Data-driven decision-making in the innovation process of SMEs

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Abstract

The increase in the amount of data which is collected every day has led to an opportunity for organizations: data-driven decision-making. Data-driven decision-making can offer various advantages to companies of all sizes, such as an improvement of the market value of a company. Also the innovation process can be improved by using data as a decision support. Previous studies about data-driven decision-making and about the innovation process focused mainly on large organizations. However, the usage of data analytics is lagging behind at SMEs. Therefore, this study aims to investigate to what extent SMEs use data-driven decision-making in their innovation process. Qualitative research has been conducted including cases of nine SMEs operating in different industries in order to elaborate SMEs' perception of data-driven decision-making and the extent to which they use it in their innovation process. The results indicate that the participating SMEs have a basic understanding of the term data-driven decision-making. However, a more comprehensive definition is necessary so that SMEs can fully understand the concept and how it can add value to their organization. Furthermore, it is argued that data-driven decision-making comes along with benefits as well as challenges, which are acknowledged by the participating SMEs. Moreover, the extent to which data-driven decision-making is used in the innovation process depends on the organization but also on the stage of the innovation process. Finally, the research shows that there is room for improvement regarding the data usage in the innovation process of SMEs. This study highlights multiple possibilities which offer potential for the future.

Key words
data-driven decision-making, innovation process, data-driven innovation, digital innovation, SME, Business Analytics

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1 Introduction

Huge amounts of data are collected every day. Nevertheless, “data is meaningless unless it helps make decisions” (Meyer, McGuire, Masri, & Shaikh, 2013). It has been proven that companies who apply data-driven decision-making are more successful than the ones that do not (McAfee & Brynjolfsson, 2012). Data-driven decision-making is, for instance, correlated with an improvement in the return on assets, return on equity, and the market value of a company (Provost & Fawcett, 2013). However, different decisions require different types of data and analytics (Breuer, Moulton, & Turtle, 2013). Therefore, it is necessary for a company to understand which data is helpful and how to handle the data.

In order to be competitive, a company needs to innovate continuously (Gubbins & Dooley, 2014; Standing & Kiniti, 2011). The increased amount of data has a significant impact on the innovation process of a company (Trabucchi & Buganza, 2019). This is as organizations can use data-driven decision-making to improve their innovation process (Sedera, Lokuge, Grover, Sarker, & Sarker, 2016). The usage of data in the innovation process is, however, not only crucial for technology companies but for every industry and sector (Tumbas, Berente, & vom Brocke, 2018; Nambisan, 2018). It offers advantages to companies, such as the possibility to gain an understanding of the customers’ needs, which makes it possible to adapt offerings accordingly (Urbinati, Bogers, Chiesa, & Frattini, 2019).

Approximately 99 percent of the companies in the EU are small- or medium-sized enterprises (SME) (European Commission, 2015). SMEs are companies which have less than 250 employees and a turnover of less than 50 million or balance sheet total of less than 43 million (European Commission, 2015). An efficient innovation process of SMEs is “critical for the European economy because of the large representation of the SME sector” (Coleman, Göb, Manco, & Pievatolo, 2016). Innovation is the most important characteristic for SMEs to be successful, to achieve a stronger growth and a high market share, and to be more profitable (Tidd & Bessant, 2009). Nonetheless, it seems like data-driven decision-making is mostly used by larger multinational companies (Reijkumar, Aswathy Asokan, & Sreedharan, 2018). This is since the usage of data analytics is lagging behind at SMEs (Parra & Tort-Martorell, 2016). Furthermore, even companies that see the benefits of the data usage experience problems with getting started (Reijkumar et al., 2018).

Several studies have been performed about data-driven decision-making. However, most of these studies focused on large organizations (e.g. Brynjolfsson, Hitt, & Kim, 2011; Brynjolfsson & McElheran, 2016; Troisi, Majone, Grimaldi, & Loia, 2019). Even though there are also studies on how technology can be used to support the innovation process, there are no studies examining how SMEs use data-driven decision-making in the innovation process. This study aims to investigate how data-driven decision-making can be used in the different phases of the innovation process and to what extent SMEs make use of that. Therefore, this study is an extension to the current literature on data-driven decision-making and to the literature on the innovation management of SMEs. It provides insights into the perception of SMEs on data-driven decision-making and how SMEs use data in order to make decisions during the innovation process. This shows to what extent the innovations of SMEs are based on data.

For the management of SMEs, it provides interesting insights as well. First, the literature review on data-driven decisions in the innovation process can help managers to gain knowledge about how data can support the decisions in the various phases of the innovation process. Secondly, it is interesting to see how other companies of the same size manage their innovation process and which decisions are supported by data.

In order to elaborate the usage of data-driven decision-making at SMEs in their innovation process, interviews are conducted to provide insights into the current practices of SMEs regarding the decision-making in the innovation process. Through this, the following research question should be answered: *To what extent do Dutch SMEs use data-driven decision-making* *in their innovation process?* For this, answering the following sub questions is necessary: *1. How do SMEs perceive data-driven decision-making?* and *2. To what extent do SMEs use data-driven decision-making in the various stages of the innovation process?* By answering these two questions, it will become clear what the understanding of data-driven decision-making is and which challenges and benefits SMEs perceive. This also shows the motivations for data-driven decision-making and what might be holding SMEs back from implementing it to a higher extent. It can be expected that this influences the extent to which SMEs use data-driven decision-making in the innovation process. Next to this, it will be elaborated how the decisions in the innovation process are made. Through this it will be possible to see to what extent these decisions are based on data.

The structure of this study is as follows. First, the theory chapter will define what data-driven decision-making is, how the innovation process looks like, and which decisions need to be made during this process. Next to this, it also provides examples of how companies can make these decisions with the aid of data. Secondly, the methodology, which is used for the analysis, is described. Thirdly, results are presented which includes the analysis of the interviews. This section should give insights on how SMEs perceive data-driven decision-making and on how the decisions in the innovation process are made. Lastly, a discussion is given, including theoretical and practical implications, limitations, directions for future research, and the conclusion.

2 Theory

In order to define the necessary terms for this paper, a literature review has been conducted. Information on this can be found in Appendix 1.

2.1 Data-Driven Decision-Making

Often, managers make decisions based on incomplete information, experience, or intuition (Baba & HakemZadeh, 2012; McAfee & Brynjolfsson, 2012). However, in order to make reasonable decisions, managers should rely on evidence (Baba & HakemZadeh, 2012). This evidence can be achieved by relying on data. The amount of data is growing continuously which is mainly caused by the internet (Delen & Zolbanin, 2018; Wielki, 2015). The internet has led organizations to use transactional databases for which they collect a huge amount of data. Next to this, the multimedia usage is growing and the development of the "Internet of Things" makes physical objects or devices collect and share data "with each other without any human interference" (Wielki, 2015, p. 193). Moreover, the growing usage of social media increases the amount of data as well. The different kind of data can be processed in order to provide value to organizations (Frazzetto, Nielsen, Pedersen, & Šikšnys, 2019; Kolomvatsos & Hadjiefthymiades, 2017) By doing so, the data can be used to improve the decision-making.

Data-driven decision-making can be defined as follows. It refers to making decisions which are not purely based on intuition or experience but on insights from verifiable data analysis (Cao, Duan, & Li, 2015; Provost & Fawcett, 2013; Reijkumar et al., 2018). In the process of data-driven decision-making, historical data is used to create new knowledge on which decisions are based (Lu et al., 2019). Moreover, organizations can also use a combination of experience, intuition, and data-driven decision-making (Provost & Fawcett, 2013). Especially in unstructured problem situations, data-driven decision-making can be extremely helpful to help solving a complex problem (Lu et al., 2019).

Data-driven decision-making is part of business analytics. "The key component of analytics is the process in which a set of various techniques transform data into value" (Delen & Zolbanin, 2018, p. 188). This value can be the knowledge necessary to make decisions and drive actions (Gürdür, El-khoury, & Törngren, 2019; Liberatore, Pollack-Johnson, & Heller Chain, 2017). For this process, specific methods can be used. These can be classified into four categories, which all provide different insights: descriptive, diagnostic, predictive, and prescriptive. First, descriptive analytics answers the question of what happened in the past or what is currently happening by collecting and summarizing historical data (Delen & Zolbanin, 2018; Frazzetto et al., 2018; Liberatore et al., 2017). For this, data visualization can be helpful for the identification of patterns and trends (Delen & Zolbanin, 2018; Frazzetto et al., 2019) Second, diagnostic analytics tries to elaborate the reason why something has happened (Delen & Zolbanin, 2018). It aims to find the underlying causes of problems by using for instance data mining or data visualization (Delen & Zolbanin, 2018). Thirdly, predictive analytics forecasts what might happen in the future (Delen & Zolbanin, 2018; Frazzetto et al., 2019; Liberatore et al., 2017). To do so, large amounts of historical data are used to create predictive models (Delen & Zolbanin, 2018). Fourthly, prescriptive analytics aims to answer what should be done by finding the best course of action (Delen & Zolbanin, 2018; Liberatore et al., 2017). It logically follows from the previous three categories since it is possible to determine which course of action one should follow when it is known what happened in the past, why it happened, and future predictions are available (Frazzetto et al., 2019). The optimal usage of the categories involves a combination and integration of all four concepts (Frazzetto et al., 2019). By combining the different methods, a holistic view can be created. Big data is often the basis for business analytics. Big data is characterized by three challenges: volume, velocity, and variety (Cao et al., 2015; Delen & Zolbanin, 2018; McAfee & Brynjolfsson, 2012; NewVantage Partners, 2012). Volume refers to the size of the data set. Velocity represents the speed of the data creation. Lastly, the complexity of different forms of data is referred to as variety. Nevertheless, big data also offers the opportunity to convert data from information to knowledge into action by an improved analytic capability (Delen & Zolbanin, 2018; NewVantage Partners, 2012).

There are various advantages of making use of data-driven decision-making. It can be said that data-driven decision-making leads to smarter and more effective decisions (Cao et al., 2015; McAfee & Brynjolfsson, 2012). Using data for the decision-making can serve as a competitive advantage – not only for online businesses but also for traditional ones (Liberatore et al., 2017; McAfee & Brynjolfsson, 2012; Reijkumar et al., 2018). "Companies in the top third of their industry in the use of data-driven decision making were, on average, 5% more productive and 6% more profitable than their competitors" (McAfee & Brynjolfsson, 2012, p. 6). This also stays true after controlling for multiple possible confounding factors (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013). Data-driven decision-making leads to an improved business performance with a higher profitability (Ross, Beath, & Quaadgras, 2013). According to Provost and Fawcett (2013), this includes a "higher return on assets, return on equity, asset utilization, and market value" (p. 53). Moreover, it can also be used to create new products and services for the customers based on their preferences (Cao et al., 2015). In general, data-driven decision-making can increase the speed and the flexibility of the decision-making in an organization (Cao et al., 2015). This is, for instance, because automating decisions based on data frees employees from making routine decisions (Ross et al., 2013). This in turn allows them to focus on other activities. In conclusion, making effective usage of data in the decision-making is a core competence to be successful (Reijkumar et al., 2018). This is due to the fact that it can improve both the efficiency and the effectiveness of the decision-making process in an organization.

However, data-driven decision-making comes along with challenges. There are cultural challenges in an organization when it comes to basing decisions on data (Gürdür et al., 2019; McAfee & Brynjolfsson, 2012). When introducing new technologies for the decision-making, the corporate culture needs to be addressed, as well, including the company values (Gürdür et al., 2019). Furthermore, there are privacy concerns which a company needs to consider (McAfee & Brynjolfsson, 2012). Besides, according to Reijkumar et al. (2018), the data quality and the analysis process are the main factors for a successful data-driven decision. Therefore, it needs to be ensured that the dataset is comprehensive and that the company is equipped with suitable tools to process the data (Gürdür et al., 2019; Long, 2018). Additionally, employees, who are in charge of making decisions, need to receive sufficient trainings in order to acquire the necessary skills (Ross et al., 2013). Moreover, the business processes need to be defined, which includes the existence of rules and regulations regarding data-driven decision-making (Cao et al., 2015; Gürdür et al., 2019). If these requirements are not met in an organization, data could be misinterpreted. A decision based on that can lead to a competitive disadvantage (McAfee & Brynjolfsson, 2012; Reijkumar et al., 2018).

To conclude, data-driven decision-making refers to decisions which are based on the analysis of data instead of experience or intuition. It is a part of business analytics and can be used by applying different methods of analysis: descriptive, diagnostic, predictive, and prescriptive analytics. Data-driven decision-making can lead to a competitive advantage and an improved business performance. Nevertheless, certain requirements need to be fulfilled in order to achieve these advantages, such as a skilled decision-maker who has the right tools.

2.2 Innovation

Innovation is a necessary part of every organization. It has been shown that the competitiveness of an organization relies on its innovation ability (Gubbins & Dooley, 2014; Standing & Kiniti, 2011). In consequence, it is necessary to define what innovation is. Innovation can be defined as an idea which is new to the organization pursuing it (Sedera et al., 2016; Standing & Kiniti, 2011). Thus, it does not need to be completely new in general - it can also be something that other organizations already did before. An innovation which is based on the improvement of already existing ideas is called exploitation (Love, Roper, & Bryson, 2011). Companies exploit and refine these existing ideas. When companies are searching for opportunities by developing new ideas, it is called exploration (Love et al., 2011). To create innovation, both exploitation and exploration, knowledge is a necessity (Tidd & Bessant, 2018). Diverse knowledge needs to be combined in order to create an innovation. This process is done under uncertainty since it is not known how the final innovation will look like and how to get to this final stage (Tidd & Bessant, 2018). Generally, innovation is referring to change in one of four areas: product innovation, process innovation, position innovation, or paradigm innovation (Tidd & Bessant, 2018).

The way of innovating has been changed in the last years. The usage of digital innovation has "transformed the ways and means of innovation in a wide swath of industries and sectors" (Nambisan, 2018, p. 104). More companies than ever make use of data in order to come up with more successful innovations (Agostini, Galati, & Gastaldi, 2019; Rindfleisch, O'Hern, & Sachdev, 2017). Consequently, it is not only crucial to technology organizations, but it also becomes more important to all other companies (Tumbas et al., 2018). Digital innovation can be defined as follows. A digital innovation is an innovation which is based on the usage of digital technology (Nambisan, Lyyntinen, Majchrzak, & Song, 2017; Yoo, Henfridsson, & Lyyntinen, 2010). This can be, for example, by acquiring, analyzing, and acting on consumer data (Rindfleisch et al., 2017; Yoo et al., 2010). Through this, an understanding of the customers' needs is enabled which makes it possible to adapt the offerings to those (Urbinati et al., 2019).

