, 2019). The research method is transparent because the findings are entirely based on the statements of the interviewees. Those statements can be traced back to the original wording in the transcripts. Second, it is reliable as each phrase was accessed uniquely and linked to an exclusive group. Last, the study can be reproduced as the information is based on the transcribed interviews. To recreate the study, future researchers can use the transcripts to perform the same analysis. While future researchers may be able to conduct the analysis the same way, they may reach a different outcome because qualitative studies allow for flexibility in the interpretation (Hsieh & Shannon, 2005). Scholars can investigate the statements and anticipate different connections between the statements because qualitative research in essence differs from the impartial quantitative approach.

3.2 Preparation

Following the guidance of Robinson to select a sample method (2014), first, a sample universe was defined. As this paper is associated with the research field of international businesses, a group of people from the business world was chosen to participate in the study. The research solves an issue of corporations rather than of start-ups, therefore, the sample universe was narrowed to major enterprises. Second, the size of the sample was limited due to the available resources of the author of this paper to a maximum of 15 interviewees. Third, the sampling strategy was based on a purposive sampling method, more specifically ‘Maximum Variation Sampling’. The sampling method dictates the group to have great variation (Etikan, Musa, & Alkassim, 2016). A heterogeneous sample was elected based on industry, company size, location, and gender. Forth, participants were recruited on a voluntary basis, without incentives other than the prospect to receive the final research paper as an abstract. Promising success, all participants agreed to a recording and were guaranteed anonymity.

Exploring the views and opinions of participants, a semi-structured interview guide was developed based on the sub-questions derived from the literature review. A semi-structured interview tolerates the inclusion of contradicting opinions and perceptions based upon personal experiences. Due to Turner (2016), profound research is required upfront to prepare the questions structurally and in-depth. At the same time, the questions do not necessarily have to be asked in a pre-defined order, instead, they should encourage conversation and leave room for follow-up questions (Kallio, Pietilä, Johnson, & Kangasniemi, 2016). The interviews were conducted in the following way: All meetings were scheduled upfront and each was commenced with an introduction to the topic as well as the interviewer’s background. After the introduction, participants were asked for consent to record the meeting to enable agility in the conversation and an unbiased review. The actual interviews were started by an introduction of the interviewee, current role and background concerning data management. As the main body of the interviews, the interview guide was used to trigger a conversation. At the end of the conversation, interviewees were invited to add final remarks. Unfortunately, two of the originally 15 conducted interviews had to be excluded from the analysis due to bias: One of the interviews was used as a pilot interview and the participant was influenced because he added recommendations about the depth of the questionnaire items. The second interview was biased through a third participant in the meeting, which created an unequal environment in comparison to the other interviews. Concludingly, 13 out of 15 interviews were esteemed appropriate.

Inter-viewee	Firm	Interviewee's Role	Firm size	Industry	Data Collection	Length	Date	Location	Gender
A1	A	Senior Vice President/ Head of IT	> 100.000	Logistics	Personal Interview	34 Minutes	27.10.19	Germany	Male
B1	B	Head of Enterprise Information	> 50.000	Finance	Personal Interview	21 Minutes	16.09.19	Australia	Male
C1	C	Purchasing Manager	> 200.000	Automotive	Mobile Interview	25 Minutes	27.10.19	Germany	Male
D1	D	Master Data Manager	> 50.000	Fast Moving Consumer Goods	Personal Interview	20 Minutes	04.11.19	Germany	Female
D2	D	Head of Purchasing	> 50.000	Fast Moving Consumer Goods	Personal Interview	37 Minutes	04.11.19	Germany	Male
E1	E	Innovation Consultant	10	Strategic Consultancy	Mobile Interview	20 Minutes	15.08.19	Germany	Female
F1	F	Enterprise Data Manager	> 90.000	Data Management Consultancy	Mobile Interview	45 Minutes	12.08.19	America	Female
F2	F	Principal Consultant	> 90.000	Innovation Consultancy	Mobile Interview	47 Minutes	06.09.19	Switzerland	Male
F3	F	Product Marketing Specialist	> 90.000	ERP Product Innovations	Mobile Interview	30 Minutes	28.10.19	Canada	Female
F4	F	Senior Project Manager	> 90.000	Project Consultant	Mobile Interview	25 Minutes	30.10.19	Germany	Male
F5	F	Business Trans-formation Consultant	> 90.000	Fast Moving Consumer Goods	Mobile Interview	41 Minutes	06.11.19	Germany	Male
F6	F	Data Innovator/ Chief Data Officer	> 90.000	Data Management Consultancy	Mobile Interview	20 Minutes	07.11.19	France	Female
F7	F	Consulting Manager	> 90.000	Tele-communications	Personal Interview	38 Minutes	11.11.19	Germany	Male

Table 1: Overview of Interviewees

To satisfy the requirement of heterogeneity, stakeholders from different industries were invited to participate in the study. A comparatively large group of consultants from one specific company were asked to contribute to this study, which is the reason why the group of interviewees from company F is comparatively large. They were asked to elaborate on insights from the industry and the companies they are currently advising. Also, to include a perspective from a small business, a member of a small enterprise was invited to share insights about data usage in business model consulting (Interviewee E1). The complete overview of participants and their characteristics is illustrated in Table 1.

3.3 Processing the Data

If an interview was conducted in another language, it was translated into English. Afterwards, all 13 interview recordings were transcribed into separate files. As proposed by Kuckartz (2019), supporting software, MAXQDA, was used in the processing of the data. Due to Mayring (2016), there are three basic techniques to analyze content, which are summarized in Table 2: Frequency Analyses, Valence Analyses, and Contingency Analyses.

	Requirement	**Expected Finding**
Frequency Analyses	The statements of participants must have similar wording, so the frequency can be analyzed statically.	The frequency can be compared to other phrases and thus provides a quantitative level
Valence Analyses	The research aims to process a feeling or attitude regarding a topic or an object of interest. Therefore, emotions are analyzed.	Sentiment analyses
Contingency Analyses	The conversations should have similar topics and points of interest, which are then placed into context.	Associations between topics

Table 2: Content Analyses adapted from Mayring (2016)

This research focuses on Contingency Analyses: The method allows the researcher to find parallels in the statements of participants, and to develop associations between topics. Frequency Analyses was not deemed appropriate as the translation to quantitative data can be ambiguous, considering the comparatively small sample. A minor change in answering can create a major percentage change and would, therefore, mislead the reader (Pratt, 2009). Valence Analyses was not applied due to its sentiment-assessing nature (Mayring, 2016). Even though this analysis draws connections between the interviewees' statements, it is not their feelings that are analyzed, but the links between topics on a content-level. Additionally, many of the interviews were translated from German, thus, their opinions might not be exactly expressed as intended, or the phrase could have lost a level of intensity. Fortunately, the content of the statements stays the same, regardless of the exact phrasing in the original language.

Increasing the level of transparency, all text passages, together with the interviewee's alias, were paraphrased and allocated a code: In total, 300 statements were identified. Avoiding bias, all statements were used singularly for only one of the separate codes. Using Directed Content Analyses, codes were defined before and during the data analyses (Hsieh & Shannon, 2005), to answer the sub-questions. The codes are therefore mixed: concept-driven and data-driven, deductive and inductive. Two examples are provided to elaborate on both categorization methods.

Deductive codes and categories were predefined before the processing of the data. They are in reference to literature or a theory (Kuckartz, 2019). Table 3 illustrates a deductive analysis.

Alias	**Sub-question**	**Code**	**Wording**	**Paraphrase**	**Category**
D1	Q1	Working with Big Data\ Problems with Big Data	'Currently, we have a technical limitation, that we are not able to prepare price analyses because we cannot detect the price trend in the specific conditions, as this something that the system does not reflect.'	technical limitation	F) Technical Challenges

Table 3: Example of Deductive Categorization

The sub-question 1 of this research is concerning the problems resulting from Big Data. The problems were previously theorized by Katal, Wazid, and Goudar, (2013), and split into six categories. Interviewee D1 stated that one of her problems with Big Data is that she is limited by a technological shortage to analyze the data. The statement represents a problem with Big Data, which is why it was attributed to the code, 'Working with Big Data/Problems'. To ease the process, the exact wording was paraphrased to summarize the meaning. As the allocation of the code was deductive, the researcher evaluated, whether the statement would fit among the categories defined by Katal, Wazid, and Goudar (2013). In this example, the statement fell under the category 'f) Technical Challenges', as the category includes a mismatch of requirement and technical capability.

