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From data to value: facilitating strategy development for connected products

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FOREWORD FROM THE EDITOR

Problem

Digitalisation enables companies to develop novel physical products which are connected to the internet. Offering connected products empowers companies, for example, to obtain insights into products' usage or user preferences. In general, connected products and their linked services constantly transmit use phase data. Having access to such use phase data provides novel insights about the product's use phase. Based on these insights, manufactures can, for example, better understand the actual usage of their products. At the same time, it is also possible to add novel product functions or derive data-driven business models. Generally, offering connected products can provide various benefits for internal and external stakeholders. Nonetheless, offering connected products should never be an end in itself because connectivity also introduces additional technical and organisational challenges that restrain companies from achieving the aforementioned benefits. From a company's perspective, it appears that organisational challenges are very critical because they already occur during the planning phase, when companies set the foundation for a successful exploitation of use phase data. A key success factor is that companies derive a comprehensive use phase data strategy. Such a strategy should make sure that companies have clear objectives and an idea of the use cases that should be realized. However, companies struggle to develop such a use phase data strategy, for instance, due to missing experience. At the same time, existing solution approaches deliver insufficient support for the structured development of a use phase data strategy because they provide only operational guidance and methodological support on a rather abstract level.

Objectives

The overall objective of this thesis is to develop a methodological support for companies in order to enable them to develop a use phase data strategy in a structured way. The planning phase is thus in focus because companies need to decide at this point about relevant use cases and required use phase data in order to then formulate a sound and consistent use phase data strategy. Thus, this thesis aims to guide companies through the steps required for developing a use phase data strategy and provide methods supporting the strategy development process. Altogether, the methodological support is intended to be applicable to all types of connected products in a B2B and B2C environment across industries.

Results

The main outcome of this thesis is the six-step process model that provides comprehensive guidance for the development of a use phase data strategy and therefore enables companies to derive a use phase data strategy in a structured way. The process model covers the process from the initiation of the strategy development through to the deduction of an initial implementation concept for the strategy. Existing research work from strategy development and data analytics provided the foundation for the development of the process model. Furthermore, empirical data from case studies, an interview study, and an industry workshop supplied input for the development of the solution approach. The process model is complemented by a method box, which consists of 15 methods that address crucial tasks during the development of a use phase data strategy. The results of applying the process model and the methods during three evaluation cases highlighted that the solution approach enables companies to derive a use phase data strategy in a structured way. Companies were also able to gain an understanding of possible use cases in order to evaluate them in relation to their suitability for the use phase data strategy.

Implications for industry

The main contribution of this thesis is the developed process model that enables companies to independently derive a use phase data strategy that fits to the company's context. The solution approach was developed using multiple case studies in order to ensure its applicability and usability in industry. The process model guides companies through the entire strategy development process and fosters, therefore, a structured procedure. At first, the solution approach supports companies in obtaining internal and external transparency in order to have a comprehensive understanding of the context that frames the development of the use phase data strategy. Secondly, the process model describes the required activities in order to collect, elaborate, and, select suitable use cases. Enabling companies to formulate use cases that fit is critical because use cases form the foundation of a use phase data strategy. The process model triggers a search for use cases that provide value for internal and external stakeholders. Furthermore, the process model and methods allow companies to derive use cases based on available use phase data or identify required use phase data. The solution approach accordingly prevents the collection of data without a clear purpose. Lastly, the process model supports companies in deriving a sound use phase data strategy and an initial implementation concept. In addition, this thesis provides comprehensive insights from case studies in industry, which further supports inexperienced companies in developing their own use phase data strategy.

Implications for academia

From an academic perspective, this thesis contributes to the research on connected products. The developed process model combines research findings from strategy development and data analytics in order to enable the development of a use phase data strategy. Therefore, this thesis supports the knowledge transfer between the two research fields, which makes existing research work applicable to connected products. The methodological support further helps to overcome the limitations of existing work by focusing on planning and managerial problems when exploiting use phase data. The comprehensive analysis of the challenges related to the exploitation of use phase data underlined the importance of the planning phase and outlined starting points for additional research. Furthermore, the developed process model, including the supplementing methods, provides for a better understanding of the steps and tasks required for deriving a suitable use phase data strategy.