Innovation can be described as a continuous process which enables companies to grow (Love et al., 2011; Tidd & Bessant, 2018). Due to an increasing digitization, the different phases of the innovation process have become more overlapping (Nambisan et al., 2017). Besides, there is no specific process which is suitable for every type of project (Salerno, Gomes, Da Silva, Bagno, & Freitas, 2015). Nonetheless, for this paper the innovation process phases will be defined to provide a structure for the research. There are many innovation process models defined in the literature (e.g. Fichman, Dos Santos, & Zheng, 2014; Frankenberg, Weiblen, Csik, & Gassmann, 2013; Salerno et al., 2015; Standing & Kiniti, 2011; Tidd & Bessant, 2018). Frankenberg et al. (2013) emphasize that "at heart, however, the process models feature a set of common characteristics". Many researchers define it as a process which starts with the searching for innovation ideas – the idea generation – and continues with the selection of which innovation to pursue, the development of the idea, the actual implementation in the market, and possible changes after the launch (Eveleens, 2010). It is emphasized that it is important to continuously reflect on the innovation process itself in order to learn from it and to improve the process (Eveleens, 2010). For this paper, the innovation process will be defined according to the literature review on innovation process models by Eveleens (2010) with the following phases (Figure 1): idea generation, idea selection, development, launch, post-launch adaption,

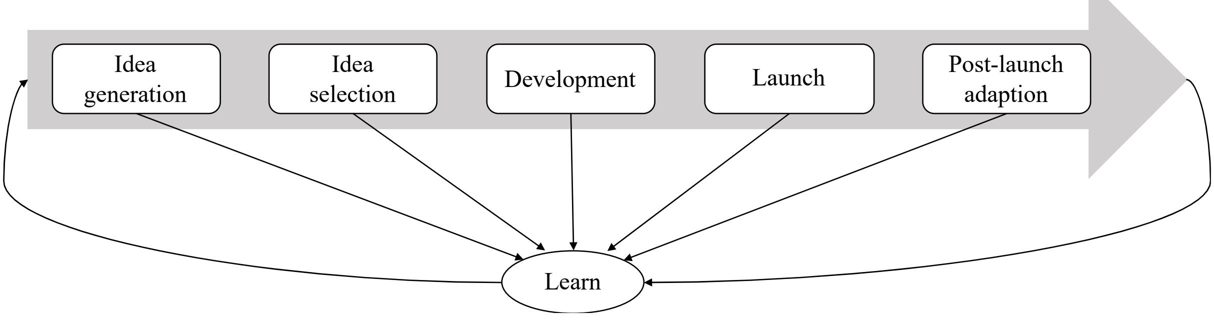

Figure 1. Innovation Process (adapted from Eveleen, 2010)

and learn. This process has been based on the review of various innovation process models (e.g. Cooper & Kleinschmidt, 1986; Jacobs & Snijders, 2008; Mulgan & Albury, 2003; Nooteboom, 2000; Rothwell, 1994; Tidd & Bessant, 2008; Verloop & Wissema, 2004). This process model has been chosen as it combines different models from the literature and includes the previously mentioned phases of an innovation process, including a learn phase to reflect on the process itself. Figure 1 shows the process.

The idea generation phase is about discovering opportunities in the environment. This contains of the search "to identify unfulfilled needs that provide the opportunity for potential innovations" (Gubbins & Dooley, 2014, p. 9). For this, the environment needs to be scanned for signals about threats and opportunities (Tidd & Bessant, 2018).

In the idea selection phase, an idea is chosen for further development. In order to be innovative, the idea selection is a crucial step. It has to be chosen to which of the identified signals, a company wants to react to (Tidd & Bessant, 2018). Therefore, it needs to be evaluated which ideas should be implemented by considering their "fit with the mission and values of an organization and ideas must also have commercial value" (Standing & Kiniti, 2011, p. 290). It should be an idea which is realistic and possible to implement (Sengupta & Dev, 2011) and which lets the organization develop in the best way (Tidd & Bessant, 2018). The decision is based on knowledge the company has (Gubbins & Dooley, 2014). A better-informed decision in this phase can lead to a higher change of success of the final innovation (Gubbins & Dooley, 2014).

The third phase consists of the development of the innovation. In this phase, it is important that the necessary knowledge and recourses are acquired through, for instance, R&D activities or through alliances (Love et al., 2011; Tidd & Bessant, 2018). Afterwards, the acquired knowledge has to be transformed into actual actions and output (Ganotakis & Love, 2012; Love et al., 2011). During this phase, prototypes are constructed of the future innovation and resources and structures are set up in order to make the innovation utilizable or producible (Standing & Kiniti, 2011).

In the fourth phase, the innovation is launched. This is the phase, in which the actual commercialization of the innovation takes place (Standing & Kiniti, 2011). In this phase, the marketing activities related to the innovation are prepared as well (Eveleens, 2010). The needs of the market have to be considered in order to enable the initial adoption of the innovation (Gubbins & Dooley, 2014).

The fifth phase consists of adapting the innovation in order to sustain it for the long term. This phase happens post launch (Eveleens, 2010). It can include a modification of the innovation (Tidd & Bessant, 2018) or a re-innovation (Eveleens, 2010) so that the acceptance of the users increases. For this, the innovation needs to be monitored since findings might be useful for adjustments (Sengupta & Dev, 2011).

The learn phase refers to the continuous learning throughout the innovation process. In every phase of the innovation process, there is the chance for the organization to learn from it (Tidd & Bessant, 2018). For this, it has to be analyzed and evaluated what is currently done in the innovation process (Mulgan & Albury, 2003). Adjusting the process based on what a company has learnt, can lead to an improvement in the management of the whole process (Tidd & Bessant, 2018).

During the innovation process various decisions need to be made. These decisions are different in each phase of the process (Klingebiel & Rammer, 2014). A simplified overview of decisions in the innovation process can be seen in Table 1.

In the search phase, the following decisions need to be made. First, a company needs to decide on strategic goals that should be reached within a specific time (Sengupta & Dev, 2011). Secondly, a company needs to decide for what they are searching – they can choose for new opportunities by improving something they currently already do or by developing something new (Tidd & Bessant, 2018). With this they decide what they might innovate. This can involve a product/service, the positioning, the process, or a paradigm innovation. Thirdly, "organizations pick up signals about innovation possibilities through exploring a particular 'selection environment'" (Tidd & Bessant, 2018, p.349). In order to do so, a company needs to decide where they want to search – they need to choose a search environment. Fourthly, the company needs to decide who is involved in the searching (Standing & Kiniti, 2011).

In the select phase, the company needs to make decisions to select opportunities the company wants to explore. The company thus has to decide which ideas from the search phase will be progressed and which not (Eveleens, 2010; Gubbins & Dooley, 2014). For this, two questions need to be answered: "Does the innovation we are considering help us reach the strategic goals we have set ourselves (for growth, market share, profit margin etc.)?" and "With the underlying competencies – do we know enough about this to pull it off (or if not do we have a clear idea of how we would get hold of and integrate such knowledge)?" (Tidd & Bessant, 2018, p. 364). Consequently, companies need to decide on how to answer these questions. This includes how they do the analysis and who is involved in this (Tidd & Bessant, 2018).

In the development phase, the following decisions need to be made. In order to acquire the necessary knowledge, it has to be decided which knowledge is necessary for the implementation of the specific innovation and how this knowledge can be gained (Tidd & Bessant, 2018). Afterwards, decisions need to be made to enable the execution of the implementation. In this stage, it needs to be decided how the actual outcome should look like. Therefore, decisions need to be made about the design of the innovation. Next to this, it also needs to be decided on a structure on how to implement the innovation, which can involve, for instance, the production process of a product or a definition of different steps in a process (Standing & Kiniti, 2011; Tidd & Bessant, 2018). After prototypes have been created, the company needs to decide if the innovation needs to be improved before the launch and if yes, how (Tidd & Bessant, 2018). For all of these decisions, it again needs to be decided who is responsible for each action.

Table 1: Decisions during the innovation process

Phase	Decision
Idea generation	Which strategic goals should be reached? What might be innovated? Where do we want to search for ideas? Who is involved in the searching?
Idea selection	Which ideas should be progressed and which not? How do we analyze the different ideas? Who is involved in the selection?
Develop	Which knowledge do we need for the innovation? How do we gain the necessary knowledge? How should the design of the innovation look like? How can the implementation be structured? Who is responsible for the execution?
Launch	How should the final innovation look like? How should we promote the innovation? How should we price the innovation? Where should we launch the innovation? When should we launch the innovation? Which objectives do we want to reach with this innovation?
Post-launch adaption	Does the innovation need to be adjusted?
Learn	Does the innovation process need to be changed?

In the launch phase of the implementation, the following decisions need to be made. It needs to be decided how the final innovation should look like (Tidd & Bessant, 2018). Next to this, decisions need to be made on the way the innovation should be launched (Tidd & Bessant, 2018). This includes decisions about the marketing of the innovation (Eveleens, 2010), for instance the place, the price, and the promotion, but also the timing of the launch. Furthermore, specific objectives have to be defined in order to be able to control the development (Tidd & Bessant, 2018).

In the post-launch adaption phase of the innovation process, the company needs to decide on how the innovation should be adjusted in order to increase the diffusion of the innovation and the acceptance of the customers high (Mulgan & Albury, 2003).

To learn from the innovation process, a decision has to be made. It needs to be decided whether something needs to be changed in the process based on previous projects (Mulgan & Albury, 2003; Tidd & Bessant, 2018). Based on this decision, the innovation process itself can be adjusted.

In conclusion, an innovation is an idea which is new to the person or organization pursuing it. In companies, innovation refers to change in one of four different areas: product innovation, process innovation, position innovation, or paradigm innovation. During the last years, the usage of digital technology during the innovation process has been increased. The innovation process goes from the search and selection of ideas to the development and implementation of the innovation. During this process, it is crucial for organizations to learn in order to improve the process itself. In the course of the innovation process, various decisions have to be made by an organization.

2.3 Data-driven decisions in the innovation process

In this sub chapter, it is shown which decisions in the innovation process might be based on data and examples are given on how to use data-driven decision-making in the innovation process. An overview of which decisions might be based on data can be found in Table 2 at the end of this chapter.

2.3.1 Idea Generation Phase

It has been found that searching for innovative ideas should be a frequent activity for each organization (O'Brien, 2020). To decide what a company might need to innovate Tidd and Bessant (2018) suggest spotting trends, apply market forecasting by extrapolation or scenario writing, compare against competitors, and also consider mistakes and failures from the past. Especially small companies can benefit from participation of external parties, such as consumers or suppliers, in the ideation stage since they can compensate for a lack of resources compared to larger companies (Chang & Taylor, 2016). The participation can be active or passive. A passive participation consists of the analysis of existing data from users or customers (Stockstrom, Goduscheit, Lüthje, & Jørgensen, 2016). During an active participation, data is created with the aid of customers specifically for the purpose of the innovation.

In passive participation, existing data is analyzed. For instance, social media, websites, and chat rooms offer customer data, which can be helpful for an organization (Muninger, Hammedi, & Mahr, 2019; Tidd & Bessant, 2018). Next to this, data from other externals, such as suppliers or competitors might be analyzed. For instance, patents from externals can be analyzed in order to find valuable ideas (Woo, Yeom, & Lee, 2019). A considerable amount of this data is in textual unstructured form (Chen, Chiang, & Storey, 2012). Natural language processing (NLP) and machine learning enable the analysis of text data (Broniecki & Hanchar, 2017). It can be distinguished between supervised and unsupervised learning (Broniecki &

Hanchar, 2017). In supervised learning, a human coder is required who labels the data. Unsupervised learning is more exploratory and tries to identify patterns in the data (Broniecki & Hanchar, 2017). One common way to retrieve value from the data is by using sentiment analysis (Chen et al., 2012). Sentiment analysis identifies the tone of a given text (Broniecki & Hanchar, 2017). Therefore, it can be found out which association customers have with, for instance, a product or service offered by a company. The basis for sentiment analysis is a dictionary comprising of words which are related to, for example, positive or negative emotions (Broniecki & Hanchar, 2017). The outcome of sentiment analysis is a sentiment score based on the relative word counts. Based on these scores the company could also identify how consumers perceive them in comparison to competitors or how they perceive one specific feature or functionality of a product or service. A company can therefore see which products or which parts of a product are perceived as negative. Thus, attention can be given to those topics when deciding what to innovate.

Another possibility to analyze text data is semantic analysis. Semantic analysis can be used in order to identify ideas based on social media posts by taking context and meaning into account (Broniecki & Hanchar, 2017; Mirkovski, von Briel, & Lowry, 2016). Posts about own products but also posts about competitors' products can be included in the analysis in order to gain a more complete picture of the desires and preferences of the consumers (Mirkovski et al., 2016). Mirkovski et al. (2016) propose to start the semantic analysis by labelling a sample of posts. This needs to be done by an employee manually. Based on this labeling, a classification scheme can be created which enables an automatic classification of further posts through the usage of an algorithm (Mirkovski et al., 2016). Mirkovksi et al. (2016), for instance, describe a classification scheme which labels posts into most and least feasible innovation ideas. Based on the classification scheme, the algorithm can identify ideas which suit the customer preferences and which implementation is feasible. Based on the most feasible ideas, a topic model can be created (Miskovski et al., 2016). Topic models "summarize multiple text documents into a number of common, semantic topics" (Broniecki & Hanchar, 2017, p. 93). This can be helpful for a company to identify topics which customers are talking about and therefore can help in deciding what the company can innovate.

In an active participation of the externals in the innovation process, people who are external to the company are asked to "share their ideas and thoughts about how firms can improve their products and services" (Hossain & Islam, 2015, p. 612). This is called open innovation. The involvement of users in the idea search phase is widely adopted and can complement the work of professionals (Poetz & Schreier, 2012). It has been shown that products and services which were created with the aid of consumer involvement achieve higher success rates than the ones generated only by professionals inside the organization (Nishikawa, Schreier, & Ogawa, 2013; Witell, Kristensson, Gustafsson, & Löfgren, 2011). Moreover, a collaboration with consumers leads to a reduction of risks during the implementation phase of an innovation (Tobiassen & Pettersen, 2018). Therefore, it can be said that it can be beneficial for a company to involve consumers in the search for innovative ideas. However, Gama, Frishammar, and Parida (2019) emphasized that SMEs first need to have systematic routines in place before they should consider an active involvement of consumers.

Companies need to decide who to involve in the active participation. In general, consumers who should be involved need to show domain-specific interest (Füller, Matzler, Hutter, & Hautz, 2012). It has been found that business customers or lead users are more valuable in an active participation due to their higher knowledge in the domain (Bosch-Sijtsema & Bosch, 2015; Chang & Taylor, 2016; Tidd & Bessant, 2018). Collaborations with suppliers and consumers are way more common than with competitors (Walsh, Lee, & Nagaoka, 2016). Hence, vertical collaborations are most common. Next to this, also collaborations with universities can lead to a higher quality of inventions (Walsh et al., 2016). Furthermore, internal employees who are not related to the innovation itself can be involved in the idea searching (O'Reilly & Binns, 2019).

There are different ways to involve externals through active participation. A number of consumers or suppliers can be invited for a focus group discussion (Schweitzer, Buchinger, Gassmann, & Obrist, 2012). The data collected during the discussion can be a basis for a company to decide in which field innovation might be necessary. Focus groups are especially beneficial when the needs of a target group should be investigated (Schweitzer et al., 2012). In contrast to focus groups, social media offers a way to involve a higher number of externals (He & Wang, 2016). Social media offers the advantage that the company can interact with the customers (Hossain & Islam, 2015). On social media, organizations can initiate the idea generation by, for instance, asking consumers for feedback about current services or products or inviting them to share ideas in order to improve those (Mirkovski et al., 2016) Misunderstandings are more likely to occur with the usage of only text-based social media applications (He & Wang, 2016). Crowdsourcing – when the consumers are asked to share own ideas – can offer a high value to a company (Poetz & Schreier, 2012). Some large organizations even have own innovation platforms on which they can interact with users (Hossain & Islam, 2015). Social media also offers the users the opportunity to discuss their feedback and ideas with each other. Besides, organizations can use customer surveys to collect feedback on products and services and to ask for ideas for improvement (Tidd & Bessant, 2018). Companies can offer incentives to the users, which motivate them to participate in the innovation search of the organization (He & Wang, 2016). This can be, for instance, reward points or vouchers. The collected data through social media, online platforms, or surveys can offer important insights which can help to decide which innovations might be beneficial.