In comparison, inductive categories were developed throughout the organization of the codes, for example, natural categories, which are common topics raised by the participants of this study (Mayring, 2016). The researcher worked through the text and applied open coding, detecting similarities between topics. Once the codes were identified, the statements were clustered into categories to reduce the level of abstraction. The code as well as the categories were named due to their content as suggested by Elo and Kyngäs (2008). Table 4 illustrates inductive analysis.

Alias	Sub-question	Code	Wording	Paraphrase	Category
F3	Q2	Data Strategy	'to understand the quantitate data better. [..] Once we know that we can put money in that budget. Before we did not know what the cause was, now we can make better decisions.'	Acting upon the findings	Commitment
F1	Q2	Data Strategy	'How would you value data? Which ones are most important, which ones are a commodity to give it away? Which ones would you open up? This is a process of data valuation.'	Data valuation	Commitment
F6	Q2	Data Strategy	'The point is governance. You should govern your data and expect the same level of quality from internal or external data.'	Ensure governance and consistency	Ensure a Consistent Language and Standards

Table 4: Example of Inductive Categorization

Throughout the interviews, numerous suggestions were made about how companies should improve their data management, which is why those statements were group under the code 'Data Strategy'. The three entries displayed in Table 4 belong to this code. The first two recommendations link financial measures to data. Interviewee F3 required the allocate of a budget to findings derived from data, thereby committing to the insights. On the other hand, interviewee F6 wants to value data objects, to achieve a prioritization and stick to the plan. Both statements suggest that managers should commit to their decision about data and data insights, therefore, the category was named 'Commitment'. The third entry suggests that all data, regardless of the source, should be managed equally. Among the interview transcripts, multiple respondents indicated the need for consistent data governance, hence, this category was called 'Ensure a Consistent Language and Standards'.

3.4 Category-based Results and Analyses

Once all data was processed, the codes and categories were finalized. The following Table 5 gives an overview of the sub-questions and codes in addition to the type of category building. In the 'Results and Analyses' section of the paper, the findings are presented. Often, the frequency of responses is indicated. As previously mentioned, the estimate is not used to perform statistical analyses, instead, it should increase the level of transparency and provide the reader with a mere tendency. A complete overview of all responses is illustrated in Figure 7 (Appendix). In the analyses of the codes and categories, the findings are put in a context, often supported through literature about the topic. With inductively created variables, the result and analysis part sometimes overlap: They are naturally intertwined since they are subjectively clustered by the researcher.

Sub-Question	Code	Category Building
1. Which hurdles do companies have to overcome when integrating data in their decision making?	Working with Data	Inductively
	Working With Data/Problems	Deductively
2. How can companies prioritize their efforts to create a data strategy?	Data Strategy	Inductively
	Critical Data Elements	Deductively
	Investments in Data	Inductively
	Experience Data	Inductively
3. In which areas can established companies harness the power of data?	Working with Data/Changes	Inductively
	Cost/Differentiation	Deductively
	New Entrants	Deductively
4. What are the limitations of using data monetization to innovate the business model?	Data Monetization	Deductively
	Privacy	Inductively
5. To what extent can data enable business model innovation and what are current examples?	Business Model Innovation	Deductively

Table 5: Category Building Style per Code

3.5 Interpretation of the Analyses through Propositions

Relating categories and concepts with each other, the concluding section of the methodology presents the development of the propositions. It is the objective of this paper to derive implications that can be used for quantitative analyses in succeeding research. Therefore, the fifth part of the methodology generates a set of propositions to answer sub-questions together with a concluding comment regarding the research questions - a method as proposed by Geletkanycz and Tepper (2012). At this stage, the theory testing will be expanded into theory building, and thus provides a contribution to academia (Doz, 2011).

4. Results and Analyses

This section outlines the codes and categories for each of the sub-questions. First, it will remind the reader of the question at hand. Second, it will give an overview of the results of the data processing in a complete, clear, and credible way, conforming to Zhang and Shaw (2012). Third, the findings will be put into context and the differences between statements will be assessed and summarized.

4.1 Codes for Sub-Question 1

Which hurdles do companies have to overcome when integrating data in their decision making?

4.1.1 Working with Big Data

Results

As a starting point, interview partners were asked whether Big Data is a part of their daily work and their decision making. Out of the 13 participants, 10 stated that they actively leverage their work by using Big Data, even on an operational level. Two of the disagreeing participants mentioned that even though their own daily work was not supported by Big Data, other departments of their company would already make usage of Big Data analytics (Interviewees C1 and D1).

Analysis

Even though some participants specifically stated that there were not working with Big Data, at a later point in the interview they provided examples in which Big Data was a key factor in a project they were working. For instance, Interviewee D1 suggested that data insights were already improving the purchasing behavior of her business unit to generate cost savings. Although it has not been the interviewee's original perception, she was using data to improve her working behavior. The same rationale applies to Interviewee C1, who makes usage of real-time data to improve the algorithm that controls the final product. Even though his individual decision making is not yet facilitated through Big Data, this team makes usage of the concept. Lastly, the remaining participant that denied working with Big Data, was included in this research to fulfill the requirement of heterogeneity. Her response differs from the rest, as she is not using Big Data in her work, nor does her consultancy firm at this moment (Interviewee E1). The reason for this contradicting view could be the size of her company, lacking economies of scale and limited resources, as there are less than 10 people active in the consultancy. Concluding, there are two points of interest to this code. For once, there is uncertainty about the definition and scope of Big Data, hence, there is a clarification need. Secondly, Big Data is already an omnipresent concept across industries as most participants already use data to expedite their work.

4.1.2 Working with Data – Problems

Results

Understanding which issues people currently have with Big Data integration can give indications where action is required. This second code is analyzed deductively, meaning it is related to literature. As mentioned in the literature review, users of Big Data face several issues. Categorizing the problems with Big Data usage, Katal, Wazid, and Goudar (2013) defined six categories of problems: a) Privacy and Security, b) Data Access and Sharing of Information, c) Storage and Processing Issues, followed by d) Analytical Challenges, e) Skill Requirement, and f) Technical Challenges. Among the participants of this study, 12 out of 13 participants referred to problems they were having with data. Of the 49 issues that were mentioned, 35 items fall in one of the categories suggested by the authors. Most of the issues fall into category d) and f), while none of the participants criticized the people skills involved, which would fall within category e). Only some responses are elaborating on problems they face with a) and b), meaning that participants face only a few problems with privacy issues of data or the access to data. A shortage of technical capability is mentioned in category c), a problem which should not be disregarded, due to its high frequency. Of the total quantity, 14 answers remain which do not fit in any of the categories explained by Katal, Wazid, and Goudar (2013).