Garching, March 2020

Prof. Dr.-Ing. Udo Lindemann

TUM Emeritus of Excellence
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PRIOR PUBLICATIONS

The following publications are part of the results presented in this thesis (chronological order):

Wilberg, J., Maisenbacher, S., and Lindemann, U. (2016). Proactive Cost Management: Integrating Use Phase Data to Reduce Uncertainty. In C. Boks, J. Sigurjonsson, M. Steinert, C. Vis, and A. Wulvik (Eds.): *NordDESIGN, Proceedings of NordDesign 2016: Volume 2, Trondheim, Norway, August 10th – 12th 2016,* (pp. 72–82). Bristol: The Design Society.

Benta, C., Wilberg, J., Hollauer, C., and Omer, M. (2017). Process model for data-driven business model generation. In A. Maier, S. Škec, H. Kim, M. Kokkolaras, J. Oehmen, G. Fadel, F. Salustri, and M. Van der Loos (Eds.), *DS 87-2 Proceedings of the 21st International Conference on Engineering Design (ICED 17) Vol 2: Design Processes, Design Organisation and Management* (pp. 347–356).

Wilberg, J., Schäfer, F., Kandlbinder, P., Hollauer, C., Omer, M., and Lindemann, U. (2017a). Data analytics in product development: Implications from expert interviews. In *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 818–822). Piscataway, NJ: IEEE. https://doi.org/10.1109/IEEM.2017.8290005

Wilberg, J., Triep, I., Hollauer, C., and Omer, M. (2017b). Big Data in product development: Need for a data strategy. In D. F. Kocaoglu and T. R. Anderson (Eds.), *Technology management for the interconnected world: PICMET '17: Portland International Conference on Management of Engineering and Technology.* Piscataway, NJ: IEEE. https://doi.org/10.23919/PICMET.2017.8125460

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Wilberg, J., Lau, K., Nützel, T., Hollauer, C., and Omer, M. (2018c). Development of a catalogue supporting idea generation for internet of things use cases. In D. Marjanović, M. Štorga, S. Škec, N. Bojčetić, and N. Pavković (Eds.), *DS 92: Proceedings of the DESIGN 2018: 15th International Design Conference* (pp. 1453–1464). Faculty of Mechanical Engineering and Naval Architecture, University of Zagreb; The Design Society, Glasgow. https://doi.org/10.21278/idc.2018.0215

TABLE OF CONTENTS

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

Carly Fiorina

List of Abbreviations

B2B	Business-to-business
B2C	Business-to-customer
BI	Business intelligence
CAN	Controller Area Network
CPS	Cyber-Physical Systems
CRC/SFB 768	Collaborative Research Centre / Sonderforschungsbereich 768
CRISP-DM	Cross Industry Standard Process for Data Mining
DESTEP analysis	Demographic, economic, social, technological, ecological, and political-legal factors analysis
DMM	Domain Mapping Matrix
DRM	Design Research Methodology
DS	Descriptive study
DSM	Dependency Structure Matrix
DTU	Technical University of Denmark
FMEA	Failure modes and effect analysis
FTA	Fault tree analysis
ICT	Information and communication technologies
IIoT	Industrial Internet of Things
IoT	Internet of Things
IP	Interview partner
iPeM	Integrated Product engineering Model
IT	Information technology
KDD	Knowledge discovery in databases
LAN	Local area network
MDM	Multiple-Domain Matrix
OEM	Original equipment manufacturer
PESTEL analysis	Political, economic, social, technological, legal, and environmental factors analysis
PGE	Product generation engineering
PS	Prescriptive study
PSS	Product-service-system

R&D	Research and development
RC	Research clarification
RFID	Radio-frequency identification
SMART	Specific, measurable, assignable, realistic, and time-related
SME	Small and medium-sized enterprise
SWOT analysis	Strengths, weaknesses, opportunities, and threats analysis
TUM	Technical University of Munich
UC	Use case

1 Introduction

Aircraft engines that trigger maintenance processes, office printers that automatically reorder consumable supplies, or irrigation systems that factor in the weather forecast. These are just a few examples of connected products and related functionalities that were not available decades or even a few years ago. Connecting products with the internet and collecting data from them unleashes many new financial and non-financial opportunities. However, companies struggle to develop a suitable strategy that takes advantage of these new opportunities. At the same time, methodological support for overcoming these challenges is missing. This thesis closes this gap by deriving a comprehensive solution approach. Thus, the first objective of this chapter is to outline the opportunities and challenges that arise together with connected products. Then, this chapter derives the related research objectives and describes the research approach in order to support companies in extracting value from data stemming from connected products and services more successfully.