Employees can be involved in several ways. Organizations can, for example, implement online suggestion systems or internal contests (O'Reilly & Binns, 2019). An online suggestion system can be composed of a standard format document which has to be filled in by the employee who wants to suggest an idea (O'Reilly & Binns, 2019). This creates a pool of new ideas, which the company can access easily. The company can use this pool as a basis to decide for what the company might want to innovate. Incentives might also be a motivator for employees to share their ideas.

In order to analyze the results of active participation by externals or employees, text analytics might be helpful for a large amount of data. Sentiment and semantic analysis might be useful to create an overview of what the participants desire and prefer (Broniecki & Hanchar, 2017).

It can be said that the decision what an organization might want to innovate can be supported by data. There are different possibilities on how to do that with different forms of participation. For SMEs, the participation of externals might provide benefits since it can compensate for a lack of resources. However, before involving externals into this process, systematic routines should be in place.

2.3.2 Idea Selection Phase

Data can also be used to support decisions in the selection phase. A formal process for the idea selection can increase the success of an organization's ideas (Eling, Griffin, & Langarek, 2016). Therefore, it is important that an organization defines a consistent process for the idea selection. Nonetheless, it has been found that reflexivity improves the effectiveness and the efficiency of the idea selection process (Hammedi, van Riel, & Sasovova, 2011). Thus, the decision makers should reflect on the objectives and the process and perhaps adapt those to special situations. There are different methods for the idea selection proposed in the literature. Also in the selection of ideas, external can be included, but the process can also be done internally.

When relying on internals, a consistent process can be created. In the first place, a decision committee can be formed, which is responsible for the selection of ideas (Mousavi, Torabi, & Tavakkoli-Moghaddam, 2013). This decision committee is responsible for defining criteria which an innovation idea has to fulfill in order to be progressed (Mousavi et al., 2013; Yarmohammadi, Rezvani, & Albotzi, 2017). These criteria might include costs and benefits of an idea, but also the feasibility in terms of technology and legal requirements (Mousavi et al., 2013; Yarmohammadi et al., 2017). A numerical scale can be determined by the committee in order to rate the ideas (Mousavi et al., 2013). Mousavi et al. (2013) propose to determine the relative importance of each criterium and to then weigh the criteria with the numerical values created by the rating. Based on this, a decision matrix can be created in which the different ideas are measured on, for instance, costs versus benefits (Mousavi et al., 2013; Tidd & Bessant, 2018). The results of this allow a ranking of the different alternatives. To what extent this process is data-driven also seems to depend on how the committee reasons the values they choose on the numerical scale – whether these are grounded in research or the intuition of the committee members. Moreover, this method looks at ideas in a portfolio perspective which offers the benefit of creating balance and a better overview (Eling et al., 2016; Tidd & Bessant, 2018).

Employees who are not part of a decision committee can also participate. Voting schemes can be used to enable employees to state their opinion about which ideas should be progressed (Onarheim & Christensen, 2012). The experience of employees can be a complement and creates a more nuanced view (Onarheim & Christensen, 2012). However, involving employees should not be seen as an alternative, but as an addition. The votes can be analyzed by looking at the descriptive statistics, which shows the frequency of votes for each alternative.

Next to these human evaluations, text mining can be used to evaluate ideas. Text mining methods offer the benefits of being less cost intensive than the human evaluations (Hoornart, Ballings, Malthouse, & van den Poel, 2017). Besides, humans can lose focus which can be ground for errors. To evaluate ideas, semantic analysis can be used (Hoornaert et al., 2017). The results can be used to make predictions about the idea's probability of implementation or about the market potential. The ideas with a high probability of implementation and a high potential can be considered for further progress by the decision makers.

Externals can be involved in different ways in the idea selection process. As stated in the search section, consumers or suppliers can be invited for a focus group meeting to discuss different alternatives (Schweitzer et al., 2012). The results can be used to support the decision about which ideas should be progressed. Next to this, social media can be used to let a large number of consumers evaluate different ideas (Hofstetter, Aryobsei, & Herrmann, 2018; Mirkovski et al., 2016). Via social media, consumers can rank or rate different ideas based on their preferences (Hofstetter et al., 2018). Furthermore, a company can ask consumers for their opinions on different alternatives (Hossain & Islam, 2015). The results of those discussions can be analyzed using sentiment and semantic analysis. Consequently, social media can provide insights into which idea the consumers would prefer. This can be used as evidence for the decision which idea to progress.

2.3.3 Development Phase

Knowledge Acquisition

To acquire necessary knowledge and resources to develop the innovation, the following data can support the process. Since many smaller organizations do not have an own R&D department, technology which has been generated by other companies can be used to decide which knowledge is necessary (Tidd & Bessant, 2018). Additionally, organizations can collaborate with externals, such as universities or research institutes (Tidd & Bessant, 2018). It has been shown that for many organizations universities and research institutes are the most important partners in the innovation process (Weber & Heidenreich, 2018). They can support organizations in research and can provide especially smaller organizations with missing knowledge and data.

Execution

In order to execute the development, data can fasten and improve the process. Organizations might want to involve users in design activities of a new innovation. For this, the organizations provide necessary tools and other support which enables the user to integrate own ideas and expertise (Russo-Spena & Mele, 2012). Companies "can develop design toolkits and apply them creatively to product design" (Muninger et al., 2019, p. 117). These toolkits might be used by customers but also by own employees. The usage of such tools is supported by other features of the internet, such as forums or wikis, in which different users can engage and exchange views about different ideas (Russo-Spena & Mele, 2012). Wikis and forums also offer the advantage that knowledge and ideas are stored and can be retrieved at any point in time (Standing & Kiniti, 2011).

Crowdsourcing can be another source of data in the execute phase. With the usage of crowdsourcing users are integrated in the process (Bosch-Sijtsema & Bosch, 2015). For example, Facebook can be "used as a test-and-learn tool" (Mount & Martinez, 2014). With Facebook organizations can easily share different pictures or create opinion polls. The results of such an opinion poll or the comments and likes for different pictures and posts can be valuable information about the preferences of the consumers (Mount & Martinez, 2014). Nonetheless, for small companies it might be more difficult to reach a high number of users via social media channels.

Furthermore, digital prototypes can be used. Based on digital prototypes, decisions can be made about the design of the innovation. Using digital prototypes instead of physical ones can save the designers around five to six weeks (Brossard, Erntell, & Hepp, 2018). Therefore, it can lead to an earlier commercialization of the innovation. Besides, 3D printing can also help to fasten the process. Prototypes created with 3D printing can be used to test the innovation and can be shown to the customers (Candi & Beltagui, 2019). Based on the results of that prototypes and the reactions of the customers, decisions about the design can be made.

In case that prototypes already exist from earlier phases or innovations, the suitability should still be tested (Lindič, Baloh, Ribire, & Desouza, 2011). Also for this, the involvement of users can be beneficial. Organizations include customers in the execution phase because they can be a source of valuable feedback about whether current ideas and prototypes are in line with the customers' needs (Mirkovski et al., 2016). However, Chang and Taylor (2016) state that the involvement of customers in the development of an innovation can lead to a delay in the process.

To decide how to structure the implementation of the innovation, employees and other users can be surveyed so that their needs and knowledge are considered (Tidd & Bessant, 2018). Based on an analysis of the feedback, decisions about how the implementation should be structured can be made.

2.3.4 Launch Phase

In the launch phase, data can improve the results. First, to make the final decision how the innovation should look like, particular concepts can be tested with customers (Bosch-Sijtsema & Bosch, 2015; Lynch, O'Toole, & Biemans, 2016). Based on the outcome of these tests, the decision can be made if the originally developed concept is accepted. This can also indicate which features or functionalities customers would be willing to pay a premium for and which could be eliminated (Zhan, Tan, Ji, Chung, & Tseng, 2017). Especially for technology, the design can be tested with a user community. For this, the new technology is made available to a test user community before it is launched (Russo-Spena & Mele, 2012). The organization collects data of the user community and can improve the final design based on it. Additionally, companies can conduct A/B testing, in which different beta versions of the innovation are released to observe the reactions to each version (Bosch-Sijtsema & Bosch, 2015; Brossard et al., 2018; Tidd & Bessant, 2018). Decisions about the final version are made by taking the data of the A/B testing into account. But also data from online customer surveys can help in deciding how the final innovation should look like (Bosch-Sijtsema & Bosch, 2015). These surveys can also be done in the form of an opinion poll on social media (Mount & Martinez, 2014). This allows companies to increase the alignment of the innovation with the actual customer needs (Mount & Martinez, 2014).

Decisions about the promotion of the innovation can be based on the preferences of the customers which can be identified by analyzing the results of the concept testing (Tidd & Bessant, 2018). This helps to define the value proposition of the innovation perceived by the customers (Lindič et al., 2011). However, next to customers, also suppliers and other stakeholders can be involved in this process of defining the value proposition (Lindič et al., 2011). Besides, competing offerings should be taken into consideration when developing the promotion plan (Tidd & Bessant, 2018).

Customer preferences and competing offerings should also be considered in the pricing of the innovation (Tidd & Bessant, 2018). Also dynamics in the market can be a basis for the price. The adoption of the so called dynamic pricing requires data about the "demand, inventory levels, competitor offerings, and customer history" (Omar, Minoufekr, & Plapper, 2019). It has been shown that dynamic pricing lead to an improved financial performance and does not have a negative effect on the price image (Omar et al., 2018).

The decision about the location of the launch should be made with the competing offers as support (Tidd & Bessant, 2018). Moreover, a company needs to do market research in order to find out where the innovation can be sold and where consumers would be able and willing to buy it.

2.3.5 Post-Launch Adaption Phase

To sustain the innovation, data can be helpful. Companies can use online surveys to receive feedback from customers (Bosch-Sijtsema & Bosch, 2015). With this input, improvement potential might be discovered by listening to the actual experience of the customers. Next to this, quantitative data of the customers, such as sales information can help in making decisions regarding the sustaining of the innovation (Bosch-Sijtsema & Bosch, 2015). The sales information provides insights into which features and functionalities are most and least favored by the customers. Furthermore, text data can be gathered on, for example, social media to get more feedback about positive and negative attributes of a launched innovation (Muninger et al., 2019). Text analysis can be used to decide whether and how the innovation needs to be adjusted. Sentiment analysis can help in identifying positive as well as negative associations with specific features of the innovation. Besides, semantic analysis can help in discovering reasons for dissatisfaction or satisfaction by taking context and meaning of the text into account. Sensors which are embedded in the product capture data which can help to identify customer requirements (Ervelles, Fukawa, & Swayne, 2016). Based on this, improvements can be made. However, this is not a common measure for most companies (Niebel, Rasel, & Viete, 2019).

2.3.6 Learn Phase

There are useful tools which can support the learn stage. Post-project reviews "are structured approaches to capture learning at the end of an innovation project" (Tidd & Bessant, 2018, p. 403). Based on this documentation of the innovation process, decisions might be made regarding changing standard procedures. For this, metrics are useful. According to Mulgan & Albury

Table 2: Overview of which decisions can be based on data

Phase	Decision	Based on data?
Idea generation	Which strategic goals should be reached?	
	What might be innovated?	✓
	Where do we want to search for ideas?	
	Who is involved in the searching?	
Idea selection	Which ideas should be progressed and which not?	✓
	How do we analyze the different ideas?	
	Who is involved in the selection?	
Develop	Which knowledge do we need for the innovation?	✓
	How do we gain the necessary knowledge?	
	How should the design of the innovation look like?	✓
	How can the implementation be structured?	✓
	Who is responsible for the execution?	
Launch	How should the final innovation look like?	✓
	How should we promote the innovation?	✓
	How should we price the innovation?	✓
	Where should we launch the innovation?	✓
	When should we launch the innovation?	
	Which objectives do we want to reach with this innovation?	
Post-launch adaption	Does the innovation need to be adjusted?	✓
Learn	Does the innovation process need to be changed?	✓

(2003), “clear measures and transparent systems for accessing the success […] of innovations are vital to robust analysis and creating cultures of learning” (p. 28). In order to make use of metrics, processes and mechanisms need to be defined. Benchmarking can be helpful to see how other companies manage their innovation process and where an organization can learn from others (Tidd & Bessant, 2018). The analysis of the benchmarking results can be a basis for improvements of the own innovation process.

2.4 Research Model

In order to investigate how SMEs use data-driven decision-making in the innovation process, it first needs to be elaborated what their perception of data-driven decision-making itself is. This is necessary since the familiarity with the phenomenon, the preparations to enable data-driven decision-making, the perceived and expected benefits, and the perceived and expected

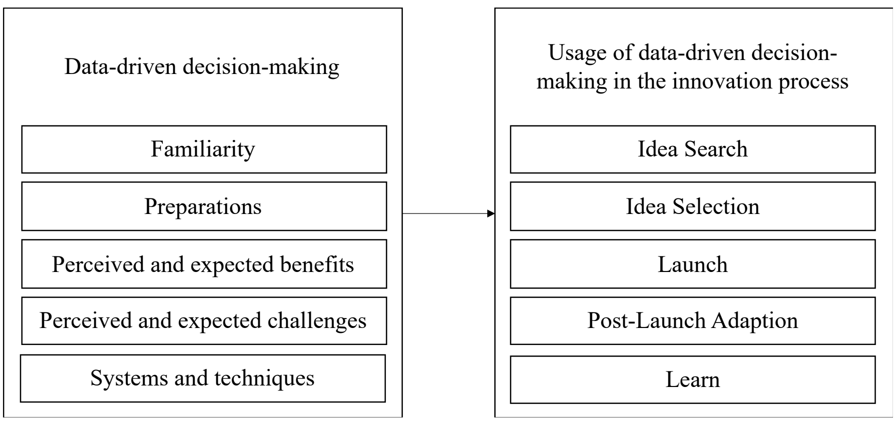

Figure 2. Research Model

challenges influence whether and to what extent SMEs use data-driven decision-making in the innovation process. After the identification of this, it has to be found out how data-driven decision-making is used in the innovation process. This step will also investigate how SMEs are making the decisions in the innovation process when not relying on the analysis of data. The results of this will lead to conclusions and recommendations. The research model in Figure 2 shows this.

The study aims to draw conclusions on how SMEs perceive data-driven decision-making, which includes the familiarity, the preparations, the benefits, and the challenges. Furthermore, it will be shown how SMEs are making the decisions which have been determined in Table 2 to be able to be based on data. Furthermore, it will be shown how SMEs are using data-driven decision-making, for instance which software they are using.

3 Methodology

To investigate how SMEs perceive data-driven decision-making and to what extent they use data-driven decision-making in their innovation process, nine cases have been chosen. Semi-structured interviews have been conducted with ten interviewees in the period of four weeks. Due to the situation regarding the corona crisis, all interviews have been conducted online.

3.1 Research Design

For the nine cases, semi-structured interviews have been conducted due to the exploratory nature of the study. Face-to-face interviews offer the advantage of perceiving social cues, for instance the body language or the tone of voice (Opdenakker, 2006). However, due to the situation regarding the corona crisis, it was not possible to conduct the interviews face-to-face. Therefore, it has been chosen to do the interviews via video calls online. Through this, the researcher and the interviewees were able to see each other which allowed for the perception of social cues to the highest extent possible. Additionally, in semi-structured interviews, a reaction of the interviewer is possible to what the interviewees say (Opdenakker, 2006). Due to the semi-structured interview style, it can be guaranteed that the interviews follow the same structure while offering room to being responsive to individual answers of the interviewees (Leech, 2002).

The formulation of open-ended questions has been chosen due to the fact that it facilitates an open conversation. Therefore, it enables topics to emerge in course of the interview which the interviewer did not think of before. These questions were divided into three different topics, namely information about the participant, data-driven decision-making, and the innovation process. Before questions about these topics have been asked, an introduction has been given to the participants, in which it has been explained for which purpose the interview is conducted. Moreover, it has been stressed that there are no right or wrong answers, that the interview is anonymous, and that the participant is able to stop with the interview at any time without stating a reason for this. Through this, it should be guaranteed that the interviewee feels comfortable to share their honest opinions and experiences. Furthermore, the participants were asked if they agree to the interview being recorded in order to not violate their privacy.