Category	**Problem Explanation**	**#**
a) Privacy and Security	Personal information of customers is of a sensitive nature that must be treated carefully. Careless behavior can result in legal consequences and security issues.	3
b) Data Access and Sharing of Information	The data is not available in time and format that it is required, regardless of whether the information is internal or sources from outside the company.	3
c) Storage and Processing Issues	Structural problems include the storage space for data and the capability to process data efficiently.	6
d) Analytical Challenges	Not having the right analytical capabilities will hinder managers to estimate which of the data objects need to be stored, process and analyzed. Differentiating which data elements are crucial for the process or the project is an analytic capability.	11
e) Skill Requirement	Missing human resources who can operate the systems has a paralyzing effect on the decision making, as individuals need to be trained to make an accurate decision about the data at hand.	0
f) Technical Challenges	Four dimensions are derived from the technical hurdles that represent problems for a company. 1. Fault Tolerance: The system is not error-prone and does not work as required. 2. Scalability: By merging different sources of data, the results will not appear on the same scale and thereby creates system failures. 3. Quality of Data: A problem derived from the volume, in which a computer cannot always estimate whether the data element is required for the decision. 4. Heterogeneous Data: The system is not able to convert all data objects into explicit information.	12
Other		14
Total		**49**

Table 6: Problems with Big Data by Katal, Wazid & Goudar (2013)

Analysis

Participants are not ignorant about the topic of data privacy, which will become apparent at a later stage. Nevertheless, they do not perceive data privacy as a dominant problem in their data management. As the participants do not consider the access to data as an extensive issue, too, it can be suggested that managers do not yet engage in a broad data collection and therefore do not experience issues with privacy and access. The high frequency of problems with analytical and technical skills suggest that participants experience issues in interpreting data, both an analytical and technical level. 35 of the 49 responses fall into the categories that were suggested by the authors in 2013, while 14 do not fall in one of the clusters. The remaining responses are grouped in a new category: Business Understanding. Desiring a higher level of comprehension for the required work is a crucial element throughout the interviews. Often, business managers perceive data as an IT topic and do not know how to handle the topic (Interviewee F1). At the same time, managers do not distribute enough resources to problems and do not commit to their decisions (Interviewee D2). A common language is missing among workers, but as long as there is no mutual willingness, consistency is difficult to achieve (Interviewee B1). Interviewee A1 suspects, that it will take at least another generation of workers until the data topic is respected across all business units. The 14 problems fall into the same category - a dissonance between awareness and the workload of data preparation. Concluding, since 2013, when Katal, Wazid, and Goudar published their research, some of the problems with Big Data have changed, while a new one has arisen. There are three strong categories among Big Data problems: Identifying the right data elements, the technical limitations, and awareness of the business side.

4.2 Codes for Sub-Question 2

How can companies prioritize their efforts to create a data strategy?

4.2.1 Data Strategy

Results & Analysis

Showing commitment to the topic, participants mostly responded with suggestions to the problems they provided. This code was analyzed inductively, meaning the statements were grouped together based on similarities. All responses in this category are recommendations on how data could be managed more strategically, which is why the code was named 'Data Strategy'. This code had the highest number of suggestions made by interviewees, a total of 67 responses. The participants have visions of how their company, or companies in general, can improve data management through the development of a data strategy. Decreasing the level of abstraction, the statements were categorized according to the objective of the recommendations. Four main categories crystallized in the process:

a) Goal-Orientation, b) Ensure Consistent Language and Standards, c) Commitment, and d) Support. The following Table 7 elaborates on the categories and provides a count of responses.

Category	Explanation	#
Goal-Orientation	Data should not be collected without a purpose, instead, it is important to link the data collection to the corporate strategy or the processes that enable the strategy. All data elements that are collected should be associated with the desired outcome and a purpose.	25
Ensure a Consistent Language and Standards	The collected data elements must have the same level of quality, regardless of their source, so they can be regarded in decision-making. All information must be managed structurally and consistently, so the findings are comparable. A common way of handling the data will prevent compliance issues.	19
Commitment	Data valuation can help to link a financial dimension to data management. Allocating a financial value to data can improve the handling, as the data is transformed into a scarce resource, rather than a commodity. Also, managers will commit to data management if there is a budget attached to the collection of the data.	14
Support	Comparing best practices in the industry can help to identify strategic choices regarding data. Searching for support is understandable as data management is often not a core capability. Also, creating synergies among companies is a suggested method to exploit the available data sources. Technological solutions on the market will help to understand data analytics.	9
Total		67

Table 7: Elements of a Data Strategy (own development)

4.2.2 Critical Data Elements

Results

Trying to establish a pattern of important data elements and their source, the code 'Critical Data Elements' was built deductively. Following the proposition of Hartmann, Zaki, Feldmann, and Neely (2016), data can be sourced from internal or external channels. The two sources can be split into more distinctive categories, resulting in a total of 10 options. Internal sources include existing data that is drawn from IT systems, which is often unused (e.g. ERP data). Another internal source is self-generated data, which can even be further segmented into crowdsourced data and tracked data. Crowd-sourced data is created by a broad set of contributors over the web or through social collaboration techniques (Gartner, 2013), while tracked data is generated for example by sensors. On the other hand, various categories belong to external data: acquired data, customer provided, and freely available data. Acquired data can be purchased from data providers, while customer-provided data files represent data flows from customers or business partners of the company. Lastly, free data is publicly available at no direct cost. Publicly available data can be further split into open data, which can be downloaded (Lakomaa and Kallberg, 2013); social media data from websites such as Facebook; and web-crawled data, which is publicly available but needs to be gathered electronically (e.g. blog entries) (Hartmann, Zaki, Feldmann, & Neely, 2016). The respondents of this research were asked about the data that would drive their decisions, and were, therefore, crucial to their working behavior. 21 of the 23 answers were provided that fall within either of the categories. Seven responses indicated internal data as crucial to their business, while eight inclined towards external information, and two found a mix of both to be important. The results are summarized in Figure 5.

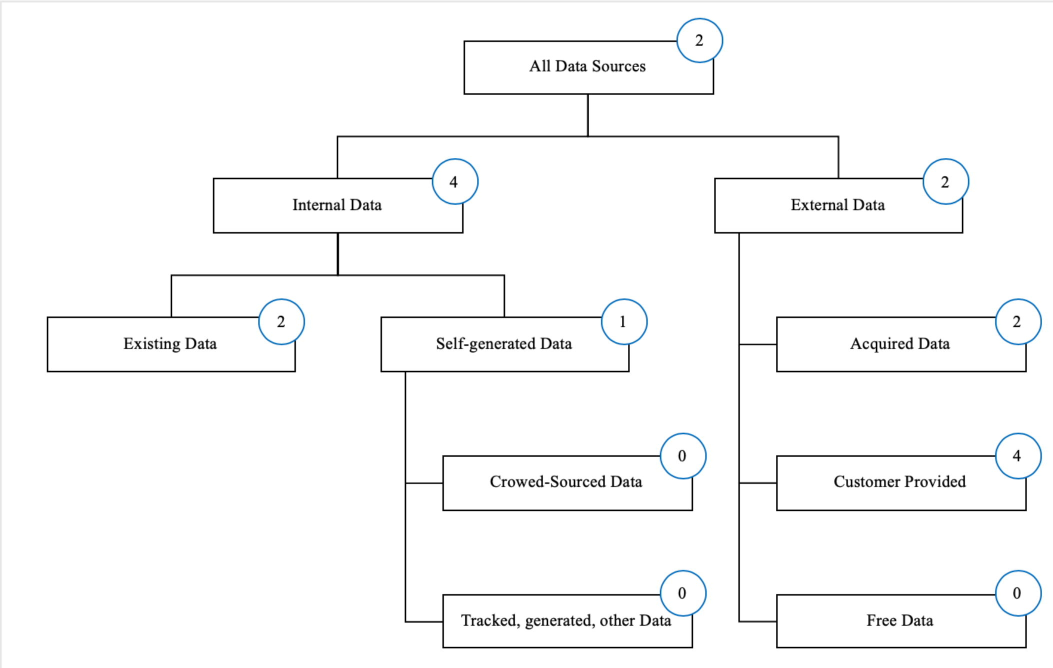

Figure 5: Internal and External Data Sources derived from Hartmann, Zaki, Feldmann & Neely (2016)

Analysis

It is apparent that both data sources are relatively balanced. The interviewees suggest, that it depends on the industry or even business units whether external or internal information can be the driving force. For instance, HR operations would benefit from a higher level of access to external information from the industry (Interviewee F3). Purchasing departments are even dependent on data provided by their vendors to make accurate planning (Interviewee D2). At the same time, some industries are less reliant on external data, like the telecommunication branch. In the first instance, players in the telecommunications industry struggle to understand their self-generated customer information, as the internal data volume is increasingly high (Interviewee F7). As the overview incorporates only 21 out of 23 responses, two do not fit in a category. The content of those two statements is that they believe that it is not important where the information comes from. However, it is of crucial importance that the data is scarce because information of singular nature is far more valuable than an object that is possessed by multiple stakeholders (Interviewees F5 and F7). The overview of sources is derived from the study of Hartmann, Zaki, Feldmann, and Neely (2016), who focused on web-based start-ups. They find that only 11% within their study base their processes on data that is only internally generated, at the same time 16% use a mix of both, while the majority, 73%, use externally produced information to drive their business. The balanced distribution in this sample drawn from corporation illustrates a completely different picture. To summarize the findings, there are contrasting views with regard to the most important source of information. According to the participants, this fact is due to divergent requirements industries.