1.1 Initial situation

A modern gas turbine generates 30 gigabytes of data every day and a CT scanner generates 60 gigabytes (Kaeser, 2017, p. 143). These examples illustrate how digitalisation shapes physical products and turns them into sources of data. However, digitalisation not only causes an increase in data, it also leads to the **convergence of physical and digital products** (Linz et al., 2017, p. 7; Peppard and Ward, 2016, p. 13). In general, digitalisation is a technology-driven trend that not only changes physical products, but also impacts industry as well as society in general by changing, for example, the way in which people communicate (Gimpel and Röglinger, 2015, p. 5; Isaksson et al., 2018, p. 123). Digitalisation advances at a fast pace and generates large data sets, which originate not only from technical products, but also from other sources like social media or business processes (Gimpel and Röglinger, 2015, p. 6; Wamba et al., 2015, p. 235). Analysing such data can, for instance, support decision making or help to reduce costs (Davenport, 2014, p. 60). When discussing the benefits of analysing data, the term 'Big Data' is often mentioned (Davenport et al., 2012, p. 22). Big Data, however, also describes tasks and approaches required for handling and analysing large data sets in order to extract value from them (Ward and Barker, 2013, p. 2). Collecting data, however, does not automatically provide value, because companies firstly need to have **clear objectives** in order to collect the right data for achieving these (Coleman et al., 2016, p. 2158; Gimpel and Röglinger, 2015, pp. 13–14).

The underlying drivers for digitalisation are advances in information and communication technology (ICT). Due to advances in ICT, many products nowadays contain embedded systems, meaning microprocessors, sensors, and actuators (Marwedel, 2018, p. 2). At the same time, companies sell their products in combination with services, which are referred to as product-service-systems (PSS) (Baines et al., 2007, p. 1545). However, in recent years more products have additionally been equipped with **connectivity**, which turns them into connected products (Porter and Heppelmann, 2014, pp. 68–69). Connectivity with the internet enables products, for example, to communicate with other products, their manufacturer, or their users. The falling price of microprocessors and spread of communication networks further accelerate this trend (Brynjolfsson and McAfee, 2014, pp. 39–43; Kaeser, 2017, pp. 142–143). Literature and research often also use the term ‘Internet of Things (IoT)’ for connected objects in general that transmit and receive data (Koreshoff et al., 2013, p. 335; Manyika et al., 2015, p. 1).

Estimations predict that the number of IoT devices will exceed 25 billion in 2020 (Ellen MacArthur Foundation, 2016, p. 13). Connected products are a main source of data nowadays (Gubbi et al., 2013, p. 1649; Marwedel, 2018, p. 14). Besides the product itself, related services also generate data. This thesis uses the term ‘**use phase data**’[1] for all data that is generated during the use phase by the connected product and related services. In the past, products were often closed systems and thus did not transmit data via the internet (Porter and Heppelmann, 2015, p. 58; van der Vegte, 2016, p. 1). Being able to now collect and exploit use phase data from connected products enables manufacturers to understand, for instance, the products’ usage or customer preferences. These insights pave the way for companies to develop, for example, new product functionalities, services, or business models (Bughin et al., 2015, p. 92; Porter and Heppelmann, 2014, p. 67), which can lead to benefits for internal and external stakeholders (Golovatchev et al., 2016, p. 2). Industry and research also mention the importance of integrating more information about customers and product usage into product development (Albers et al., 2017b, p. 30). Thus, a successful exploitation of use phase data from connected products can generate a number of financial and non-financial benefits (Uckelmann and Scholz-Reiter, 2011, p. 229). Overall, offering connected products has an impact not only on companies, but also on competition within many industries (Châlons and Dufft, 2017, p. 14).

Due to the fact that connected products lead to an increasing amount of use phase data, data analytics approaches play an important role because they enable companies to exploit data (Ochoa et al., 2017, p. 82). Thus, both technologies act as enablers for transmitting data (connectivity) and exploiting data (data analytics). However, companies need to collect the right data in order to extract value from it. Turning data into value requires companies to have a **strategy** in order to ensure that the product, service, and data form a coherent concept that provides the intended benefits (George et al., 2014, p. 324).