Before the interview, it has been prepared what the company is doing in general so that the time of the participants is not wasted with topics that can be found online. For this, the company websites and the social media channels, such as LinkedIn, YouTube, and Facebook, and news releases about the company have been considered. Things that remained unclear after the internet search about the company have been asked during the interview.

As a beginning, the first topic of the interview has been about the participant himself. It has been asked what his current function is, how long he already is in the current function, and what his main responsibilities are. These questions were used to get an overview of the interview participants but also to make the interviewee feel more comfortable in giving answers.

The second topic has been about data-driven decision-making. First, the interviewee has been asked to define data-driven decision-making. With this, it has been aimed to find out what the general understanding of the term is. This shows to what extent the interviewees are familiar with the term data-driven decision-making. Afterwards, the definition of the researcher has been given in order to create a common basis for the following questions. After that, the reasons for the (non-)usage of data-driven decision-making have been discussed and the perceived and expected benefits. Besides, it has been asked how the company of the interviewee prepared or is planning to prepare to enable data-driven decision-making. Moreover, the participants were asked which challenges they experience as an SME regarding data-driven decision-making and which other challenges they might expect in the future.

The last topic has been about the innovation process. In order to ask questions about the different stages of the innovation process, it has been explained to the interviewee which phases the innovation process has in the definition of this study and what these phases consist of. After that, it has been asked for each innovation phase how the companies are managing the stage and how they make specific decisions in the stages. With this, it could be identified to what extent the SMEs use data during this process. Moreover, it has specifically been asked how they use data, for instance, which programs they use, who is responsible for this, and how to they analyze data.

3.2 Interview Participants

Nine interviews have been conducted with ten interviewees. Thus, one interview has been conducted with two participants. All participants work at SMEs in a leading role. These have been inclusion criteria since the study deals with companies who are small- or medium-sized and it is crucial that the participants have decision rights in the company. Besides, the companies are clients of Leap, which ensures that they are engaging in innovation plans. The managing consultant of Leap has been asked to select SMEs for the study. Those have first been contacted by Leap to inform them about the research and afterwards have received an invitation by the researcher to participate in the study. 20 SMEs have been contacted from which eight were willing to participate. One more interviewee who is no client of Leap has been asked to participate additionally by the researcher.

The included companies are all active in different industries, which can be seen in Table 3. Of the nine SMEs, six are small SMEs with less than 50 employees, and three are medium-sized SMEs with more than 50 employees.

Table 3: Interview Participants

No.	Industry	No. of employees	Interviewee function
1	Nanotechnology	11-50	Business Development Director Finance Manager
2	Logistics & Supply Chain	50+	CTO
3	Internet	11-50	CEO
4	Chemicals	11-50	CTO
5	Textiles	50+	R&D Manager
6	Leisure, Travel & Tourism	11-50	CEO
7	Mechanical/Industrial Engineering	11-50	Managing Director
8	Food & Beverages	11-50	CEO
9	Industrial Automation	50+	Project Manager

3.3 Data Analysis

The interviews were conducted using Google Meet since this allowed for an easy recording of the interviews. The transcription has been done with the aid of Amberscript and by revising the created transcript manually. In order to interpret and analyze the interview results, content analysis is used, in which the data is labeled and categories are created (Blair, 2015). An initial code book has been created by defining the main code categories based on the literature. The subcategories were then derived from the literature, as well. Since software packages such as ATLAS

TI require an initial effort to become proficient with the software (Blair, 2015), it has been decided to code the data manually.

With the list of codes as a basis, the first and the last interview were coded by the researcher and a second coder in order to see whether the initial codes are applicable and whether there is consensus between the two coders. The first and the last interview have been chosen due to the fact that insights that might be gained during the data collection phase can have an impact on “follow-up questions or narrow the focus of observation” (Graneheim & Lundman, 2004). As a first step, the content has been reduced by summarizing the answers to each question while taking care that no information is lost. Afterwards, the content has been divided into the different main categories which have been defined with the aid of the literature. Finally, subcategories have been used to structure the content in more detail. During this process, the codebook has been refined based on the discussion between the researcher and the other coder and supplemented by additional codes which derived from the interview data. Consequently, the coding has been done deductively based on the literature and inductively based on the interview data. This combination of deductive and inductive coding allows for an increased thoroughness as prior literature is considered and new findings can emerge from the interview data (Thomas, 2006). The final codebook can be found in Appendix 3.

In order to analyze the results of the interviews, the data for the different interviews is displayed according to the codes. Using such a data display is especially helpful when multiple cases need to be compared (Forman & Damschroder, 2007). By organizing the data systematically according to the codes, patterns can be recognized more easily and the different cases can be compared to each other and to the presented theory (Forman & Damschroder, 2007). Moreover, it can be identified how frequent specific concepts are mentioned by the participating companies.

3.4 Validity, Reliability, and Generalizability

Validity, reliability, and generalizability are terms used in quantitative research. Validity refers to whether the applied methods are appropriate so that the findings actually reflect the data (Noble & Smith, 2015). Next to this, reliability represents whether results and processes are replicable (Leung, 2015) and thus, whether the procedures are consistent (Noble & Smith, 2015). Generalizability is described as “the transferability of the findings to other settings and applicability in other contexts” (Noble & Smith, 2015, p. 2). Even though these terms are used for quantitative research mostly, qualitative research also aims to be trustworthy. Therefore, Noble and Smith (2015) created alternative terminologies for the three terms which are more suitable for qualitative research, which are truth value, consistency, and applicability.

The truth value (validity) is enhanced by giving each participant the same introduction and also the same definition of data-driven decision-making and the innovation process. Therefore, each participant starts with the same basis so that the results are comparable and reflect the actual situation. Moreover, the discussion with a second coder increases the truth value. Additionally, data triangulation has been used by examining the company websites, the social media channels, and news releases. Furthermore, the audio recording and the transcribing allows for revisiting the data multiple times in order to avoid misunderstandings. Besides, everything has been documented including the communication with the interviewees, the interview process, and the coding process.

The consistency (reliability) is ensured by a transparent documentation of the research process. This includes the process of the literature review but also by explaining the process of the interview conduction, transcription, and coding.

Applicability (generalizability) is enhanced by providing details of context for each participating company and the study itself. This enables “the evaluation of study conclusions and transferability to other […] units” (Noble & Smith, 2015, p. 3).

4 Results

This chapter describes the perceptions of the SMEs regarding data-driven decision-making. This includes the understanding of data-driven decision-making, the preparations that SMEs consider as necessary, as well as benefits and challenges. Next to this, systems in use and techniques are presented. Furthermore, it is described how SMEs make decisions in the innovation process in order to evaluate the extent of data-driven decision-making.

4.1 Data-Driven Decision-Making

4.1.1 Understanding of Data-Driven Decision-Making

When asked to define data-driven decision-making all participants gave a description of what it entails according to them. As presented in the theory chapter, data-driven decision-making refers to decisions which are based on the analysis of data instead of experience or intuition. The individual understanding of data-driven decision-making of the participants can be seen in Table 4. All participants stated that data-driven decision-making means that decisions are made based on data.

Analysis is mentioned by four of the participants as part of data-driven decision-making. This shows that these participants notice the importance of not just having data but also to analyze the data in order to be able to make a decision based on it. Additionally, Participant 7 describes data-driven decision-making *"as continuous positive feedback loop where you just analyze what you have done and make decisions based on what you analyze"*. Therefore, this participant also indicates that data-driven decision-making is not a process with a fixed start and end, but a continuous process. This is due to the fact that the data that you analyze lead to decisions and these decisions again lead to new data based on which decisions can be made in the future.

Table 4: Understanding of Data-Driven Decision-Making

Company	Definition
Company 1	*Looking into the market data and make decisions based on the analysis of this data.*
Company 2	*For me it's really just to use the data that you have to come to decisions. So really to have some fundamentals behind your decisions rather than taking them just on some gut feeling.*
Company 3	*You have to make decisions based on your feelings but also on data. For me data-driven decision-making is that you make choices based on data.*
Company 4	*I would define it that you gather enough data to make a decision that fits best with the situation you are in and is well thought of and not based on some kind of emotional impulse.*
Company 5	*Data-driven decision-making means that you make decisions based on the analysis of data that you have.*
Company 6	*For me data-driven decision-making is collecting data, looking at what I want to do in the future, analyze the data, and make a decision based on that.*

Company 7	*I would describe data-driven decision-making as continuous positive feedback loop where you just analyze what you have done and make decisions based on what you analyze.*
Company 8	*Data-driven decision-making is basically making a decision based on certain facts, on data that you get.*
Company 9	*I would say it refers to Big Data normally. But data-driven decision-making can mean a lot of things. You gather as much data as possible to make your decision measurable. In the end, it's of course, always also about feelings.*

Feelings are also named by four of the participants. It is mentioned that data-driven decision-making makes it possible to make decisions based on fundamentals and not just based on own feelings. For instance, Participant 4 stated that data-driven decision-making leads to a decision which *"fits best with the situation you are in and is well thought of and not based on some kind of emotional impulse"*. However, it is also emphasized that *"in the end, it's of course, always also about feelings"* (Participant 9). Therefore, it is acknowledged by the participants that data-driven decision-making can help to compensate for variations in feelings and opinions of different people. Nevertheless, feelings cannot be fully disregarded.

However, four participants also expressed difficulties in defining data-driven decision-making. For example, Participant 7 said: *"I try to make objective decisions based on arguments and numbers. And rational. But I'm not really sure if that is already data-driven decision-making"*. Participant 1A also stated that it is an abstract term which they do not use in the company. Moreover, the daily business requires thousands of decisions and therefore, it is not clear to Participant 1B which decisions are meant with data-driven decision-making. Furthermore, Participant 9 was the only one to name Big Data. This led to the confusion whether decisions which are not based on Big Data but on other data could also be referred to as data-driven decision-making. Therefore, it has been important to give a definition to all participants of what data-driven decision-making is.

The majority of the participants (seven participants) stated that data-driven decision-making is becoming more important when the company grows. Participant 7, for instance, said: *"The need for data-driven decision-making is higher when you have a big company. We still have a lot of face-to-face contact with the clients"*. The other four participants also mentioned that for a small company keeping track of everything without using data is easier. However, *"when the company is getting bigger and bigger, you also need more data to support your decisions"* (Participant 3). This is due to the fact that everybody needs to have an overview of what current priorities are and on what basis decisions have been made. In consequence, the participating SMEs consider data-driven decision-making to be more crucial for larger organizations. However, they also see the necessity to implement it more in their businesses. For instance, Participant 1A stated: *"We definitely think that we need to implement data-driven decision-making more"*. Thus, in order to grow they consider it to be important to support their decisions to a higher extent with data.

4.1.2 Preparations for Data-Driven Decision-Making

The preparations that the participants had to make or are planning to make in order to enable data-driven decision-making are mainly in the areas of business processes, employee trainings, and software. Four of the participants stated that adaptions in the business processes need to be made. Participant 6 mentioned that the processes had to be changed in order to enable the collection of relevant data. This has been done in the past at the company. Participant 5 said: *"We need to be able to measure more and we actually also need to do it. For that the processes of* *how we do things here would need to be adapted"*. This indicates that current business processes might not be suitable to collect the necessary data.

Training for the employees has also been named as a necessary preparation four times. Participant 6 stated: *"Employees needed training to ensure that they also use the tools in a correct way"*. Participant 2 and 4 emphasized as well that training was necessary so that the employees are able to analyze the data in a correct way. In contrast, Participant 9 said that his company buys analyses from other companies which are specialized in it. Therefore, they know that the necessary expertise is in place and they do not need to train their own employees in that.

Another important preparation is the software of a company. Participant 1A talked about the following plans: *"We have plans to improve our ERP system. And to automate a lot of things that we do manually now and to incorporate that in our ERP system"*. This means that there is still the need for an external to adapt the software of the company in order to improve the possibilities for data-driven decision-making. At company 6, a software expert had been hired to create a system which fits the needs of the company. Consequently, it can be seen that own expertise in these fields might be lacking for smaller companies and that they are dependent on the hiring of experts. Besides, Participant 2 stated that the systems which were used in the company had to be changed in order to fit to the adapted processes.

4.1.3 Benefits of Data-Driven Decision-Making

Data-driven decision-making can offer benefits to companies. Those benefits perceived or expected by the participants can be seen in Table 5. Through this, it can be seen which benefits are mentioned most.

Six participants argue that data-driven decision-making can lead to an increased speed. Two different reasons for an increased speed have been identified during the interviews. First, data-driven decision-making increases the probability that the right decision is made from the start. Thus, later adaptions might not be necessary. Participant 9 argued: *"It prevents you to make a bad choice because in the end, it takes time and it takes a lot of money"*. Second, the decision-making itself is sped up. This is due to the fact that the data give you fundamentals to decide on. As Participant 6 stated: *"If you have clear data, you do not need much time to make a decision because the situation is clear. You do not need to discuss about it"*. This makes it clear that the participants consider discussions to be easier when they have clear data with which they can prove how something should be done. Therefore, data-driven decision-making increases the speed due to less adaptions and due to a decreased need for long discussions.

Five of the participants generally stated that the usage of data to make decisions leads to better decisions. This is due to the fact that it gives you more security, as Participant 3 said: *"It is nice when you make a decision and know that it is based on data because it gives you more security in the decision-making"*. It is also argued by Participant 4 that more data lead to a higher security. This high security is important for the participants to make reliable decisions. For instance, Participant 2 stated: *"The decisions that you make are more reliable because you have fundamentals to base it on because some people will always have a good story. But just from talking to different people, you don't always get a clear picture."* Hence, data-driven decision-making can increase the reliability of decisions, which offers a higher security to companies. This is why the participants consider data-driven decisions as better compared to decisions which are not based on data.

Four of the eleven participants think that data-driven decision-making improves the business performance. Participant 1A thinks: *"I think the output will be higher, so the efficiency will be higher. We would lose less days because we do not run out of stock"* and Participant 1B added: *"We would not disappoint customers when there is no stock and we cannot supply"*. Based on that the company could sell more and improve the business performance as a result.

Company 2 uses data-driven decision-making in order to monitor developments within the company and in the market. This enables them to react more quickly in case something is not going as planned, which improves the performance. Participant 8 argued that processes can be improved due to the analysis of data from previous projects. Consequently, the participants experience and expect that data-driven decision-making can improve the overall business performance of the company.

A competitive advantage can be a result of the usage of data-driven decision-making. Three of the participants stated that the usage of data as a basis of the decisions can offer an advantage with regards to competitors. For example, Participant 3 said: *"It can help you to make clients happier, which can give you an advantage compared to your competitors"* and Participant 6 mentioned: *"It gives us a competitive advantage that we analyze data and actually know what the customers ask for"*. In consequence, it gets clear that data-driven decision-making can help to discover what the customers actually prefer, which in turn can lead to a competitive advantage.

Increased predictability is another possible benefit of data-driven decision-making. Three companies experience or expect that data can help to predict what might happen in the future. Participant 7 said: *"Clients are, of course, unique. But eventually, if the numbers are large enough, everyone's the same"*. Therefore, it is possible for the company to make predictions about what different customer segments prefer. Also Participant 1A and 1B expect that data-driven decision-making would help to improve the supply of the customers because the stock can be adapted to the forecasted demand. In consequence, data-driven decision-making improves the predictability in a company. This can be beneficial for discovering what customers might buy in the future and to adapt the offerings and stock accordingly.