4.2.3 Investments in Big Data

Results

Investigating the nature of Big Data investments, this code was created deductively. The categorization was developed before the interviews were conducted, however, it does not build on a specific theory. The code investigates the current status of investments and resource focus. The investments illustrate where companies place their emphasis since these are the areas in which they are willing to allocate their budget. Two directions are interesting for this research: training of employees and technology. This split is in line with the investment placed in Big Data, examined by Gartner (2014; 2016). The research retrieved 21 responses throughout the interviews. Categorizing the responses, the investments in technology received 14 replies, while five reactions highlighted the importance of allocating resources to human capabilities. The remaining two answers desired an equal split between the two categories.

Analysis

Throughout this research, participants often shared similar views and lines of reasoning. On investments, however, the opinions are very contradicting. Favoring technology, interviewee F5 compares the investments in a system with the investments in training sessions for employees. He estimates that the financing of a sophisticated system will have a better return on investment than training sessions for people with a less advanced system. Interviewee F3 shared a similar view, as she suggested that the technology evolves more and more, which in turn will require less involvement of data scientists. Instead, the systems will take over data scientist's tasks. On the other hand, other interviewees emphasized the importance of fostering human capital. Exemplifying the importance, Interviewee D2 referred to a colleague in the production planning, where human interaction is essential to the process because of experience, intuition, and network relationships. Based on his feeling, he opts to secure volume, while a system might not trigger an action. His gut-feeling has proven reliable many times, which is why the interviewee would prefer to invest in trained workers rather than systems. Also, interviewee A1 indicated that there is high demand for employees with a strong mathematical-technological background to interpret analytics understandably. This reasoning is in line with the literature, highlighting the importance of data scientists (Merendino et al., 2018). Acknowledging the abilities of humans in comparison to a machine, IT developers create tools to follow people's patterns of decision making. A report by Bloomberg (2018) suggests, that Big Data investments will increase at least until 2021 with the main objective to develop learning systems with an 'autonomous sense of judgment'. Thereby, they aim to combine technical automation and human intuition based on algorithms. At this moment, however, the technologies are still in the development phase (Bloomberg, 2018), making human judgment irreplaceable. All in all, the importance of technological evolvement should not be underestimated, but at this moment, human skills are required to leverage Big Data.

4.2.4 Experience Data

Results

The code 'Experience Data' was developed inductively and text-based, as it was a common denominator among the participants (Kuckartz, 2019). It fits within in the scope of the second sub-question as it gives a suggestion which data types managers should consider in their decision-making. Reappearing over the course of the interviews, the topic of 'Experience Data' seems to be a topic on participants' minds. Without a direct question to the topic, six of the respondents contributed examples and provided insights on how experience data from their eco-system would benefit their work.

Analysis

Putting the topic in context, in 2007, Meyer and Schwager already elaborated on the way that companies try to collect subjective responses of customers to adjust their offering. So-called 'touchpoints' are means to collect data about customers. The authors defined that there were three main problems with customer experience data, namely, the high investment necessary to analyze the data generated by the touchpoints, the unsynchronized data flow, and the 'fear of what the data might reveal' (Meyer and Schwager, 2007). Those issues can be tackled with modern technology: The costs of Big Data technology decreased (Interviewee A1), and real-time data can be analyzed quicker. Applying an agile approach, managers are instructed to adopt a 'fail fast' way in data management, to ''reveal, share and assess failures as learning moments, without condemnation or blame, to nourish team engagement and innovation'' (Friedman, 2019, p.7). Drawing insights from the interviews, experience data is no longer attributed to customers. Instead, it can give exposure to other relationships in a company's ecosystem. One example is the benefit to understand the nature of vendor relationships, whether it is trustworthy or dubious (Interviewee D1). Turning the view into internal company processes, Interviewee F3 suggests that experience data can be helpful to generate HR-related insights, so trends are detected, and measures taken. For example, experience data can give reasons for a high turn-over rate, as it estimates the feelings and sentiments of employees (Interviewee F3). Additionally, the collection of experience data becomes easier over time, as businesses and customers are connected by an increasing number of 'touch points'. Due to evolving digital opportunities, companies can learn to leverage social media and extract experience data to create a customer journey (Interviewee F5). All in all, this code has highlighted that experience data is a prominent topic in Big Data. Problems that limited the usage in 2007 are no longer valid. The feelings and emotions of customers are not the only points of interest anymore, instead, the intrinsic motivation of suppliers and employees becomes important.

4.3 Codes for Sub-Question 3

In which areas can established companies harness the power of data?

4.3.1 Working with data/ Changes through Big Data

Results

This code captures the benefits that are already enabled by access to Big Data. Recording the processes that have already changed, it gives a comparison, where interviewees already perceived a shift. The research gathered 27 responses, which were analyzed inductively. Assessing the similarities between the statements, the results fall into three main categories: Technology, Better Decision Making, and Improved Operations. An overview is provided in Table 8.

Category	**Explanation**	**#**
Technology	Technology is the enabling factor in the process, as computing power has increased. Also, there are more and more tools that will provide answers to problems managers might not even know about yet.	10
Better Decision Making	Big Data enabled better and consistent decision making. Also, it contributed to better customer behavior understanding and resulting strategic orientation.	13
Improved Operations	Automation, continuous updates, and improvements are enabled through Big Data.	4
Total		**27**

Table 8: Changes through Big Data

Analysis

Keeping in mind the definition of Big Data in the business glossary, Big Data ''enable[s] enhanced insight, decision making, and process automation'' (Gartner, n.d., p.1), the three categories seem to identify similar benefits of data than the participants of this study. Interviewees place an emphasis on the technology that fosters decision making. Some interviewees even attribute most benefits alone to technological opportunities, as the 'software gives us the right questions to ask and then the answer to them' (Interviewee F3). Other participants consider technology as a factor among others. Through Big Data integration, managers can make better predictions (Interviewee D2), automize systems (Interviewee D1) to the point of Machine Learning (Interviewee F5). Internal as well as external improvements can be achieved through Big Data, as customers are differentiated better to their characteristics and companies achieve an improved position in the market through tailored offerings (Interviewee F7). Confirming the assumption that Big Data has already found its way into business, this code has tried to reason what Big Data has already changed in corporations. Most focus was placed on the ability to make better decisions.

4.3.2 Cost/ Differentiation

Results

Trying to create a competitive advantage against competitors, companies often focus on either cost or differentiation. Due to Grant (2016) companies improve their processes to translate the cost-saving to the customers to create a cost advantage, for example, by employing higher capacity utilization or lower costs. Differentiation, on the other hand, can be achieved on both the demand and supply side. For instance, on the supply side, there is differentiation potential on levels of human resource management or within the firm infrastructure. On the other hand, the demand side is denoted by customer's requirements. Identifying the key attributes that customers are looking for or the motivation that a customer is looking for in a product or service is part of the differentiation strategy (Grant, 2016). Considering the impact of data, this code aims to estimate the capability of data, whether it is a cost-reducing factor or facilitates differentiation. The categories were derived from literature and are therefore deductive. Recognizing statements for this code, 19 responses showed a specific tendency for either cost or differentiation, resulting in a split of six to 12. The remaining response mentioned that the dimensions were naturally intertwined: there cannot be customer differentiation in a process that is not optimally developed (Interviewee F6).