1.2 Problem description

Besides the benefits mentioned previously, exploiting data also creates additional challenges that hinder companies from extracting value from the data. Survey findings indicate that only approximately one third of data analytics projects are described as successful (Colas et al., 2014, p. 3). Without a doubt, being able to collect and analyse data can create new opportunities, but at the same time companies face additional **technical and organisational challenges** (Atzori et al., 2010, p. 2788). Technical challenges include, for instance, ensuring the reliability of connected products, achieving the interoperability between different connected products, or ensuring data security (Al-Fuqaha et al., 2015, pp. 2362–2363; Porter and Heppelmann, 2014, p. 84). In general, technical challenges can occur during data generation, transmission, storage, and analysis. Organisational challenges are, for instance, the identification of suitable

[1] A detailed definition of the term ‘use phase data’ is provided in Section 2.3.6

application areas or the integration of insights from data analytics into the decision making processes (Barton and Court, 2012, p. 80; Wirth and Wirth, 2017, p. 33). Such challenges occur when companies start to exploit data because they need to undergo a transformation process (Troilo et al., 2017, p. 617). Therefore, the related challenges involve processes, people, or planning. Nevertheless, organisational challenges do not only occur when companies start to exploit data; it appears that technical challenges occur more frequently at a later point (Schroeck et al., 2012, p. 15). However, findings indicate that organisational challenges seem to be more critical from the company's perspective (LaValle et al., 2011, p. 23; McAfee and Brynjolfsson, 2012, p. 65; Pureswaran et al., 2015, p. 2). Forecasts predict that the number of connected products will increase, which makes it likely that more and more companies will face the organisational challenges that occur early on when planning to exploit use phase data.

A crucial aspect is how companies approach the exploitation of data. It is not beneficial to merely collect as much data as possible or hire data analysts right from the outset (Fitzgerald et al., 2014, p. 12; Wirth and Wirth, 2017, pp. 32–33). Furthermore, companies should not add connectivity without knowing which data they want to collect (Kranz, 2017, p. 175). The starting point therefore should not be the collection of data, but the **development of a comprehensive strategy** that describes which objectives a company wants to pursue (Davenport, 2014, p. 59). This work uses the term '**use phase data strategy**'[2] to highlight the strategy's focus on use phase data. Having a clear strategy ensures that the physical and digital parts are aligned (Fleisch et al., 2017, p. 1). Therefore, companies need to identify **use cases**[3] (UCs), which describe how a company wants to benefit from data stemming from connected products and services (Wirth and Wirth, 2017, p. 32). A use phase data strategy thus describes which use cases a company wants to implement in order to turn use phase data into value.

However, **identifying suitable use cases** and **developing a strategy** are tasks that companies struggle with (Kane et al., 2015, p. 5). One reason might be that a large range of use cases exist, which makes it difficult to identify relevant ones (Morabito, 2015, p. 17). Furthermore, engineering companies often have less experience with data-driven use cases (Kampker et al., 2018, pp. 1–2). Without doubt, the development of connected products and services also increases the level of complexity of the planning and development phase (Porter and Heppelmann, 2015, p. 59). Therefore, different disciplines (e.g., engineering and IT) need to collaborate closely when deriving use cases (Roth, 2017, p. 4; Svahn et al., 2017, p. 14). Connectivity does not only change the product itself; it also requires organisational changes and step-by-step integration (Kranz, 2017, p. 175; Wixom et al., 2017, p. 22). Nevertheless, selecting relevant use cases is important in order to benefit from connected products (Hunke et al., 2017, p. 2). Therefore, companies need to first identify and select suitable use cases in order to derive a sound strategy.

Therefore, the **central problem** during the planning phase that this thesis addresses is that companies do not know how to proceed to derive a suitable use phase data strategy, which requires them to decide which use cases they want to implement. In order to overcome this

[2] Section 2.3.6 derives the definition of the term 'use phase data strategy'

[3] Within this thesis, a use case (UC) describes the process of how selected use phase data is processed in order to provide value for defined stakeholders

problem with strategy development, companies should follow a structured approach when developing a use phase data strategy. However, companies require additional methodological support for a successful exploitation of use phase data (Jacobson et al., 2017, p. 48; Roth, 2017, pp. 4–5; Saltz, 2015, p. 2066).