4.1.4 Challenges of Data-Driven Decision-Making

There are also challenges related to data-driven decision-making. Table 5 shows the challenges perceived or expected by the participants with the frequency it has been mentioned. Through this, it can be seen which challenge is perceived the most by the participating SMEs.

The data collection is a challenge which is mentioned by eight of the eleven participants. Thus, it is the most-named challenge. There are two different facets of this challenge. First, participants experience that the right data is not available. Participant 1B argued that *"for a lot of questions, the right data is not available because it is so unique"*. This is also mentioned by Participant 6 who claimed that *"if you want to do new things, there is no data that can help you, because nobody did that before"*. The participants consider it to be difficult to collect data when they do something which is new in the market. Second, there is the difficulty of gathering enough data to base decisions on. For instance, Participant 4 stated: *"You want to have a huge amount of data to be certain that you make the right decision"* and Participant 7 argued that for a small company the client base is not as big as for large companies, which makes it more difficult to gather enough data to make the outcomes significant. Therefore, data collection is considered to be a challenge due to the fact that it is difficult to get the right data when doing something new and because of the amount of data which would be necessary to get meaningful results.

Four participants consider the data quality to be a challenge. As Participant 3 stated: *"The data needs to be correct. Otherwise you're basing your decisions on wrong data and that's not what you want."* Basing decisions on data with a lower quality might also lead to decisions which are not optimal. Therefore, it is crucial to check whether the quality of the data which is used is sufficient. Participant 8 argues that *"sometimes you take data too easy for granted without checking if it's valid or not. Sometimes you are maybe a bit too happy with getting data, so that you don't double check it."* Consequently, organizations should be aware of the fact that the data quality has to be checked. Participant 2 suggests *"to really keep on top* *and try to find a process to make it easier, more understandable, and to have less errors. That's continuous."* Thus, it is crucial to continuously check the data quality to be sure that no decisions are based on data which includes errors. For this a fixed process might help.

In order to enable data-driven decision-making, current processes need to be redefined. This is perceived as a challenge by four of the participants. Participant 5 stated: *"We always lose information because not everything is documented. That is how we work. But if you want to analyze the data, we would need to change our processes and document everything"*. Moreover, Participant 1A mentioned that their processes in the company would need to be changed in order to enable the usage of certain standard software. This would be necessary in case no tailormade software is used. Therefore, the companies realize that the current processes might be changed in order to enable data-driven decision-making. Participant 3 argued that they always redefine their process to improve it further. Thus, it is a continuous process to always ensure that the processes are fitting to the current situation the company is facing.

Having suitable software can also be a challenge. Three of the participants consider it to be difficult to find a software which is suitable for the company. Participant 1A and 5 stated that they would not know which software to use because it would need to be adapted to the current business processes of the organization. For instance, Participant 1A said: *"I don't recognize data-driven decision-making as a subject where people are selling software for. So it's not like SAP or Exact will deliver a package for SMEs where they say: 'This is the data-driven decision-making package'"*. That is why Company 6 hired an IT specialist who created a software especially for their purposes. If companies do not want to adapt the business processes to fit to the standard solutions offered by companies, it could be a solution to let IT specialists create tailor-made software for them. However, this might come at a higher cost than using standard software.

Even though predictability is considered to be a benefit, unpredictability is considered to be a challenge by three participants, from which two are from Company 1. The participants claim that when a company does something new and is still growing, the predictability is limited. For instance, Participant 1B said: *"So there's no steady. If you have a company who does the same for 20 years, then it's easier to predict"*. Also Participant 6 argued that *"if you do something for ten years, it's easier to predict. But as soon as you do something completely new, data-driven decision-making reaches its boundaries because there is no data"*. This shows that the participants consider it to be difficult to predict what might happen in the future because they are still growing. Moreover, they state that it is not possible to find data to make predictions about something completely new, such as a new product or service.

Although trainings were mentioned to be an important preparation, only two participants stated that they experience the challenge of missing skills. Participant 8 mentioned that most of the employees in the company have a technological background, which is crucial for the key processes within the organization. Nevertheless, skills are missing for other areas, which would help in getting and analyzing certain data. Due to limited resources, it does not seem to be always possible for SMEs to hire employees with the necessary skills.

The organizational culture can also be a challenge. Two of the participants experience challenges which are based on the culture of the organization. For instance, Participant 1B stated that somebody else in the company is responsible for the software programs and that he *"does not ask: 'What do you want from the data base?'"*. Therefore, data that he needs is sometimes missing. Moreover, Participant 2 said that the subsidiaries in the different countries *"do things differently and that creates some struggles because you cannot really compare those figures"*. Therefore, it shows that participant experience different problems regarding the organizational culture. Nonetheless, it seems to stand out that predefined regulations and processes could help to overcome this problem. Through regulations and defined processes, it could be guaranteed that processes and documentations are the same in different subsidiaries and that the needs of all users are considered in the creation of the software.

Table 5: Benefits and Challenges of Data-Driven Decision-Making

Benefits	Times mentioned	Challenges	Times mentioned
Increased speed	6	Data collection	8
Better decisions (more reliable)	5	Data quality	4
Improved business performance	4	Adaption of business processes	4
Competitive advantage	3	Suitable software	3
Increased predictability	3	Unpredictability	3
		Employees' skills	2
		Organizational culture	2
		Time consuming	2
		Amount of data	1
		Privacy concerns	1

Even though one of the identified benefits of data-driven decision-making is the increased speed of decision-making, two participants consider it to be time consuming. Participant 4 stated that they do not use data-driven decision-making because *"it's pretty time consuming. Getting all the data takes a lot of time sometimes"*. Also Participant 8 argued that collecting and validating the data might be time consuming. Therefore, SMEs might forgo the benefits of data-driven decision-making because they are not able or do not want to invest the necessary time in it.

Although it is considered to be a challenge to gather enough data, having a large amount of data can also be a challenge. Participant 6 stated that *"software is getting slower when the data amount is growing"*. Therefore, the software needs to be suitable for handling large amount of data. If this is not the case, the computing process takes longer or the software might not be able to handle it at all.

Even though it is an important topic, privacy concerns have only been mentioned by one participant. Participant 9 stated that the usage of sensors in their products to collect data during the usage by the customers is not possible. This would help to make products in a more dedicated way. However, Participant 9 said: *"I think it's very difficult to implement in the world because everybody is protecting their own data."* This shows that the protection of the customer data can sometimes limit the opportunities of a company.

4.1.5 Systems and Techniques

During the interviews it got clear which systems and techniques SMEs are using. All of the companies except for two mentioned that they make use of data visualization to analyze their data. According to Participant 6, it has the advantage that they can see what the data says in a quick way. Additionally, Participant 2 stated that *"visualizations help to see whether things are going well and whether action needs to be taken"*. The participants mainly use the visualizations to get an overview of what happened in the past or what is currently happening in the company and in the market. Therefore, they mainly make use of descriptive analytics. As described in the theory chapter, visualizations can be a helpful tool for descriptive analytics. Some of the companies also described that they use the visualizations in order to find out why something has happened in the past, which means that they also make use of diagnostic analysis. However, this is only in a limited extent done and only with the aid of visualizations. Data mining is not used by the companies. For instance, Participant 3 stated: *"We do data mining for our clients, but not for ourselves. I don't see the benefit for now. But we are able to do it"*. This shows that it is not necessarily due to missing skills when SMEs do not use data mining to analyze their data. Participant 6 mentioned that one of their employees is currently doing research in order to create a prediction model for the customer demand. Therefore, the company is trying to develop a predictive analysis model, which can help to find out what might happen in the future. In conclusion, it stands out that the SMEs in this research make mostly use of descriptive analytics and only little of diagnostic and predictive analytics. A combination of the different techniques could help in getting a more holistic view and might therefore be beneficial.

The system used for the data visualization which was named by most of the companies is Excel. Eight of the companies explicitly mentioned that they use Excel in order to visualize their data. It got clear that most of the participants consider Excel to be a simple tool, which is not as sophisticated. For instance, Participant 9 said: *"The way we do it, we don't need software. The common office stuff we use – Excel and PowerPoint"*. Hence, Excel is used by most of the participants, which can offer a good basis for data-driven decision-making. This is due to the fact that it offers flexible data visualization functionalities which can be sufficient depending on the needs of a company (Marr, 2020). Next to Excel, other tools are used as well by the participants to get a visual overview of the data. For instance, Klipfolio is used to create a dashboard with the most important figures and numbers by Company 3. Moreover, Company 8 creates a dashboard in the CRM system PerfectView, in which the numbers from, for instance, finance and marketing are visualized.

To make data-driven decisions, visualization tools are important to present the data in a more comprehensible way (Marr, 2020). However, some of the companies are not making use of the full potential of data visualizations. For instance, PowerBI, Tableau, and QlikSense are useful visualization tools for businesses (Marr, 2020). Marr (2020) also names Google Charts as a free alternative, which can also be used by people who are less experienced.

4.2 Innovation Process of SMEs

In this chapter, it is presented how the organizations manage the different stages of the innovation process and how decisions in these stages are made.

4.2.1 Idea Generation Phase

Customer requests and collaborations are for seven of the participating companies the main source of new ideas for innovation. There are two different ways of how the companies involve the customers in this process. However, both are a type of active involvement and not passive. The first way is that the companies get a request of the customer. Participant 8 stated: *"Typically, our customers come to us with a request or a need."* Furthermore, Participant 7 argued: *"Searching is also costing energy, of course. And all the clients can give you the direct information that you really need."* This indicates that the companies rely on the ideas of the customers because they can save time and resources which can compensate for missing resources. Moreover, this also ensures that the company is developing something for which there is customer demand. Second, the companies can ask the customers actively for new ideas. This can be done by either asking specific customers about their desires but also by sending surveys to a larger number of customers in order to receive feedback and ideas. Company 6, for instance, sends a survey to all the customers once a year, in which the customer is asked whether he/she has ideas to improve what the company is offering. Through this survey, the company has a pool of new ideas. The company is analyzing the results manually by reading the answers. Nevertheless, if the customer base increases, the number of responses might also increase. In that case, the usage of NLP might save time for the company. Furthermore, Company 4, 7, and 9 stated that they actively contact customers to ask them about current issues or ideas. Company 7, for instance, mentioned that they ask *"customers what challenges they come across and what they are doing at the moment to then develop solutions for their challenges"*. Since the customers are contacted individually and in a limited number, manual consideration of their responses is possible for the company. It gets obvious that the companies are not using any NLP or machine learning to analyze social media or forum posts. Additionally, one of the companies mentioned that they are collaborating with suppliers and knowledge institutes in order to identify new ideas. Participant 4 said: *"Besides, we talk a lot with suppliers and knowledge institutes. And of course, they always work on totally new processes, products, etc. And that may inspire us to innovate in that direction."* This shows that collaborating with suppliers or knowledge institutes can give important insights into developments in the markets. Moreover, it can also be the basis for a further collaboration in the innovation process, which might be beneficial to compensate for missing resources at a small company.

Market research can provide companies with new ideas. Six of the companies stated that they are doing market research to discover ideas for innovation. This includes that the companies are researching what competitors are doing but also that they look at publications in journals or newspapers. For example, Participant 7 mentioned that they regularly check scientific publications to see what is currently done in the market. Moreover, Participant 6 looks at magazines and newspapers to discover what the company could innovate. Besides, he is doing research about which search terms consumers are using in Google to discover their current interests. This might be a good data basis to see what customers are actually interested in at the moment. Moreover, Company 1 scans patents from other companies and people because through this they can see: *"What are developments? What is coming up? What are competitors and customers doing? What is on their mind? What is their main interest at the moment?"* This is done in a manual way by scanning single patents.

Events such as seminars, conferences, or fairs are another source of new ideas for five of the participating SMEs. Through this it is possible to identify developments and potentials in the market, which the company might not have considered before. As Participant 6 stated: *"We want to learn from the best and that's why we also want to learn from other companies, industries, and fields. For this we visit fairs – to see what's new".* Thus, fairs can be beneficial for companies to discover how own offerings might be improved but also to identify ideas for new offerings. Participant 5 mentioned that the innovations shown on fairs might be a good basis for own innovations. In consequence, it can be said that visiting such events is not data driven. However, it represents a good opportunity for an SME to get inspirations for new ideas.

In conclusion, it can be said that the extent to which the participating SMEs use data to make the decision what they want to innovate is limited. However, it gets obvious that most of the companies rely on the collaboration with customers. As identified in the theory chapter, especially smaller companies can benefit from that as it can compensate a lack of resources (Chang & Taylot, 2016). Consequently, the companies rely on the opinions and desires of customers in order to make the right decisions. The participation of customers is not passive but active. Hence, only individual customers are considered. However, most of the companies stated that the products are also produced individually for one customer and not for a bigger market. Moreover, the analysis of the data, which the companies get from the collaboration with their customers or from the market research, is done in a manual way, which might cost the companies time and effort.

4.2.2 Idea Selection Phase

The criteria for selecting an innovation idea is for most companies based on the expected profit it can create for the business. Two of the participants stated, however, that the first thing they look at is whether it fits to the company and whether they are capable of doing it. This is an important question to consider since a realistic evaluation at this point in time can save expenses and efforts created by the continuation of the process. Moreover, Participant 2 argued that it is important to look at what is really the biggest issue and most urgent at the moment. Based on this, it can be decided what has to be innovated first. Seven of the participants mentioned that they calculate how much the innovation would cost and how much profit it could create in order to calculate a net present value of the project. Participant 7 stated: *"For us it's rather straight-forward. If the margin is big enough, you can decide if you like to proceed with the project"*. According to Participant 9, this calculation is done based on experience of previous projects. Also for the other companies it does not seem to be based on data but more on experience. For example, Participant 3 said: *"We don't use data to make choices about new innovations. It's about whether we think that we can do it."*

One company argued that they are collaborating in this phase with the customer. This is due to the fact that the risk becomes too high if no customer is interested in the innovation. Therefore, Company 8 prepares a business case calculation for an innovation idea and contacts potential customers with that. Based on this, customers can decide whether they are interested in the innovation and whether they would like to invest in it. Participant 8 said: *"If there is no customer in the second phase who is interested in our technology, then most of our projects are already stopping right there because we are too small to take the risks."* This shows that smaller companies are not able to fund big projects themselves without having specific customers in prospect. Although the other participants did not mention that specifically, it seems to be also true for some of them as well. Most of the participating companies are already relying on customer requests in the search phase. Therefore, they already have specific customers who are interested in the innovation, which decreases the risk for them.

The decision about which idea to select is mostly made internally by the higher management. For this, there mostly is a discussion between employees from departments, which are involved in the innovation, and the management. The direction is responsible for the final decision. In some cases, the customers are involved as well, for example in the case of Company 8. For this, they mostly contact customers individually but sometimes they also organize small events in which they present and discuss their ideas with multiple potential customers. Outcomes of this discussion might be a good basis for deciding which idea will be selected. Nonetheless, none of the companies mentioned that they have a formal process for the selection of ideas. Besides, the companies do not make use of any voting possibilities, even though by using this, the opinion of the customers might be considered in an easy and fast way.

4.2.3 Development Phase

Knowledge Acquisition

In order to find out which knowledge is necessary and to acquire this knowledge, most of the companies rely on collaborations with externals. Four of the participants mentioned that they work together with their suppliers. During this collaboration, the suppliers provide the companies with knowledge and insights necessary to plan the implementation of the innovation. Participant 7 said that suppliers *"are willing to help you because they know that you are a good customer"*. Therefore, it is important to maintain a good relationship with suppliers in order to be able to use their resources.