Analysis

In the previous code about changes, readers could observe a strong focus on better decision-making concerning customer preferences. In a similar fashion, participants highlight differentiation potential through data usage, resulting in innovative products and services. At the same time, process improvements were recognized, to lower costs, but participants stated that in relation, the power to innovate outweighs the potential to streamline operations: the potential to innovate will generate new revenue opportunities, which weight more in the long term than cost savings (Interviewee F6).

Focusing on the demand side, participants highlight the potential to group customers based on their preferences and characteristics and create customized offerings accordingly (Interviewee C1). A data-enabled differentiation can improve customer experience, creating loyalty and retention (Interviewee B1). This code, along with its two categories, has shown that data can foster both, cost and differentiation. Nevertheless, there is a tendency towards the latter, which might be correlated with the strategic objectives of the participants in this sample.

4.3.3 New Entrants

Results

The last code belonging to this sub-question aims to evaluate whether Big Data can be used to shield corporations against external threats, more precisely new entrants and 'digital natives' trying to earn market share. The deductive code was based on the findings by Liang, You, and Liu (2010), who proposed that IT capabilities should be fostered as they can create a strong firm performance and solid positioning on the market. In 2010, when the paper was published, there was little reference to the concept of Big Data, therefore, this research reconsiders the propositions with a current perspective. As a result of the line of questioning in the interviews, 11 statements were contributed to this question, but none of the participants were convinced that data could have a direct impact on firm performance. To illustrate the attitude, Interviewee D2 explained that losing business to competition because of a promotion advertisement is based on the opposing managerial decision and cannot be avoided through Big Data access. Generally, interviewees prefer to use data to improve their core activities, which would then improve their competitive positioning. Instead of developing own processes, like Amazon with its recommendation algorithm (Interviewee F2), interviewee C1 suggests building alliances with more data-driven companies, like Google, improves mutual positioning as it balances the competencies.

Analysis and Example

The reasoning of the participants is on the same lines as the findings of Liang, You, and Liu (2010). The authors observed an indirect significant effect of IT resources on firm performance. The mediating factor in the study by Liang, You, and Liu (2010) is the capability, internal and external, to leverage the resources. In this data-based research, participants also perceive data as an indirect factor on firm-performance: Data on its own cannot enable an improved positioning, however, data access will improve processes which then strengthens the firm performance. The code 'New Entrants' has shown that the resource data alone is not considered as an adequate response to the threat of new entrants. The following example, contributed by Interviewee A1 will illustrate why data can be an enabling factor, but not a decisive factor.

The company Uber is a classic example of a ‘digital native’. Uber, the app-based that matches drivers with customers that request a ride, is programmed on an algorithm that links the closest possible driver to a consumer. The pricing of the ride is dependent on market conditions: Facilitated by the access to Big Data, Uber adjusts the pricing to account for the customer’s willingness to pay in times of high demand. Real-time data enables the pricing strategy to reflect the true market of supply and demand (Cohen, Hahn, Hall, Levitt, & Metcalfe, 2016). Uber is, therefore, a truly data-driven company. In addition, Uber Freight is currently trying to enter the German market for cargo and parcel delivery, thus challenging the current market situation (Uber, n.d.). In anticipation of the change, interviewee A1 gave the example of MyWays, a DHL start-up that mirrors what Uber is for human transportation for parcel delivery. It was a crowd-sourced delivery provider, engaging people on their daily work routines to collect parcels on the way. Employees could participate in the delivery service in addition to their regular job. As people were on their commuting way to work, they could collect parcels and distribute them on their path (Dablanc et al., 2017). However, the venture was not feasible and was shut down after a 9 months trial period (DHL, 2013). Interviewee A1 remarked it was not Big Data that failed the project, but human and ethical problems that hindered successful delivery. For once, it was difficult to estimate legal consequences for private people in the case the parcel was lost or damaged, secondly, couriers prioritized their work over the punctual delivery of a parcel if there was traffic. Lastly, couriers could not make any scale of economies like logistics provider. The professionals distribute multiple parcels at the same time and can thereby offer a low price, regardless of the location in the country. Private people received only a small remuneration, regardless of the distance. This example shows that there are problems that cannot be solved by data, even though there is enough access to data and there are best intentions to fight new entrants. To this point, Uber has not found a solution to the personal problem either (Interviewee A1).

4.4 Codes for Sub-Question 4

What are the limitations of using data monetization to innovate the business model?

4.4.1 Data Monetization and Privacy

Results

The code ‘Data Monetization’ considers the implications of selling data and thereby changing the whole business model. As most participants who were confronted with the idea associated privacy issues with the topic, the code ‘Privacy’ was inductively added in this context. Deriving the data monetization code deductively, there is research regarding the topic: Najjar and Kettinger (2013) suggest that selling data as an asset to other parties is called data monetization and is usually in exchange for a monetary value. The rise of Big Data is facilitating the opportunities to sell data files on a high frequency. Engaging in data monetization can represent a shift in the whole business model (Najjar & Kettinger, 2013). Woerner and Wixom (2015) identified that companies engage in data monetization in three ways, namely selling, bartering, and wrapping. Selling is a classical activity, exchanging an information offer for monetary assets. Bartering on the hand is associated with a trade, the data asset in exchange for a favor, service or deal. Lastly, wrapping means that a piece of information is attached to a product or service: The authors provide the example of United Parcel Service, a logistics provider delivering parcels to customers. The provider communicates tracking information, for example to a retailer. The retailer can thus improve the offering to customers. Therefore, there are three categories linked to the topic of data monetization. Being confronted with the topic of data monetization, many participants emphasized the importance of privacy regulations in data management. Nine responses were collected for this code, and three of the participants provided examples of data monetization in their industries: In total, there were four examples, one categorized among data selling and three among data bartering.

Analysis and Examples

Creating a service or product around data is called ‘data as a service’ because the data is of unique value. Interviewee F1 states that there is a high level of work required to transform the data into something tangible, and worth selling. At the same time, a quote of hers might cause room for speculation that data selling is supported more in some countries than in others: ‘‘Meaning you take your data, apply some analytics and give them back as a service. This is a typical way how companies make money with their data, especially in the U.S!’’(Interviewee F1). As mentioned in the analyses, participants regard privacy as a crucial factor in the decision whether to engage in data selling or not. Interviewee F7 estimates that privacy regulations as the GDPR (General Data Protection Regulation) in Europe limit the implementation of data monetization. His example from the U.S. is regarding data bartering: Drawing from insights in the telecommunications industry, a company engaged in influencer analysis. By analyzing a network of people who were constantly calling each other, main influencers could be crystallized. The company submitted the research so that the telecommunications provider could target the influencer strategically. Due to Interviewee F7, this kind of data exploitation is restricted in Europe.

At the same time, Interviewee A1 reports about a marketing effort, in which customers are approached depending on their characteristics (Siegfried Vögel Institute, n.d.). Companies, using print media to approach customers, submit different offerings based on the address fields of their clients. If the customer address field entails a ‘doctor’ title, it is assumed that the purchasing power is higher and therefore a differentiated offering is provided (Interviewee A1). This method is currently conducted in Europe, which triggers the question of how far the GDPR is limiting data monetizing really.

The last example from a business division in China shows an example of data bartering. Using own generated data and open data, for example by the UNO, a logistics provider analyses the flow of goods, and how they are delivered. Based on this knowledge, the logistics provider approached local communes to build an industrial park and suggests an optimal location to create a site. If the communes decided to build the park, the logistics provider would claim a part of the property to base its delivery hub or to sell the property part at a later stage (Interviewee A1).

A research that is considering the synergies of data and business models must not neglect the concept of data monetization, as it a related topic. Increasing the utilization of assets appears to be an intriguing concept because the data as a resource is harnessed more than once. A limiting factor of the implication is privacy regulations, which are stronger in some countries than in others.

4.5 Codes for Sub-Question 5

To what extent can data enable business model innovation and what are current examples?

Recording how data can create a new business model in the previous question, this section tries to deductively answer in which other variations data can trigger innovation in business models. It will start with a comparison of *value creation*, *value delivery*, and *value capture*. The result and analysis sections conclude with examples, in which the whole business model was innovated through means of data. The upcoming categories all belong to business model innovation but are presented as their own codes for clarification reasons.