1.3 Research objective and scope

The description of the initial situation and the subsequent problem description outlined the opportunities and obstacles that engineering companies face when planning to exploit data from connected products and services. The **intention** of this thesis is to enable engineering companies to exploit use phase data in a methodical way in order to derive benefits for both internal and external stakeholders.

Companies that aim to exploit use phase data should start with the development of a strategy in order to formulate clear objectives and a solid direction. Use cases are central to a use phase data strategy because they describe how a company plans to exploit use phase data in order to reach its objectives. However, deriving a strategy seems to be especially challenging for companies also because limited support for the development of a use phase data strategy exists. Therefore, the **overall research objective** of this thesis is to provide methodological support for companies that enables them to develop a use phase data strategy in a structured way.

The **first objective** of this thesis is to gain an understanding of the challenges that companies face when planning to exploit use phase data. Obtaining an understanding of such challenges ensures that the methodological support addresses the relevant aspects. Due to the close connection between data analytics and connected products, both topics lead to similar challenges (Marwedel, 2018, p. 14).Thus, the analysis of challenges considers both domains. The research approach is not only to analyse literature, but also to collect empirical data.

The **second objective** is to provide operational guidance for the tasks required for the development of a use phase data strategy. This includes empowering companies to understand the internal and external factors that influence the strategy development. Due to the diversity of possible use cases, it is also important to foster a structured identification, elaboration, and selection of suitable use cases. The support should ultimately help companies to derive a use phase data strategy and to understand the related implications for the products, services, and organisation.

The **third objective** is to provide methods that support the tasks that companies need to perform when developing a use phase data strategy. Over the course of the development process companies need to perform additional tasks (e.g., identify dependencies between use cases). Therefore, the objective is to develop additional methods that support companies in carrying out these required tasks.

After outlining the objectives, it is possible to define the **research scope** of this thesis. The process of exploiting data consists of many different steps. However, the focus of this work is on the planning phase of the process because it is during this phase that companies should develop their use phase data strategy. This thesis also aims to provide a solution approach for all kinds of connected products, including PSS (e.g., dishwasher, heating system, or car). Furthermore, the solution should be applicable for engineering companies independent from the industry background. In addition, the methodological support for companies should work in either a B2B (business-to-business) or B2C (business-to-customer) environment. Nevertheless, this thesis does not discuss data analytics approaches (e.g., clustering) on a detailed level. This work further recognises the importance of issues related to data privacy and data security, but it does not provide a solution for this matter.

1.4 Research methodology and environment

This section outlines the research methodology for the development of the solution approach and describes the research environment of this thesis.

1.4.1 Research methodology for this thesis

The research process of this work follows the structure of the Design Research Methodology (DRM) of Blessing and Chakrabarti (2014). The DRM provides a structured and generic approach for design research, which aims to support the researcher in understanding the underlying problems, but also in designing a solution approach that helps to overcome the identified problems (Blessing and Chakrabarti, 2014, p. 9). In general, it is possible to adjust the DRM to the particular needs of the research projects (e.g., use multiple iterations or set different starting points). As the research objective is to enable engineering companies to exploit use phase data more successfully, an understanding of the needs of companies is therefore crucial. Case study research therefore played an important role because it allows for the derivation of a solution approach that is of value in both research and industry (Eisenhardt and Graebner, 2007, pp. 25–26).

The DRM consists of the following four steps (Blessing and Chakrabarti, 2014, pp. 15–17): research clarification (RC), descriptive study I (DS I), prescriptive study (PS), descriptive study II (DS II). The following paragraphs describe how each step was performed for this thesis.

The main objective of the **research clarification** is the definition of a research objective and an intended outcome. Within the context of this work, an analysis of existing literature on data analytics and connected products helped to reveal the opportunities and challenges that the successful exploitation of use phase data offers. The experience of the author further complemented the insights of the initial review.

Afterwards, the intention of the **descriptive study I** is to obtain a detailed understanding of the current situation and related problems. Furthermore, the findings of this step highlight, which factors research should address in order to improve the situation. This thesis used literature as well as an empirical driven approach to outline challenges that hinder the exploitation of use phase data. These insights then allowed for the assessment of the existing support and identification of related shortcomings. Additional empirical data from initial cases studies, an interview study, and an industry workshop helped to deepen the understanding of the specific problems that companies face when planning to exploit use phase data. The findings led to the definition of the requirements for a solution approach.