Three of the participants work together with knowledge institutes. Participant 4 stated: *"We have chemical knowledge but maybe not all the knowledge that we need. The knowledge institute can do some fundamental research for us and we can transfer that into a product"*. Knowledge institutes are for many organizations important partners since they can provide smaller companies with missing knowledge and data (Weber & Heidenreich, 2018). Therefore, this is a cost-effective alternative for SMEs to get insights about, for instance, specific processes or developments.

Customers can also be involved in the acquisition of the necessary knowledge. Two of the participating companies mentioned that they work together with their customers in the acquire phase of the innovation process. Participant 9, for example, argued that they have several customers who they can contact in case they need support in the knowledge acquisition process.

Those customers do research for the company so that they can develop the innovation for the customers. For smaller companies, also this collaboration can compensate for a lack of resources.

Next to the collaborations with externals, own research is conducted. This has been stated by four of the companies. For instance, Participant 7 stated: *"First, you search yourself for the information that you need for it. That's by using the idea that everyone can learn everything"*. This emphasizes that internal employees can do research even though they might not have a lot of experience with it. Participant 7 emphasizes that this is possible due to the internet since a large amount of valuable information can be excessed there.

The acquire phase is for the companies mainly based on the collaboration with externals and the data that these externals provide. Decisions about which skills and resources are necessary are based on these insights. Especially for smaller companies, the collaboration with, for instance, knowledge institutes can be beneficial since it can be a compensation for missing knowledge and data.

Execution

To test how the final product will look like, the participating companies create prototypes. Also in this phase, the customers can be involved. One of the participants mentioned that they involve the customers to decide how the product should look like and which features it has to offer. By doing so they want to make sure *"that [they are] making the right choice and getting the right data"* (Participant 9). Through the involvement of the customers, it can be ensured that the product is adapted to the customers' needs. However, the involvement of customers at the company is only done on an individual basis and not via, for instance, wikis or forums. Next to the involvement of customers, other externals, such as suppliers, can be involved in this phase. Two of the participants mentioned that they involve partner companies by, for example, trusting the expertise of those partners. This is also done on an individual basis and does not require the analysis of data.

The prototypes itself are created in different ways at the participating companies. For instance, Participant 1B said: *"We find out a lot with 3D printing. We learn a lot from the parts which come from there"*. Using 3D printing can fasten the innovation process since it can be used to test the innovation and can also be shown to consumers (Candi & Beltaugi, 2019). The results of this can be analyzed and decisions can be made based on it. However, most of the participating companies show a prototype to an individual customer, which means that also the feedback is given directly to the company. At half of the companies, the decision whether the prototype is sufficient and if not, how it needs to be changed is therefore done by the customer and not based on the analysis of data. Digital prototypes are only used by the companies which offer digital products. The other companies do not consider it to be value-adding for their products because *"you need to experience how the product feels"* (Participant 5). Additionally, Participant 9 argued: *"In the end, you can do everything from your computer. But in reality, you always run into errors and problems"*. Therefore, they do not make use of digital prototypes although it can save designers around five to six weeks (Brossard et al., 2018). Participant 7 mentioned that they can often make use of existing prototypes from previous projects. For this, it is important that the suitability of the prototype is also tested for the current project (Lindič et al., 2011).

The decision how the process should be structured is made internally at all of the participating companies. This is done without relying on the analysis of data but more on experience. Participant 5 stated: *"If you know how to do in the lab, which steps you need, then we can also do it like this in big in the production"*. Therefore, the opinions of the employees who are involved in the prototype phase are considered in this decision. Additionally, Participant 9 mentioned: *"We are not that big of a company to directly set the process for the capacity which will hopefully be running in a few years. We start slow. So we also have time to structure the* *process"*. Thus, SMEs often do not have the resources to set up the final process from the start. Therefore, this decision about the process is done in steps. The companies did not mention that they survey employees or other users of the final process. This could be useful because by listening to their opinion their needs and knowledge are considered (Tidd & Bessant, 2018).

In conclusion, the decisions made in the execute phase are for most of the participating SMEs not based on data but on the feedback of an individual customer or on own experience. Involving the individual customers is still beneficial since they can provide valuable feedback about whether current ideas are in line with their needs (Mirkovski et al., 2016). Only the two companies who offer a software product make use of digital prototypes in order to test the software.

4.2.4 Launch Phase

The decision of how the final innovation should look like before launching it is based on the feedback of an individual customer for six of the companies. However, two of the participants use a test user group in order to find out whether the current design fulfills their need. Those two companies offer software, which makes it possible to provide it to the test user group digitally. Participant 3 said: *"So we can test our product in a test phase and we can ask users if it is user-friendly and if it does what it needs to do"*. This ensures that the software provides the functionalities the users demand and that every feature is understood by the users. *"They help us by looking at it from an external perspective. Their feedback is via meetings, for example calls or emails"*, Participant 2 mentioned. Including users in the testing can be beneficial because it can also indicate for which functionalities customers would pay a premium and which are not demanded by the customers (Zhan et al., 2017). Also the literature indicates that especially software can be tested with consumers (Russo-Spena & Mele, 2012). One of the participants mentioned that his company uses a test market for new innovations. Participant 6 stated: *"We test something new in a small part of the market and look how it performs. So we test whether people demand it and decide based on the collected data if we roll it out"*. This test shows whether it makes sense to actually launch the innovation in the whole market. Based on quantitative data, which is collected during the test phase, the company decides whether the innovation is profitable enough to roll out. Through this, the probability of launching an innovation which becomes a failure can decrease. It gets clear that a test user group or a test market is only used by the two companies which provide software products and by the B2C company. Also no customer surveys or A/B testing are used by the other companies because they align the innovation to the needs of individual customers and not to a larger target group.

For the promotion it stands out that most of the companies stated that they actually do not do any promotion. For instance, Participant 5 mentioned: *"Actually, we don't have any marketing. Our sales people go to potential customers and tell them what we have but we do not promote our products otherwise"*. This is due to the fact that they consider their market to be relatively small so that potential customers already know them. Also Participant 1A stated that they barely do any promotions expect for promoting their products on their own websites. In contrast, other participants aim to find a suitable strategy for their promotion. For example, Participant 6 argued that the decision of how to promote their innovations is mainly driven by the cost efficiency. He states, for instance: *"As a small company our marketing budget is limited, so we need to use it in a controlled way. If you use the internet, such as Google, everything is transparent and you get data for everything so that you can understand and retrace it"*. Therefore, for an SME, the decisions about how to promote the innovation might be based on the costs relating to it. Furthermore, Participant 7 stated that they recently decided to involve a marketing agency which will take care of the promotion. This is due to the fact that the resources are missing to do it within the company. The two companies who make use of a test user group consider the test users' feedback in order to determine how to promote the innovation. By analyzing the feedback, they know which value propositions are most important to the consumers and can focus on those in the communication. Therefore, these companies use data to decide how to promote their innovation. This can be beneficial since the innovation might seem more appealing to the consumers when communicating the most important features.

The price decision is made by all of the companies by doing a cost calculation. In this calculation, all of the costs associated to the innovation are included and added up. Next to this, the participants stated that they add a margin to come to the final price. This margin is based on different aspects. Participant 8 mentioned that this margin is also based on the exclusivity of the project: *"If the customer wants exclusivity, we calculate that in the price because we cannot sell it to other customers then. That's of course much more costly for us"*. Additionally, Participant 5 said that the margin also changes depending on the amount the customer orders. Participant 6 said: *"Every week we look at how expensive it is at other sites, do a comparison and adapt prices accordingly"*. For this, they create visualizations of the price developments of competitors. Moreover, they also analyze the capacity utilization and adapt the prices in case they are not fully booked. In consequence, most of the companies mostly base the decision about the pricing on the costs related to the innovation. However, some adaptions are made by changing the margin. Company 6 is using a dynamic approach, which takes competing offerings and changes in the demand into consideration. This approach can lead to an improved financial performance (Omar et al., 2019). Furthermore, it seems like it is especially appropriated for the tourism industry.

Since most of the participating companies create an innovation for a specific customer, the decision about where to launch the innovation does not need to be made anymore. However, Company 6 mentioned that they do a market analysis in order to elaborate where the demand is the highest. Participant stated: *"We look at data of, for instance: How many people live in that region? How often do they search for the innovation on Google? How high is the purchasing power?"* Thus, by doing this analysis they find out in which region the consumers are demanding the innovation and are actually able to buy it. Consequently, this decision is based on data for Company 6. For the other companies it is not based on data.

Overall, the companies which offer digital software and the one B2C company use data in their decision-making in the launch phase. The other companies base their decisions mostly on the feedback of individual customers and on internal calculations which are based on existing knowledge about the process and experience.

4.2.5 Post-Launch Adaption Phase

After the innovation has been launched, three of the companies do not make adjustments to the innovation. Therefore, the decision of how the innovation can be sustained for the long term is not made at those companies. Company 5, for instance, argued: *"Products are not developed without the request of a specific customer and afterwards, not that much is happening anymore"*. This might be due to the fact that each customer receives a product adjusted to their individual needs. Other customers do not receive the same product and thus, it is not necessary to make changes to it after it has been sold. Participant 4 stated something similar: *"Most of our products are pretty unique for one customer"*. Hence, Company 4 has the same reason as Company 5 for not making adjustments to the product after the launch. However, Participant 1B states a different reason for his company: *"It is very difficult to make changes in the pharmaceutical market. Then you have to make a dossier on every change. I think in some other markets it will be easier"*. This indicates that depending on the industry a company is operating in, changes to a product might be difficult to make and are connect to a high effort.

Two participants mentioned that the analysis of the customers' behavior is helping in deciding whether the innovation has to be changed. Participant 6 stated that every week they make a comparison between the to-be and the as-is state in order to find out what is performing good and what is performing worse than expected. Based on this, it is decided which innovation or which feature needs to be adapted. Participant 3 said: *"With, for example, Google Analytics we know which functions customers are using and which not and if they find their way in the application. So we track the visitors' usage of the software and on that basis we make improvements"*.

A customer survey is used to discover improvement potentials by three of the companies. All three participants stated that the customers get a short survey in order to find out whether they have been satisfied with the services and the products of the company. For instance, Participant 7 said that they use the results of the survey *"to improve the process and meet up with clients expectations, which is really hard because not all clients expect the same"*. Using surveys to receive feedback can be an important source of improvement potentials (Bosch-Sijtsema & Bosch, 2015). Two of the companies make use of rating scale questions in order to receive a numerical value which can be compared easily. However, through this, they do not get insights into the reasoning behind the given score. One of the three companies makes use of open questions in order to receive improvement potentials. However, Participant 7 states: *"We analyze the survey results in a crappy way. The answers are collected in a portal at the back end of the website but it's not really analyzed. It's flat text which is just read by an employee and forwarded to the quality manager"*. By making use of sentiment or semantic analysis, this process might be sped up because the employee would not need to filter all the answers first. Additionally, Participant 7 mentioned that they use employee suggestions in order to improve processes and products after the launch. Through this, insights are gathered from the work floor. Next to the customer feedback via online surveys, direct customer feedback is used by the companies to improve their innovations. This is done on an individual customer basis. Participant 3 argued: *"We try to stay in contact with the users of our products and we learn from their experience. It is important to listen to data but also to listen to the customers about their experience"*. Through this, they can discover improvement potentials.

The collection of quality data is used by four of the companies to find out what needs to be improved. This includes that the companies are keeping record of which problems occur and how high the quality of the product is. Through this, they can see which problems keep occurring and can try to find a solution for it. This is documented and visualized by the companies so that they can see quickly where improvement potential exists. Participant 2, for example, mentioned: *"We keep track of all the problems that occur. We have a new automated dashboard for it"*. The other companies still look at the data in a manual way, which *"takes a lot of time"* (Participant 9). However, the monitoring of the quality of the products can ensure that quality issues are discovered and can be changed timely.

Sensors in the products are not used by the participating companies. Nonetheless, Participants 9 stated that *"if you could use sensors in the product – if that's allowed by the customer, of course – then you would get so much data. You could learn what do with your products"*. Through this, it would be possible to improve the products based on the actual usage of the customers. However, *"it's really difficult to implement in the world because everybody is protecting their data"* (Participant 9). This could also be a reason why the other companies are not using sensors in their products, although it is helpful to identify consumer needs (Ervelles et al., 2016).

In conclusion, the sustain phase is based on data by the majority of the companies. This is done in different way, such as using online analytics, online surveys, or the usage of a quality documentation. Through this, the companies try to ensure that the innovation is sustained for a longer time by listening to the experience of the customer and by monitoring the quality level.

4.2.6 Learn Phase

In order to learn from the innovation process and improve it accordingly, four of the companies stated that they make use of process indicators. These process indicators include, for instance, a percentage of requests that actually become a product or the comparison between precalculated costs and actual costs. Participant 4 said: *"We monitor these indicators and we set a percentage for it. And if it does not meet it, we need to find out why"*. With the process indicators, the companies can discover whether there is the necessity to adapt the process. Therefore, the decision whether the innovation process needs to be changed can be done based on this data.

Four companies use management meetings to decide whether the innovation process needs to be changed. In those meetings, the management discusses whether they see the need for a change in the process and how they could change it. This can be based on the process indicators but also on experience. For instance, Participant 5 said: *"That's more based on experience. We look at what is going well and what not and how it can be improved"*. Consequently, the companies who do not make use of process indicators do not use data but experience as a basis for this decision. Next to this, Participant 7 argued that it is important to include the employees in this decision because their experience can be valuable and the employees *"feel heard about their complaints or suggestions and that makes them feel committed to the company. When they see that their suggestions are implemented, it's something they're proud of"*. This indicates that even if the decision is based on experience and not on data it is important to not only consider the opinion and experience of the management but also of the work floor employees.

In conclusion, four of the companies actually make use of process indicators as a basis for deciding whether the innovation process needs to be adapted. The other companies base this decision on experience. By basing it only on experience, important field of actions might be overlooked. Besides, none of the companies makes use of benchmarking, which might be helpful to see how other companies manage their innovation process (Tidd & Bessant, 2018).

4.2.7 General Overview

Table 6 provides an overview of what the participating companies use as the basis for their decisions in the different stages of the innovation process. The list includes methods which are based on the literature but also additional ones mentioned by the participants. Therefore, it includes methods which are data-driven and ones which are not. Thus, the left column shows whether it is data-driven (DD) or rather whether it is likely to be data-driven. The table also makes it possible for the SMEs to see where there might be room for improvement. Some of the companies may also use a method without analyzing data, even though it is a method for which it would be possible. Furthermore, there might be improvement potential for the usage of data for companies even though they already make use of data-driven decision-making.

In the idea generation phase, the most used methods are ones which are not data-driven, namely to rely on individual customer requests or collaborations with single customers and to visit events such as conferences, seminars, or fairs. However, five of the SMEs explicitly mentioned that they search for inspiration by looking into current literature or by analyzing what competitors are doing. Therefore, data also plays an important role for SMEs in the search phase. Some of the SMEs also use other data-driven methods, such as conducting an online customer survey or looking at existent patens from other companies.

The selection of ideas is done at eight of the companies by the management team. Therefore, this is not based on a data-driven method. The most important criterium for the selection is for seven of the companies the potential profit of the innovation. The calculation of how much profit it might create can be based on experience but also on the analysis of market potentials.

In order to acquire the necessary knowledge and to decide which skills and resources are necessary for an innovation, most of the companies rely on collaborations with either knowledge institutes, suppliers, customers, or other partners. Through these collaborations the SMEs receive research results including data based on which they can decide what is necessary. The two other companies rely on own research through which they also receive data which is analyzed for the decision.