Results

In sub-question three, among others, the power to improve either costs or differentiation by data was analyzed. In this question the focus lies upon real innovation, meaning a fundamental change within the business model (Foss & Saebi, 2017). In total, 38 responses were received and clustered among *value creation*, *value delivery,* and *value capture*. Additionally, there were responses in which all dimensions changed, which were then grouped in a separate category: complete business model innovation (BMI). Figure 6 provides an overview of the frequencies of responses. Most examples are directed towards value capturing, thus changing an internal part of the company.

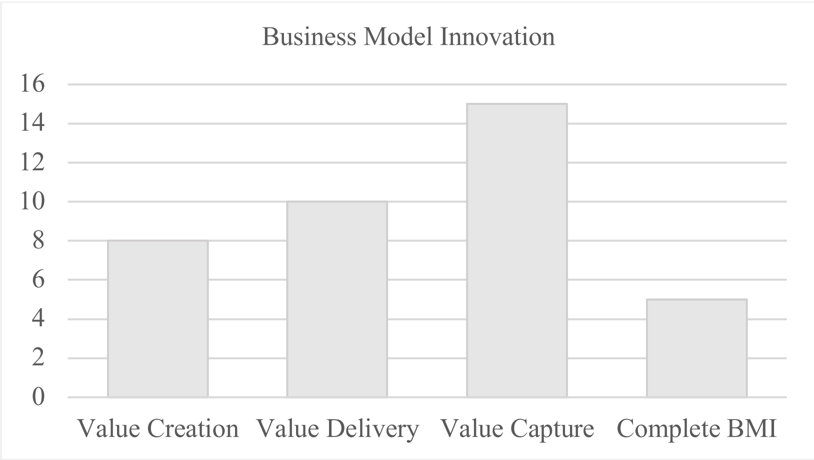

Figure 6: Split of Business Model Innovation enabled by Data

Analysis

4.5.1 Value Creation

The first dimension, *value creation*, elaborates on the benefits for consumers. Managers can learn about customers when leveraging data and develop innovative solutions: Combining material data and customer insights on a very granular level can support managers in creating a product or a service that is completely aimed at customer preference (Interviewee F6). Generating a rich customer experience, providers can provide tailor-made solutions with a high level of customization (Interviewee B1, F5). A degree of customization is also provided through a delivery service, who notifies the receiver at which time the parcel will be delivered. The information is based on Big Data, including the traffic and the route the courier will take (Interviewee A1). Last, there is an additional value generated through transparency in processes: Interviewee B1 aims to provide as much clarity about data as possible: The customer should know and consent what his data is used for. Open communication is crucial to keep the customer's trust. If successful, the company can create a data-enabled solution for the customer exactly when he needs it. Considering the code 'Cost/ Differentiation', innovation in *value creation* must be set apart from incremental changes as they are explained in the preceding code. Instead, tailor-made solutions provide customers with innovative solutions. Summarizing, value creation can be facilitated through data, especially since Big Data can provide insights about clients that will lead to customization opportunities. Big Data gives companies the option to identify similar customer groups demanding a specific feature - introducing the customization feature can lead to an advantage since it differentiates the offering from alternatives.

4.5.2 Value Delivery

The second category in the business model innovation context is *value delivery*: It describes the way customers are involved in the transaction of a good or service. A basic example of how data can shape the value delivery is by cross-selling or up-selling opportunities. Managers are assured by data, how the sales of products are connected and can thus change the offering, even though the products themselves stay the same (Interviewee F6). Marketing expenses are appropriated to the best fitting customer segments, which can be analyzed through Big Data (Interviewee F7). Even in a B2B environment, the value delivery can be innovated: Through better predictions and systems, the offering can be perfected as the customer will receive the product volume they need, with less surplus or shortage (Interviewee C1). Lastly, the delivery route can be optimized by access to Big Data, as real-time data can provide the courier with a better route and decrease CO2 emissions at the same time (Interviewee A1). Concluding, data can trigger innovation in value delivery. To illustrate how companies already use data to impact the value delivery, two cases give evidence of this suggestion.

A – Value Delivery –Weather Example

This example was provided by Interviewee A1. Through the support of Big Data external influences can be mitigated. Internal processes, like planning, can be reengineered if external insecurities are diminished. A logistics provider, for instance, is strongly impacted by the weather. People are usually more inside than outside on a rainy day, hence the chances are higher that people cross off their to-do lists in the house, like the dispose of goods from the cellar. They might choose to sell items online on eBay, and, with a delay, there will be a higher stream of goods that is mailed, creating a higher workload for a logistics provider. Being able to incorporate this knowledge into the planning and attaching a specific volume to the trend can enhance the processes, for example through additional couriers or more staff at the delivery hubs. These functions will improve the delivery, as a customer receive their parcels without a delay and resource-efficient.

B – Value Delivery – Social Plastic Example

Through data mining, companies can detect consumer trends and act upon them, for example, there is a strong demand of customers for sustainable products. Interviewee D2 elaborated an initiative of in the FMCG industry in that regard: A provider adapted his packaging to recycled social plastic because he had identified the requirement using Big Data mining. The idea of recycled plastic is self-explanatory; however, social plastic is retrieved from beaches or oceans and people that collect the plastic bottles receive a remunerated for their efforts. By using recycled bottles, the producer changes the packing, whereas the product itself stays the same. Integrating the recycled plastic in the packaging is associated with a higher cost, meaning the provider wants to estimate the acceptance of social plastic at a higher cost first before he launches the product. Through Big Data, the producer receives insights among which target groups and through which delivery channels the new packaging will be adopted. Even though the packaging is changed in this example, the actual product remains the same, therefore this is an example of innovation through data in the value delivery.

4.5.3 Value Capture

The third category in the business model is *value capture*. All in all, this is the category in which most participants contributed examples of data-enabled innovation. This dimension considers internal changes. Some topics were already regarded in previous codes, for example, the concept of experience data. Interviewee F3 relates that experience data can even be a source of innovation, as it creates unprecedented opportunities: Knowing the root cause of internal problems can lead to initiatives that build processes to improve the situation, for instance, the development of a peaceful working environment. Another field of interest that has emerged through Big Data usage is the detection of fraud (Interviewee F4). Analyzing outliners based on Big Data will trigger an alarm so companies can shield their activities from external threats (Veeramachaneni, Arnaldo, Korrapati, Bassias, & Li, 2016). Another used case is vivid in the telecommunications industry: Tracking the location of users will provide guidance for telecommunication providers at which location a network distributor should be constructed. Having a clear estimation because of data access will optimize the location of the distributors so it can cover as much area as needed. More satisfied customers with access to the network will translate to a higher value capturing for businesses (Interviewee F7). Having already seen a diverse set of applications for data in value capturing, it is striking to see that seven out of the 15 responses for value capture revolve around automation. Interviewees emphasize that through Big Data, they receive a complete picture of information in an automatic way. Especially with financial considerations, an automated stream of data simplifies, for example, the reporting, accounting processes or risk assessment (Interviewee F6, D1, F7). Moreover, through a continuous stream of information, processes can be reengineered. Assimilating real-time data of materials in agriculture, growth rates can be investigated, and automated watering processes installed to respond to the plant's requirements (Interviewee F4). All things considered, data has multiple applications in value capturing, leading to innovative ideas. In this research, vale capture obtains the highest count in business model innovation through data, with special attention on automated processes along the value chain. In the following, examples illustrate the impact on value capture.

C –Value Capture – Accounting Example

This example from the telecommunications industry was provided by Interviewee F7: The accounting standards for telecommunication providers were changed and thereby created a new set of regulations for the companies. Before the imposed accounting change, customers could purchase a two-year contract together with a smartphone and the costs for the phone were accounted at the time of the purchase. The revenue stream was considered in full at one point in time. Demanding a consistent distribution of revenue, the new standard requested the provider to allocate the amount evenly over the two-year period, forcing companies to change their approach. Leveraging Big Data was crucial to separate all existing contracts and to load them into the system in a compliant way because otherwise, the providers would not have known which amounts required balancing. The systematic shift represented a high additional workload for providers, but they realized the opportunity of streamlining the process: Attaching a value to customers, target groups could be clustered realistically, and profitable consumers could be differentiated from costly. The accuracy in information could be used for other projects, too, for example for marketing initiatives. Turing a threat into an opportunity, in this example, Big Data played a crucial role to reengineer the accountancy process and thereby in the value capture.