The following **prescriptive study** builds upon the understanding of the problem and the requirements in order to develop a suitable solution approach. For this thesis, the process model for the development of a use phase data strategy and related methods were developed. The final process model was developed using two iterations. The first version of the process model was derived from a synthesis of existing work on strategic management and data analytics. Afterwards, the application of the process model at three companies helped to test and refine the process model. Furthermore, it was possible to derive additional supporting methods.

Applying and evaluating the developed solution approach is the objective of the **descriptive study II**. The developed process model was thus applied during three different case studies in industry. A questionnaire and interviews allowed for the evaluation of the developed process model and related methods. An additional interview with a railway company provided further insights about the benefits and disadvantages of the developed solution approach. Overall, it was possible to assess the applicability, usability, and usefulness of the process model.

1.4.2 Environment for this research and practical experience

The findings of this thesis are based on the author's work as a Research Associate in the Institute of Product Development at the Technical University of Munich (TUM).

The main results of this work originate from research work during the third funding period within **Collaborative Research Centre 768** (CRC/SFB 768) in subproject A10 ("Supporting innovation of PSS through model-based assessment of PSS use phase information"). The CRC 768 and its subprojects are funded by the German Research Foundation (DFG). The main objective of the subproject was to enable PSS providers to innovate their PSS based on information collected during the use phase. Vogel-Heuser et al. (2014) describe the scope and structure of the CRC 768. The research work also included comprehensive collaborations with **industry partners** from different sectors in order to design and evaluate the solution approach.

Important academic input also originated from a collaboration with the Engineering Systems Division at the **Technical University of Denmark (DTU)**. The collaboration with Professor Anja Maier and Sebastiano Piccolo assessed how data can support and improve engineering design. The collaboration under the EuroTech Alliance partnership included four workshops and two conference publications (Piccolo et al., 2018b; Piccolo et al., 2018a). An additional five week-long research stay at the Engineering Systems Division also shaped this thesis.

The research for this thesis also uses the findings of multiple **student theses** (see Section 0 for details). All student theses were supervised closely by the author. Some theses focused on theoretical aspects and others were conducted in collaboration with partners from industry.

1.5 Structure of the thesis

This thesis consists of nine chapters in order to achieve the research objective. Figure 1-1 provides an overview of the structure of this thesis and highlights important outcomes of each chapter. The figure also depicts the link between the chapters and the four phases of the DRM.

Driven by the overall research objective of this thesis, **Chapter 2** analyses existing literature on digitalisation (Section 2.1), data analytics (2.2), and connected products (2.3). Each section describes the technological drivers, potential benefits, and challenges. Additionally, recommendations are described that support companies in mastering the change process that each topic triggers within companies. Furthermore, Section 2.3.6 defines the terms ‘use phase data’ and ‘use phase data strategy’. Then, Section 2.4 summarises the findings and highlights the importance of a use phase data strategy for the successful exploitation of use phase data.

Chapter 3 focuses on the analysis of data from empirical data on the exploitation of use phase data. Section 3.1 summarizes the learnings from four initial case studies. Afterwards, Section 3.2 discusses the findings of an interview study that focused on the opportunities and challenges for data analytics in product development. Based on these findings, an industry workshop was conducted, which is described in Section 3.3. Then, Section 3.4 presents the overall conclusion of the empirical studies and discusses challenges and opportunities linked to an exploitation of use phase data of connected product.

Subsequently, **Chapter 4** analyses the findings of the previous two chapters in order to outline the research gap and needs. Section 4.1 outlines the challenges that hinder companies in exploiting use phase data and details, based on this, the scope of the required methodological support. Afterwards, Section 4.2 derives formal, functional, and application requirements for a solution approach. These requirements provide the input for a comprehensive analysis of existing process models for data analytics projects in Section 4.3. Finally, Section 4.4 outlines the need for a process model supporting the development of a use phase data strategy.

The **Chapter 5** represents the first development step leading towards the process model by deriving the fundamentals and a conceptual design of the solution approach. First, Section 5.1 derives the structural and functional design of the process model for the development of a use phase data strategy by analysing existing process models for data analytics projects, strategy development, and problem solving. Then, Section 5.2 summarizes the findings of the initial application of the process model concept during three orientating case studies. Afterwards, Section 5.3 outlines implications for the development of the final process model.