For the execution part in the development phase, it stands out that the participating companies are following different strategies. Next to this, this phase is not data-driven for almost all of the participating companies. Only two companies rely on digital prototypes since they provide software to their customers. In general, the decisions about how the innovation should look like is based on experience and on the desires of an individual customer. Therefore, this phase is not data-driven for most of the participants.

Also in the launch phase, most of the companies do not rely on data to make decisions. Six of the companies stated that they consider the feedback of individual customers in order to decide how the final innovation should look like. Moreover, also six of the companies use a cost-plus calculation in combination with the addition of an individual margin as basis for the price of the innovation. There are, however, three of the participating companies (Company 2, 3, and 6) which use more data-driven decision-making in this phase since they use a test group or a test market to define the final design, the promotion, and also rely on an analysis of the market to determine the price.

In the post-launch adaption phase, more data-driven decision-making is used. Four companies rely on the analysis of data about the quality of the innovation in order to discover fields of action, two use the analysis of customer behavior online and three conduct online surveys in order to identify improvement potentials. One of the companies uses also quantitative data to analyze where there is potential for improvement.

Four of the participating companies use data in the learn phase for the decision whether the innovation process needs to be adapted. This data results from the usage of process indicators, such as a comparison between the pre-calculated and the actual costs. The other five companies rely on experience and the discussion within the management team. In consequence, these companies do not make use of data-driven decision-making in the learn phase.

In general, it gets obvious that there are similarities at the nine companies. The majority of the companies make decisions in the innovation process in collaboration with individual customers. Therefore, data is only used for particular decisions. For instance, two companies (Company 4 and 5) stated that they do not use data-driven decision-making. Nonetheless, there are also differences between the companies, which can also be seen in Table 6. It especially stands out that the companies which offer digital products (Company 2 and 3) and the one B2C company (Company 6) use data-driven decision-making to a higher extent.

Table 6: Basis for Decision-Making in the Innovation Process

DD	Basis for decision-making	1	2	3	4	5	6	7	8	9
	Idea Generation									
✓	Data from social media, websites, etc.									
✓	Existing patents from other companies	✓								
✓	Literature and market research (e.g. competitors, journals)	✓		✓			✓	✓		✓
✓	Focus group discussions									
✓	Social media for active involvement of customers									

✓	Crowdsourcing									
	Individual customer requests and collaborations	✓		✓	✓	✓		✓	✓	✓
✓	Customer survey or feedback		✓				✓			
	Supplier and knowledge institutes collaborations				✓					
	Seminars, conferences, fairs, etc.	✓	✓			✓	✓	✓	✓	
✓	Employee online suggestions									
	Idea Selection									
	Criteria									
	Fit to company			✓						✓
✓	Potential profit	✓	✓		✓	✓	✓	✓		✓
	Customer willing to collaborate								✓	
	Way									
	Higher management makes decision	✓	✓	✓	✓	✓	✓	✓		✓
	Customers make decision								✓	
	Formal process for selection									
✓	Voting on social media by customers									
✓	Voting by employees									
	Development									
	Knowledge Acquisition									
✓	Collaboration with research or knowledge institutes				✓		✓	✓		
✓	Collaboration with suppliers				✓	✓		✓	✓	✓
✓	Collaboration with customers							✓		✓
✓	Collaboration with other partners		✓							
✓	Own research	✓		✓	✓			✓		
	Experience									✓
	Execution									
✓	Design: Involvement of users/customers									✓
✓	Design: Involvement of employees									
✓	Design: Involvement of other externals, e.g. suppliers		✓						✓	
✓	Design: Crowdsourcing on social media									
	Design: Show prototypes to individual customer	✓		✓	✓	✓		✓	✓	✓
✓	Design: Digital prototypes		✓	✓						
✓	Design: 3D printing for prototypes	✓								
	Design: Adaption of proven concepts							✓		
✓	Structures: Surveying employees and other users									
	Structures: Individual employees decide					✓				
	Structures: Decision made in steps								✓	
	Launch									
✓	Final design: Testing with users/customers		✓	✓						
✓	Final design: Test market						✓			

✓	Final design: A/B testing									
✓	Final design: Online customer survey									
	Final design: Feedback of individual customer	✓			✓	✓		✓	✓	✓
✓	Promotion: Analysis of testing phase		✓	✓						
	Promotion: Involvement of suppliers/other stakeholders									
✓	Promotion: Analysis of competing offerings									
	Promotion: No promotion except for own website	✓				✓				
	Promotion: Based on cost efficiency						✓			
	Promotion: Marketing agency							✓		
✓	Price: Analysis of customer preferences or competitors	✓	✓							
✓	Price: Consideration of dynamics in the market						✓			
	Price: Cost calculation plus margin	✓			✓	✓		✓	✓	✓
✓	Location: Market research about demand, etc.						✓			
✓	Location: Analysis of competing offerings									
	Location: For specific or limited number of customers	✓			✓	✓		✓	✓	✓
	Post-Launch Adaption									
✓	Online surveys to receive feedback			✓			✓	✓		
✓	Quantitative data, e.g. sales data						✓			
✓	Analysis of customer behavior online			✓			✓			
	Direct customer feedback			✓						
✓	Text data from social media, etc.									
✓	Usage of sensors embedded in product									
	No change after launch	✓			✓	✓				
✓	Analysis of data about quality of innovation		✓					✓	✓	✓
	Employee suggestion							✓		
	Learn									
✓	Post-project reviews at end of project				✓			✓	✓	✓
	Benchmarking									
	Experience	✓	✓	✓	✓	✓	✓		✓	
	Employee suggestion							✓		
	Management meetings		✓		✓	✓	✓			

5 Discussion

5.1 Theoretical Implications

5.1.1 Perception of data-driven decision-making

The first research question deals with SMEs' perception of data-driven decision-making. The research reveals the following dimensions of data-driven decision-making according to the participating SMEs. First, data-driven decisions are decisions which are based on data. Second, the analysis of the data is necessary in order to create meaning from the data. Third, feelings are still part of the decision-making, but the analysis of data ensures that feelings are not the main driver. Fourth, data-driven decision-making has to be seen as a continuous process. Through this, the current literature is extended by indicating what SMEs' understanding of data-driven decision-making is. This is interesting since the usage of data analytics is lagging behind at SMEs compared to large companies (Parra & Tort-Martorell, 2016). However, the results reveal that data-driven decision-making can be difficult to define for SMEs, which might be due to the fact that they do not know to what extent a decision needs to be based on data in order to call it data-driven. This raises the need for a more comprehensive definition in order to increase the understanding. Furthermore, the interviews show that the SMEs consider data-driven decision-making as more important when a company is becoming larger. For an SME with a lower number of customers it seems to be easier to talk individually to a customer and to fulfill individual requirements. This gets more difficult when the company grows. Moreover, it might also become more difficult to keep an overview of the business when the organization is larger due to an increasing number of employees. For this, it can be helpful to make use of data-driven decision-making because decisions can be justified more easily.

In order for SMEs to make use of data-driven decision-making, some preparations are necessary. There might be the necessity to adapt current business processes. With current business processes it might not be possible to implement the collection or the analysis of the data. Next to this, employees need to be trained before being able to make use of data-driven decision-making. Otherwise skills might be missing and data might be misinterpreted. Moreover, it seems like own expertise for implementing suitable software is often missing at SMEs. If the preparations are not made, data could be misinterpreted, which could lead to a competitive disadvantage (McAfee & Brynjolsson, 2012; Reijkumar et al., 2018).

The theory suggested that data-driven decision-making offers advantages to companies. These advantages suggested by theory are competitive advantage, improved business performance, increased speed, and smarter and more efficient decisions. The research shows that the participating SMEs are aware of these benefits. Besides, they also added that increased predictability is another advantage of data-driven decision-making. This shows that data-driven decision-making is indeed a core competence to be successful (Reijkumar et al., 2018) – also for SMEs. However, the results show that data-driven decision-making also comes along with challenges. The literature suggested that the corporate culture, privacy concerns, data quality, suitable tools, employees' skills, and the definition of the business processes might be challenges related to data-driven decision-making. All of those have also been mentioned by the participants. Next to those, the participants added that the data collection, the unpredictability, the time consumption, and the amount of data are also challenges which they perceive or expect. From this, the data collection is perceived as the biggest challenge for most of the companies, which indicates that there is room for improvement at SMEs especially regarding the collection of data.

The results indicate that SMEs mostly make use of descriptive analytics. This might be due to its simpler nature compared to diagnostic, predictive, and prescriptive analytics.

However, it would be helpful to use a combination of all four methods. By doing so, the companies could create a more holistic view (Frazzetto et al., 2019). Next to this, the SMEs do not make use of the full potential of data visualizations due to mostly relying on Excel. By making use of other software, the analyses could be enhanced. Since the companies only make use of visualizations of the data, there are also potentials regarding the usage of other techniques, such as data mining or text mining, for instance NLP or machine learning. This can be helpful since a considerable amount of the data found online is in textual form.

5.2.2 Data-driven decisions in the innovation process

The second research question is about to what extent data is used to support decisions in the innovation process of SMEs. In the idea generation phase, the SMEs mostly rely on customer requests and seminars, conferences, or fairs, which shows that the decision about what could be innovated is not based on data for most of the participating SMEs. This might be due to the desire for personal contact to the customers. Since the SMEs in this sample have a limited number of customers, personal contact and also the individual personalization seems to be possible. Furthermore, involving the customers is a good way to compensate for a lack of resources (Chang & Taylor, 2016) and can help to ensure that the innovation fulfills the customers' demands. Nevertheless, by focusing only on customer requests, important opportunities might be missed by an SME. The SMEs in this research do not make use of social media or online forums to search for new ideas. This could be because the reach of SMEs – and especially those active in the B2B area – on social media seems to be limited and therefore, the interaction between customers and the company could be low. Next to this, the companies might not consider it to be necessary to interact with their customers on social media since they try to stay in contact with the customers on an individual basis.

The decision about which innovation to select for implementation, is made by calculating the potential profit and using this as a decision basis. Therefore, this decision is not made on intuition by the SMEs. That the companies rely on this data, implies that they do not want to take high risks related to an innovation which might not lead to a profit. Moreover, the selection is made by the higher management in most of the cases and the customers are only involved in one of the participating SMEs. This might be due to the fact that the participating SMEs mostly do not select an idea from a larger pool of ideas but focus on one request of a customer at a time. Other employees are mostly not involved in making the decision at the SMEs, which could be due to simpler hierarchies and a higher involvement of the higher management in the daily business compared to larger organizations. Furthermore, the research revealed that the SMEs in this sample do not have a formal process for the selection of their ideas, which could limit the success of the innovations (Eling et al., 2016). This might be because SMEs consider their innovation projects as not frequent or large enough in order to require a formal process.

For the development phase, the results reveal that the knowledge acquisition is based on data to a high extent for the SMEs. Suppliers and universities are often involved due to the fact that it can compensate for missing resources in a small company (Weber & Heidenreich, 2018). Therefore, the SMEs do not need to hire own researchers but can profit from the expertise of other companies/institutes. Next to this, SMEs also conduct own research, which might be to keep the control over the project and to save time. In the execution stage of the development phase, most of the SMEs in this sample do not base their decisions on data. This is since the companies mostly rely on experience from previous projects and on the feedback of individual customers. Involving a higher number of customers in this phase might be considered to be too time consuming or not effective enough. However, the involvement of individual customers can still be beneficial since it can provide valuable feedback about whether current ideas are in line with the customer's needs (Mirkovski et al., 2016). Digital prototypes are only used by the SMEs which offer digital products because the other SMEs do not consider it to have an added value. Experiencing the physical product can therefore be seen as important to the SMEs.

The research also shows that the decisions in the launch phase are for the majority of the participating SMEs not based on data. For the final design, this might be because they want to satisfy one individual customer and not a larger target group. Nonetheless, the results indicate that testing concepts with users might be easier for SMEs which offer digital products. The one B2C SME uses a test market, which provides important insights about the possible success of an innovation. The other participating SMEs do not make use of that because they only target individual B2B customers. Therefore, the feedback of the customers is received directly via, for instance, meetings or email communication without the need for collecting larger amounts of data. Furthermore, most of the SMEs do not promote their new innovations but sell it to the customer who requested it, as they might believe that other customers do not have the same demand. However, opportunities might be lost by not promoting it since potential customers are not aware of the product. For the decision about the price, a cost calculation plus margin is used as a basis by the majority of the SMEs, which is due to the fact that the SMEs do not want to take the risk that costs are not covered, which would lead to a loss. However, also competing offerings are not taken into account in a sophisticated way by the majority of the companies, which might be because they consider offerings of competitors as not similar enough to compare it. The SMEs do not research where to best launch the innovation, which is because they do not launch it for a bigger market but for a specific customer. The B2C company in this sample conducts research about the market and about possible locations in order to reach a bigger target group and ensure the success of the innovation.

The majority of the SMEs in this research use data in the post-launch adaption phase to measure the quality and the success of the innovation. Through this they want to ensure that the innovation is creating a profit and that the quality is sufficient so that customers do not get dissatisfied. Three of the companies also send out customer surveys, through which they receive interesting insights which can be used to improve the innovation. By doing so, the companies want to make sure that customers keep being satisfied and the innovation stays successful in the long term. However, the analysis of the results is done without using more sophisticated analytics. Semantic or sentiment analysis might be good additions. Also for companies which do not offer software the usage of analytics, such as Google Analytics, can help in finding out which products/services are most demanded by analyzing what customers search for on the company's website. That some of the companies do not change their innovations after the launch is because they only produced it for one individual customer. In consequence, they do not consider that other companies might be interested in the same product after slightly adapting the innovation. Through this, opportunities might be missed by the companies. Also in this phase, social media is not used by the companies to decide whether the innovation has to be adapted. Again, this might be due to the lower reach of SMEs on social media and the focus on individual customers.

Almost half of the participating SMEs uses data in order to decide whether the innovation process itself needs to be adapted. For this, they use process indicators which show whether there is the necessity for an adaption. This seems to be a suitable way for the SMEs due to its measurability. However, the remaining SMEs do only rely on experience and the results of management meetings. This might also be partly because they do not have a defined innovation process and thus, also no defined procedure on how to measure or improve it. Benchmarking is not used by the companies, which could be because the SMEs assume that competitors are not similar enough regarding their products or services.

In general, it can be said that the extent of data-driven decision-making depends on the phase of the innovation process. For instance, in the execution of the development phase most of the SMEs do not base their decisions on data. This shows that there is the potential to implement it to a higher extent. The identified benefits of provide a motivation to SMEs to implement data-driven decision-making. Faster and more reliable decisions are also crucial for the innovation process and might therefore be a motivation to implement it to a higher extent in the future. Nonetheless, SMEs need to understand what data-driven decision-making entails and which possibilities there are related to it. So far, it seems like SMEs do not make use of data for many decisions in the innovation process because they do not know that and how it can provide a benefit for a specific decision. Therefore, it is important that it will be researched in more detail for which decisions in the innovation process data can provide the strongest advantage. Moreover, especially the data collection seems to be difficult for SMEs, which shows that SMEs needs to improve their data collection processes in order to be able to enjoy the benefits of data-driven decision-making in the innovation process.

However, there are also differences between the participating SMEs. Two of the SMEs stated that they do not use data-driven decision-making at all. Both of these companies are producing textiles, which might indicate that SMEs in this industry use data-driven decision-making to a lower degree. Surprising is that there are companies who do barely document anything, which makes it almost impossible to analyze any data. Moreover, especially the two SMEs which offer digital products make use of data-driven decision-making to a higher extent, which can be due to the acquaintance with the digital environment. Besides, the participating B2C company is using data to support many of their decisions. This might be because the B2C company wants to reach as many customers as possible and thus, analyzes their behavior in order to investigate how to best reach them. In contrast, the B2B companies have less customers but customers buy larger amounts. Thus, they might not feel the necessity to analyze the behavior of the whole target group but focus on individual customers.