D – Value Capture – Automation Example

In the result section, a claim was made that most examples from participants about data in value capture were aimed at automation, the following example will provide evidence of this statement. An example of automation from the FMCG industry was suggested by Interviewee F5. To leverage global retail data, the consumer goods producer 'Beiersdorf' developed a tool that would allow managers to source information in a standardized way from all over the world. Before the introduction of the tool, a third party provided suggestions about the market, leveraging the information of the company. Seizing power over the own supply chain, this task was now in-sourced. The marketing analytics became a central part of the processes of the company because all information streams were centralized to this department and through the newly integrated tool. A user-friendly customer-face facilitated the success of the initiative (vom Brocke, Fay, Böhm, & Haltenhof, 2017). A similar case is suggested by Interviewee D2, in which the development of a bot created automation: To secure production and material flow, a bot was trained, based on real-time data, to track stocks in all globally dispersed production facilities. By means of a feature, the bot was capable to consider the facilities' planning schedules and confirmed delivery dates to create an accurate picture of available materials. If material runs short in one production, the bot triggers an automated alarm and suggests whether the volume can be provided from another facility as close as possible. The bot leveraged real-time data to achieve optimal capacity utilization as it decreases material surplus and limits shortages in facilities.

4.5.4 Complete Business Model Innovation

This category, the complete business model innovation, represents the cornerstone of the analysis as it proves that data has the potential to impact all dimensions of the business model at once. In a previous code, the technique of data monetization was already discussed, however, the following two examples will show that businesses do not necessarily need to sell their data to innovate the whole business model.

E – Complete Business Model Innovation – Synergy Example

A lot of experience in the telecommunications industry enabled interviewee F7 to contribute this example of a provider, who responded to a threat with a business model shift. Many telecommunication providers had to adjust their offering because of changing market conditions: In the past, people were billed on conversation data - the more they called people, the more SMS they send, the more they had to pay at the end of the month. With the rise of mobile data on mobile phones, the billing process became more complicated, as the providers were facing issues with massive amounts of customer data, which was difficult to process. Introducing flat rates, the value creation for customers experienced a shift, as customers were billed a fixed amount, regardless of the number of calls or mobile data usage. At the same time, the fixed costs for the providers remained the same so they had to reconsider their value capture in order to stay competitive. Retrieving additional revenue, providers engaged in cross-selling opportunities with other service providers. For example, the provider complemented his offering with an abonnement from a video streaming service in one package deal. The value delivery for the customer was adapted as he would receive two offers in one, even though the services stayed the same. Reconsidering the value capture, the telecommunications provider was later reimbursed by the video streaming service provider because customers were more likely to continue the abonnement and stay loyal. Hence, revenue for the telecommunications provider would now come from a different source but was enabled by information about customers. With this shift, the two service providers created a synergy by adjusting the complete business model.

F – Complete Business Model Innovation – Compressor Example

This last example concerns a producer of compressors in a B2B environment and was provided by interviewee F5: A manufacturer was producing compressors for construction sites. To collect real-time data about their compressors, the company decided to integrate sensors in their products to check the compressor's valves. Leveraging process data about the valves, the producer created insights about his valves, and which were causing problems. The sensors allowed him to organize maintenance for the components in the right way, as the sensor gave evidence which part of the valves was damaged. Facilitating the value of the data objects, the manufacturer developed a tool that would compare the current characteristics, like the temperature in the valve, with historic information to see whether the current manufacturing process would lead to a problem. Applying predictive maintenance, the provider was able to repair minor damages before an incident happened at a customer's construction site. Realizing the knowledge, the company had gathered about their compressors, the provider decided to build their business model around data. Instead of selling their machines, they switched their offering into selling 'hot air': they no longer sold compressors, but instead only the service the customers required. Charging only the usage of the machines, the customers did no longer have to consider maintenance expenses or troubles with down-time. The compressors stayed in possession of the provider, who would maintain the whole machinery and could thereby guarantee an excellent service level.

5. Propositions and Conclusions

In the following, propositions are formulated to evaluate how data and data-driven decisions can lead to business model innovation. The propositions are based on the statements given by participants of this study and evaluation that was given in the previous chapter. Answering the sub-questions, the definition for overarching research question was evolved piece by piece.

5.1 Propositions for Sub-Question 1

The first sub-question to this research is the following item: *Which hurdles do companies have to overcome when integrating data in their decision making?* Considering the underlying assumption, it is worth mentioning that at the time of the study not all participants were working with Big Data. Nevertheless, most of the participants were experiencing issues with data management, since they were able to identify hurdles and obstacles in integrating data in their decision making.

1. Participants do not find any deficiencies in the capabilities of data scientists suggesting that there are no shortcomings in the skills that are required. **Personnel that is hired for data analytics is accepted in the workforce.**
2. There are only a few remarks regarding privacy issues in the integration of data in decision making. Also, data access does not appear to be a major problem in data management, indicating that **neither data privacy issues nor the access to data represents a hurdle.** An explanation for this circumstance might be insufficient knowledge about data opportunities.
3. Even though data technology has evolved strongly over the past years, there is still some concern about the right storage and processing of data. One might argue that **systems must become more user-friendly and simpler to respond to demand.**
4. Both analytical and technical skills present major difficulties to participants of this study. **Identifying eligible data elements is a difficulty for managers**, consequently, they must develop a strategy to priorities data requirements. Simultaneously, **managers feel limited in their decision making through technological capabilities**. Often, their technology expectations are not fulfilled because they do not have the appropriate software.
5. The single most critical problem with Big Data appears to be a cultural one: **People struggle with too little acceptance and awareness for their work effort** in data management.

Analytical issues, technical problems, and a lack of sufficient support are the most prominent hurdles that managers have when handling data. As the last cultural category has not yet been included in the literature, it is this research's recommendation to do so and to investigate the severity of the relationship.

5.2 Propositions for Sub-Question 2

The second question to this research is the transition from problems with data to implementing data in the decision making: *How can companies prioritize their efforts to create a data strategy?* The answer to this question is a stream of recommendation. Receiving the highest response rate, top management should consider the suggestions by participants, as they have a vision for their company and want to be engaged in strategic decisions.

1. Encountering the analytical challenge, the **activity to collect and process data has to be conducted with a clear strategy and purpose** in mind of what that the data is supposed to facilitate.
2. Across the business, data should be named, stored and **treated consistently** to derive the greatest benefit from the resource.
3. It is crucial to link data to a monetary value. **Data valuation and commitment of the principal is necessary to account for the work** that is invested in the collection, the processing, and interpretation of data.
4. Creating **synergies between companies** is one way to entrust some of the workload to a business partner, which has more efficacy in data management. This way the focal company can continue to focus on its core activities.
5. Considering the discrepancy within the opinions of participants of this, there is no tendency regarding a most important data source. Nevertheless, **companies are advised to first study internal data assets and develop an understanding** before they extend their data analytics with external information.
6. While the investment focus in Big Data technology lies upon the technical side, **human resources are indispensable** for many tasks that involve creativity or require judgment. Hence managers must allocate sufficient resources in both, advanced systems and educated staff.
7. Diving into a new type of unstructured data, **experience data** can provide extensive insights about customers, but also about **internal processes** or **stakeholder management**.

While external data sources might promise comprehension about customer behavior, they should not be regarded as a universal solution to problems. Instead, companies should investigate the information that customers already share and extend their efforts in data management to internal processes.

5.3 Propositions for Sub-Question 3

Having understood the problems and measures to improve data integration, this section will evaluate the benefits of in the third sub-question: *In which areas can well-established companies harness the power of data?* The statements of participants are considered as benchmarks to assess the capabilities and limitations of data.