The process model and the supporting methods for the structured development of a use phase data strategy are presented in **Chapter 6**. At first, Section 6.1 provides an overview of the six-step process model and describes its application. Afterwards, Sections 6.2 until 6.7 describe each of the six steps and the integrated methods in detail. Then, Section 6.8 concludes with a summary of the developed process model.

The industrial evaluation of the developed process model and the methods is the scope of **Chapter 7**. Therefore, Section 7.1 describes the objectives of the evaluation and its design. Afterwards, the following sections describe the application of the process model in three evaluation cases: connectivity solutions for laundry rooms (Section 7.2), washing machines (Section 7.3), and dishwashers (Section 7.4). Afterwards, Section 7.5 summarizes the results of an interview-based evaluation at a railway company. Then, Section 7.6 summarises the evaluation feedback concerning the process model and the developed methods.

Afterwards, **Chapter 8** reflects the results of the previous chapters. Therefore, Section 8.1 discusses the research approach and the research results. Then, Section 8.2 outlines the contribution that this thesis provides for research and industry

Finally, **Chapter 9** summarises the overall results (Section 9.1) and outlines potential topics for research in the future (Section 9.2).

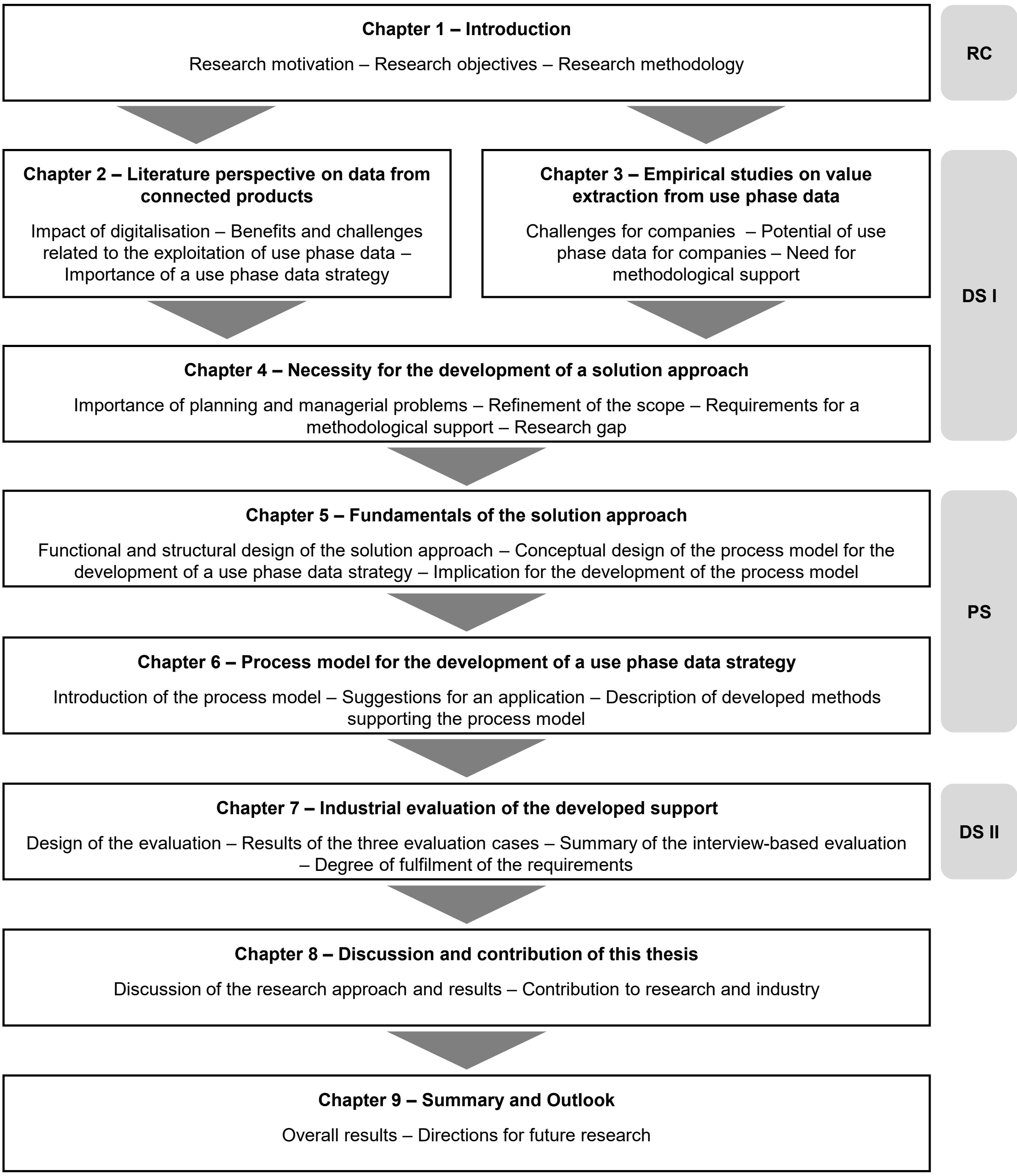

Figure 1-1: Overview of the structure of this thesis

2 Literature perspective on data from connected products

The second chapter introduces the theoretical foundation of this thesis and outlines the opportunities as well as challenges that arise with data stemming from connected products. First, Section 2.1 outlines the comprehensive changes that digitalisation has triggered due to advances in information and communication technologies (ICT). Digitalisation is creating an increasing amount of data. Therefore, Section 2.2 introduces Big Data and data analytics, which help to store, process, and analyse data in order to derive insights from it. Digitalisation is also leading to a change in the product portfolio of engineering companies because an increasing number of products are being equipped with connectivity. Section 2.3 discusses the concept of connected products and the Internet of Things (IoT). All three sections highlight opportunities and challenges that arise due to the technological development within each field. Finally, Section 2.4 summarizes the findings of a literature review on data stemming from connected products in order to provide a conclusion.

2.1 Digitalisation – Managing the digital transformation

The introduction highlighted how digitalisation enables data analytics and the connectivity of technical products. Therefore, the objective is to understand how digitalisation facilitates companies to extract value from connected products.