5.2 Practical Implications

Next to the theoretical implications, there are practical implications for the participating companies and other SMEs. The participants acknowledge that data-driven decision-making is crucial when an organization is becoming larger. Therefore, in order to grow, they need to consider implementing data-driven decision-making to a higher extent in their innovation process. Moreover, SMEs need to adapt their business processes in such a way that data collection becomes possible so that they have a basis for their analysis. In case own expertise for implementing suitable software is missing, the SMEs should hire experts for it. By using not only descriptive analytics but also diagnostic, predictive, and prescriptive analytics, the SMEs can create a more holistic view. Next to this, it could be beneficial for the SMEs to not only focus on data visualizations but to also make use of other techniques, such as text mining.

In the idea generation phase of the innovation process, patents can be a good way to elaborate what other companies in the market are doing. This is only considered by one of the participating SMEs and offers therefore a potential for the other companies. It can be done in an automated way by using text mining (Woo et al., 2019), but also the manual way can provide interesting insights and can help to not lag behind competitors. Besides, using social media could add value by providing an easy and cheap way to stay in contact with customers. Through this they can receive feedback which might offer inspiration for new innovations. This is also possible with a smaller reach on social media.

By involving customers in the idea selection phase, insights about the customers' preferences can be taken into account by the SMEs. Next to this, involving other employees than the higher management might offer the benefit that their experience can complement the decision-making (Onarheim & Christensen, 2012). Therefore, the SMEs should consider involving those employees in the decision-making. Furthermore, the definition of a formal process on how to select an innovation can be helpful to create an equal basis for different innovation projects.

Basing the decisions in the execution part of the development phase to a higher extent on data can add new insights for the SMEs and might thus improve the innovations. For this, the customers can be involved in this phase but also other partners might be able to add value due to a high expertise. Moreover, the usage of digital prototypes can help to make the decision about the design faster (Brossard et al., 2018). Therefore, the companies should consider it for the first prototypes of new innovations.

In the launch phase, some of the SMEs do not promote their innovations. However, by promoting it with the benefits it can offer to customers, new customers might be acquired. Although the innovation has been demanded by a specific customer, other customers might have a similar demand. For the pricing decision, the SMEs should also analyze competing offerings to not offer a product with a too high or too low price depending on the demanded positioning in the market.

In the post-launch adaption phase, the SMEs should acknowledge that after launching an innovation for an individual customer, other companies/consumers might be interested in something similar. Therefore, they need to consider to slightly adapt the innovation also after it has been launched. Additionally, social media should also be taken into account in order to identify how the innovation needs to be adapted. Also smaller companies can build up an interaction with their customers on social media.

The SMEs should not only consider the opinion and experience of the management in order to make decisions in the learn phase. Instead, they should take the opinion of the employees who are involved in the innovation process into account. By doing so, the employees feel appreciated and might be more motivated. Additionally, using benchmarking can offer benefits to the SMEs because it allows to see how other companies manage their innovation process, which could give interesting ideas for an improved approach.

5.3 Limitations

There are limitations of the research, which should be acknowledged. First, due to the qualitative nature of this research with the conduction of nine interviews, generalizing the findings is not possible. Therefore, the results shown in this research do not indicate that other SMEs do not use data-driven decision-making in different ways and to a different extent. Even in this research, the participating SMEs showed differences in terms of extent and way of usage of data-driven decision-making in their innovation process.

Second, it has to be considered that single informant bias can be a methodological limitation. This is because in eight of the nine interviews, only one interviewee participated for each company. This decreases the validity of the research because the interviewed participant of the SME might not have all relevant information in order to provide a holistic overview of the practices of the company.

Third, it is impossible to indicate precisely what the extent of data-driven decision-making for each decision in the innovation process is. This is due to the fact that it has not specifically been asked for each of the decisions separately. Instead, the extent of data-driven decision-making for the various decisions in the innovation process is based on the interpretations made by the researcher. Consequently, the actual extent of data-driven decision-making might deviate from the results presented in this research.

5.4 Directions for future research

There are further venues of research, which should be considered in the future. First, it should be considered to focus on creating a more comprehensive definition of data-driven decision-making due to the difficulties in defining it for the participating SMEs. Through this, it will be clearer to SMEs what data-driven decision-making entails and whether it could add value to them. When the understanding and the added value of data-driven decision-making becomes clearer, more SMEs might consider implementing it to a higher extent.

Second, in order to create generalizable results, a quantitative research study can be conducted. The quantitative research can create statistically significant results. For instance, it can be tested in which phase of the innovation process it is most important to base the decisions on data in order to increase the success rate of a company's innovations. In case of a qualitative design, future research can avoid single informant bias by interviewing multiple participants from one company. This can ensure that all relevant aspects of one company are taken into account and a holistic picture is created. Through this, the validity of the research can be increased. In the future, it might be interesting to research qualitatively how SMEs can implement data-driven decision-making to a higher extent by interviewing SMEs which have more experience with it.

Third, a research concerning data-driven decision-making in the innovation process of SMEs should be conducted separately for B2B and B2C companies. In this current research, only one B2C company has been involved. However, it got clear that there are differences between this company and the other participating B2B companies. Therefore, it is interesting to investigate whether this difference remains when a larger sample of B2B and B2C are included. Consequently, conclusions can be drawn on whether B2C companies are using data-driven decision-making to a higher extent or in a different way than B2B companies.

5.5 Conclusion

This study has shown to what extent SMEs use data-driven decision-making in their innovation process. For this, the SMEs' perception of data-driven decision-making and the extent of data-driven decision-making in their innovation process have been investigated by conducting semi-structured interviews with nine SMEs. This study shows that there is a basic understanding of the term data-driven decision-making but also that there is the need for a more comprehensive definition. This is important so that SMEs understand the concept and how it can add value to their company. Furthermore, it is argued that data-driven decision-making comes along with benefits as well as challenges, which are acknowledged by the participating SMEs. Moreover, the results indicate that the extent of data-driven decision-making is different for the participating SMEs, which can be, for instance, due to the products/services they offer or the industry in which they are active. Finally, the research shows that there is room for improvement regarding the data usage in the innovation process of SMEs. There are multiple possibilities highlighted in this study which the SMEs do not make use of, which offer potential for the future. Nonetheless, due to the beforementioned limitations of this study, future research is necessary to create generalizable results.

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Appendix 1: Literature Review

On the database Web of Science, a literature review has been conducted. The search terms and filters can be seen below with the according number of results. In some articles, articles or books have been cited which were helpful for this paper. These have been used, as well.

Types of decision

Search terms:	"types of decisions" OR "types of decision" OR "decision types" OR "decision type"	769
Refined by		
Document types	Article OR Book chapter	709
Web of science categories	Management OR Psychology Social OR Business OR Psychology Applied OR Psychology Multidsciplinary	116
Languages	English OR German	113
Publication years	2001-2020	92
Reading abstract		24
Full text		13

Data-driven Decision-Making

Search term	"data-driven decision making" OR "data-based decision making" OR "data-driven decision-making" OR "data-based decision-making" OR "evidence-based decision-making" OR "evidence-based decision making"	1848
Publication year	2011-2020	1480
Document type	ARTICLE OR BOOK REVIEW OR BOOK CHAPTER OR REVIEW	1211
Categories	MANAGEMENT OR COMPUTER SCIENCE THEORY METHODS OR COMPUTER SCIENCE ARTIFICIAL INTELLIGENCE OR COMPUTER SCIENCE INFORMATION SYSTEMS OR COMPUTER SCIENCE SOFTWARE ENGINEERING OR BUSINESS OR COMPUTER SCIENCE INTERDISCIPLINARY APPLICATIONS	112
Abstract		32
Full text		16

Innovation

Search terms	"innovation management process" OR "digital innovation" OR "Innovation process phases" OR "phases of innovation process" OR "innovation process stages" OR "stages of innovation process" OR "innovation process" AND "stages" OR "Innovation process" And "phases" OR "process of innovation"	5058
Categories	Management OR business	632
Document type	Article OR review OR book chapter	443
Language	English OR German	414
Years	2011-2020	303
Index	Social Science Index	218
Abstract		64
Full text		29

Decisions innovation process

Search terms	"idea search" OR "idea screening"	118
Refined by		
Publication years	2011-2020	84
Languages	English	83
Abstract		18
Full text		9
Search terms	"idea generation" AND innovation	698
Refined by		
Publication years	2011-2020	529
Languages	English OR German	528
Index	Social Science Index	285
Categories	Management OR Business	173
Abstract		20
Full text		5
Search terms	commercialization AND "innovation process" OR launch AND "innovation process" OR implementation AND "innovation process" OR prototyping AND "innovation process"	770
Publication years	2011-2020	553
Language	English OR German	529
Index	Social Science	214
Abstract		43
Full text		12

Appendix 2: Interview Questionnaire

I am conducting this interview as part of my master thesis. Through this, I aim to find out how data can be used to support the decisions in the innovation process.
There are no right or wrong answers, it is only about your personal experiences and opinions. Furthermore, your answers are anonymous, thus, nobody will know that you gave these answers. You can always say when you want to stop with this interview or do not want to answer a specific question.
Do you agree to the interview being recorded so that I can transcribe it afterwards?

1 Participant
1.1 What is your current position in the company?
1.2 What are your responsibilities (in short)?
1.3 Since when are you in this position?

2 Data-driven decision-making
2.1 How would you define "data-driven decision-making"? → refers to decisions based on analysis of data instead of experience or intuition. An example: company is analyzing text data, e.g. from social media or customer forums by using text mining to find out how the current product/service should be changed in order to increase customer satisfaction.
2.2 Do you currently use data-driven decision-making? If not, are you planning to do so?
2.3 Why do you (consider to) use data-driven decision-making? Why don't?
2.3.1 Which benefits do you experience or expect?
2.4 Did you make preparations for data-driven decision-making or do you plan to do so? *E.g. Adaption of corporate culture, consideration of privacy concerns, data quality and software, trainings for employees, definition of process*
2.5 Which challenges do you expect or experience for your SME regarding data-driven decision-making? *E.g. missing/not suitable software, missing skills, data amount and quality, data collection*

3 Innovation process
The innovation process can be divided into different phases, which are idea generation, idea selection, development, launch, post-launch adaption, and learn.

In the idea generation phase, you are looking for opportunities for innovation and scan the environment for new ideas.
3.1 How do you decide what you can innovate as a company?
3.2 Where do you search for new ideas?

The idea selection phase is about selecting which of the ideas you want to choose for further development.
3.3 How do you decide which idea should be progressed and which not?
3.4 Based on what criteria do you decide which idea should be selected?

The development phase is about acquiring the necessary knowledge and resources for the innovation. Afterwards, the acquired knowledge and skills have to be transformed into actions and output. This can include the creation of prototypes and the set-up of structures.
Knowledge acquisition
3.5 How do you know which skills and knowledge you need in order to implement the innovation?
3.6 How do you gain the knowledge and skills? *E.g. collaborations*

Execution
3.7 How do you decide how the innovation should look like? Design etc.
3.8 How do you develop prototypes?
3.9 How do you decide how the implementation/launch will be structured?

The launch phase is about the actual commercialization of the innovation.
3.10 How do you decide how the actual product should look like?
3.11 How do you decide how you promote the innovation?
3.12 How do you decide how much the innovation should cost?
3.13 How do you decide where and when you want to launch the innovation?

The post-launch adaption phase is about sustaining the innovation for the long term, which includes monitoring and adjusting the innovation.
3.14 How do you decide whether the innovation needs to be adapted after the launch?

The learn phase is about learning throughout the process in order to improve the innovation process itself.
3.15 How do you decide whether the innovation process itself can be improved?

Appendix 3: Code Book

Understanding of data-driven decision-making

Code	*Description*
Description of data-driven decision-making	How the participants define data-driven decision-making
Problems in defining	The participants experiences problems in defining what data-driven decision-making is

Perceived benefits

Code	*Description*
Better decisions	Data can improve the decisions made
Competitive advantage	DDD lead to a competitive advantage
Improved business performance	The business performance is improved by DDD
Increased speed and flexibility	The speed and flexibility of decision-making is improved by DDD
Need for data-driven decision-making	Explanation of when participant thinks DDD is necessary
Increased predictability	DDD can help by predicting what will happen

Perceived challenges

Code	*Description*
Organizational culture	The organizational culture does not fit to DDD
Privacy concerns	Privacy of customers etc. needs to be protected which can be a challenge
Data quality	The data quality is not always sufficient to base decisions on
Suitable tools	Suitable tools are not available to enable DDD
Employees' skills	Employees do not have sufficient skills for DDD
Adaption of business processes	Current processes do not fit to DDD
Unpredictability	Challenge to predict what will happen in the future
Right data not available	The data necessary for DDD is not available
Not enough data available	The amount of data available is too low to base decisions on

Time consuming	DDD is considered to be more time consuming
Amount of data	Challenges in processing a large amount of data

Preparations

Code	*Description*
Adaptions in systems	Systems need to be adapted or implemented to enable DDD
Adaptions in processes	Processes neet to be adapted to enable DDD
Employee training	Employees need to be trained to acquire necessary skills for DDD
Process indicators	Process indicators need to be created

Search

Code	*Description*
Customer collaboration/request	The collaboration with customers or the request of customers leads to new ideas for innovation
Collaboration with suppliers	The collaboration with suppliers leads to new ideas for innovation
Collaboration with knowledge institutes	The collaboration with knowledge institutes leads to new ideas for innovation
Seminars, conferences, fairs	The visit at seminars, conferences, or fairs leads to new ideas
Market research	Market research is conducted in order to discover new ideas
Inclusion of stakeholders	Stakeholders are included to come up with new ideas
Customer survey	Customer survey is basis for new ideas

Select

Code	*Description*
Criteria	Criteria on which decision about which ideas are implemented are made
Way	Way in which decision is made

Development: Knowledge acquisition

Code	*Description*
Collaboration	Collaboration with partners (suppliers, knowledge institutes, …) helps in deciding which knowledge is necessary and in acquisition of knowledge
Literature research	Literature research is conducted in order to define which knowledge is necessary and to acquire it
Experience	Experience is used to define which resources and skills are necessary for an innovation

Development: Execution

Code	*Description*
Prototypes	Way in which prototypes of the innovation are created
User test	Users test innovation
Set up of structures	How structures for the implementation are set up

Launch

Code	*Description*
Final design	How the final design of the innovation should look like
Pricing	How the innovation is priced
Promotion	How the innovation is promoted
Place	Where the innovation is launched

Post-launch adaption

Code	*Description*
No changes after launch	The innovation is not changed after it has been launched
Usage of analytics	Analytics are used in order to find out how innovation needs to be adapted
Customer survey	Customer survey is used in order to find out how innovation needs to be adapted
Documentation	Documentation is used to find out how innovation needs to be adapted
Employee suggestions	Employees make suggestions to help improving the innovation

Direct customer feedback	Customers give direct feedback about product and what should be adapted

Learn

Code	*Description*
ISO Standard	ISO standard is used to structure, document, and monitor the process
Meetings	Meetings are used to discuss how the innovation process can be adapted
Process indicators	Process indicators are used to indicate where the innovation process can be adapted
Experience	Improvements of the process are based on experience
Employee suggestions	Employees make suggestions about how to improve the innovation process

Usage of data-driven decision-making

Code	*Description*
Systems in usage	Systems which are currently used in the organization
Responsible person	Person who is responsible for making decisions
Techniques	Techniques that company uses to analyze data, e.g. data visualization, data mining, text mining
Extent of data-driven decision-making	Extent of DDD in comparison to decision based on experience or intuition