1. The **appropriate technology is a crucial factor to expedite data integration**, however, it is complicated to define technological requirements.
2. Data can aid to make **better informed decisions and create knowledge about customers**.
3. Operations can be improved through Big Data, as it **concludes about potential cost savings**.
4. Comparing the utilization of data to reduce costs or to create novel offerings, there is a clear **emphasis to use data for innovative purposes**.
5. Even though Big Data is considered more in decision-making processes, **data alone cannot be employed as a shield against competitors**. Instead, companies should strengthen their core activities with data to create a strong position on the market.

There is a clear focus on differentiation potential with data integration, even more than on cost advantage. At the same time, an increased focus on innovation will provide a better position against threats, as the companies' abilities are strengthened from within.

5.4 Propositions for Sub-Question 4

While the previous question has already defined data potential to incrementally improve value offering, the answer to the fourth sub-question is diving deeper into the business model: What are the limitations of using data monetization to innovate the business model?
Data monetization is a path to reconstruct the whole business model into an innovative version.

1. Data monetization impacts **all three dimensions** of the business model.
2. Data privacy regulation is the strongest factor in manager's hesitance to engage in data monetization. Leveraging the data potential in a way other than direct selling, **managers engage in data bartering**.
3. Since the data privacy regulations in Europe are strict, there are few employments of data monetization in the area. The regulations do not extend to the same level in the U.S., suggesting that data monetization is **conducted more in the U.S. than in European countries**.

In the concept of data monetization, there are different intensities and managers engage in some more than in others because of data privacy. Identifying country differences, company agents must learn about the regulations first before they implement data monetization. There are clear benefits to data monetization, but companies must carefully assess the preconditions because if they don' they might face legal trouble or lose customer's trust.

5.5 Propositions for Sub-Question 5

The final sub-question is the peak of this thesis as it combines all elements previously mentioned elements as it considers the impact of data on business model innovation: *To what extent can data enable business model innovation and what are current examples?*

1. Data has the potential **to stimulate innovation in all dimensions** of the business model.
2. The impact of data on value creation is the potential to create an innovate product or service for customers, often by **developing tailor-made or customized solutions**.
3. Big Data can positively impact the value delivery, **as it provides new opportunities to transmit the product or service without impacting the actual offering**.
4. Data is **mostly used to reengineer internal structures**, especially by means of automating processes. The dimension of value capture experiences the highest number of change possibilities enabled by data.
5. Companies can create innovation throughout their whole business model by reviewing the **involved stakeholders and partnerships** and their respective relationships to data. Also, companies must be courageous to **realize the value of their data and act upon it**.

Data can enable business model innovation to the full extent, as there are application examples in all business model dimensions. This research has given several examples in which companies were able to identify opportunities and translate data-driven insights into their strategy.

5.6 Conclusion

Analyzing the impact of Big Data on businesses, one could observe that there are still insecurities among managers on how to handle data flow. At the same time, people are eager to change this situation and turn data availability into an opportunity. Starting with incremental changes, data can be used to improve processes by decreasing costs or suggesting options for differentiation. Considering data as a resource, managers can increase resource utilization by selling data after its initial use. However, privacy regulations restrict the implementation of data monetization, which makes the option less powerful. Coming back to the research question, namely, **how data and data-driven decisions lead to business model innovation**, there are three success factors that enable the data integration on all business model dimensions. The first aspect is realizing the value of internal data: Understanding own processes and internal operations through data analyses can path the way for business model innovation, as managers become aware of opportunities and correlations. Secondly, companies should be courageous to investigate new types of data since experience data will provide observations about internal relationships as well as external conclusions. A third consideration is the implications of automation processes. Even though there are cultural obstacles that should be considered, continuous updates can contribute to the creation of an accurate business perspective.

6. Limitations and Future Work

6.1 Methodological and Contextual Shortcomings

The propositions were derived from statements of the participants of this study, a sample that was selected purposively. Accounting for a small sample size, the suggestions are not representative across industries but merely reflect a tendency. As the goal of this thesis was to test grounded theory and develop propositions, nonetheless, the aim was achieved. Another shortcoming in the methodology is the interview conduction: Despite a cautious line of questioning and exclusion of an overly biased interview, a certain level of guidance throughout the interview could have biased the discussion to some degree. Next to methodological limitations, there are two limitations on a content level. First, the privacy regulations about data monetization have not been investigated thoroughly for the involved countries due to its extensive nature and the resource scarcity of the researcher. Second, all statements were associated exclusively and for one code only, which means that if data was impacting two dimensions, such as *value creation* and *value capture*, it was associated with either or, not both. The consistent behavior in that regard was conducted to increase transparency. Future studies can investigate the impact on multiple dimensions and account for correlation.

6.2 Prospective Research

As this qualitative research provides theoretical propositions, the fifth chapter is intended as suggestions for future research in a quantitative way to estimate the intensity of the relationships. Next to the propositions, there are contextual elements that demand further investigation. Following a chronological approach, the concept of business model patterns is an interesting approach to transform business models into something more tangible. Research to explore which pattern is most suitable for Big Data involvement is an intriguing topic. Moreover, this research elaborated on data valuation to associate a significance with a data element, which can be extended by the concept of data entropy. Currently, there are few disclosed used case studies in the research field of data or information entropy. Measuring the probability of an event, the concept of data entropy associates a specific value with a data element and its influence on the event (Shannon, 1948). Liang, Shi, Li, and Wierman (2006) use the topic in uncertainty management and quantitatively assess the significance of data elements. An understanding of the underlying calculations could give insight into the analysis of ‘Critical Data Elements’ along with the most prominent sources: This way, researchers could give a substantiated suggestion from which sources companies will draw most benefits from data. Lastly, the legal consequences of engaging in data monetization have not been presented in detail in this research, however, a guide to implement the concept within its legal boundaries could be interesting for companies of any kind.

7. Appendices

7.1 Semi- Structured Interview Guide

Introduction of the interviewer and the topic.

Part A

1. Who are you and what is your role at your company?

Part B

2. Do you work with Big Data? If yes, did you change your working behavior due to the access to it? If no, what are the reasons that hinder you from doing so?

3. Do you think your company already uses Big Data efficiently and if yes, in which way?

4. Did the product/service offering to customers, the pricing model or the channel to communicate with the eco-system change due to the access to it?

Part C

5. In which areas do you currently invest in data?

6. What are the most important data elements and where do they come from?

Part D

7. Do you provide data insights or knowledge to other stakeholders? Are you able to translate files for data monetization?

8. Is your market share challenged by the new entrances, like digital natives, and if yes, how do you respond to the threat?

Part E

9. Are there any other points you would like to stress out?

Thank you.

7.2 Frequency Overview of Participants’ Responses

Alias	Business Model Innovation	Business Model\Value Capture	Business Model\Value Creation	Business Model\Value Delivery	Cost\Differentiation	Critical Data Elements	Data Monetization	Data Strategy	Experience Data	Investments in Big Data	New Entrants	Privacy	Working with Big Data	Working with Big Data\Changes	Working with Big Data\Problems	Total
A1			1	3	2	2	4	2		4	3	2	1	6	5	**35**
B1			3		3	2		11		2	3	2	1		5	**32**
C1				1	3	1		1		1	1	1	1	1	6	**17**
D1		2				1		4	1				1	2	3	**14**
D2		2		3		2	1			2	1		1	3	4	**19**
E1						2		1					1		2	**6**
F1					1	1	3	18		1		2	1	1	5	**33**
F2						2		4	1		1		1			**9**
F3		1			2	1		2	5	3	1		1	7	1	**24**
F4		2	2		1			6	1	1		1	1	1	1	**17**
F5	2	3	1	1	1	4		7	1	2			1	2	6	**31**
F6		1	1	1	5	3		8	1	2			1		9	**32**
F7	3	4		1	1	2	1	3		3	1	5	1	4	2	**31**
Total	**5**	**15**	**8**	**10**	**19**	**23**	**9**	**67**	**10**	**21**	**11**	**13**	**13**	**27**	**49**	**300**

Figure 7: Total Frequency Overview

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