2.1.1 Foundation of digitalisation

The foundations of digitalisation stem back to technological developments many decades ago that allowed for the representation of information in a digital way through use of the binary number system (Weber, 2017c, p. 16). However, in recent years the relevance of digitalisation has increased because the topic has turned into a more comprehensive subject in comparison to the purely technical understanding of the term in the past (Linz et al., 2017, p. 6). Digitalisation nowadays represents a trend that impacts all kinds of organisations because it triggers changes on many different levels (Rachinger et al., 2018, p. 3).

Literature mentions two different terms to distinguish the technical perspective of digitalisation from the holistic perspective (Schallmo and Williams, 2018, pp. 4–5). The term **digitization** describes the process of converting analogue data into digital data (Rachinger et al., 2018, p. 3). With respect to photography, in the past cameras required physical films to store pictures. Nowadays, cameras have memory cards that store the pictures in a digital format. This technical change leads to new possibilities and functionalities. However, there are many other examples of digitization in other domains. In contrast, the term **digitalisation** describes the impact that advancing digitization has on companies, organisations, and society (Gimpel and Röglinger, 2015, p. 5). Therefore, this term describes the technology-driven change process in organisations. Looking at the photography example, the digitization of pictures requires new products, which allows new companies to enter the market. At the same time, possibilities for new services arise (e.g., design of customised postcards). Overall, the topic has a far-reaching influence and therefore also involves cultural, political, and social aspects (Weber, 2017b, p. 3). This thesis ultimately interprets the term 'digitalisation' as the generation and exploitation of digital objects. The term **digital transformation** describes how an organisation increases its maturity in order to take advantage of the possibilities that digitalisation offers (Wolf and Strohschen, p. 64). The focus of this work is on digitalisation in industry.

The underlying foundation for digitalisation are the advances in **information technology (IT)** in the last years, which further accelerated the transformation process (Linz et al., 2017, p. 5; Wolf and Strohschen, p. 57). Peppard and Ward (2016, p. 3) define IT as the technology (e.g., hardware, or software) that facilitates the acquisition, processing, storing, delivering, and sharing of data or information in different formats. Nowadays, IT is an important enabler and success factor for the economy (Carr, 2003, p. 41). Due to the fact that IT and communication technology are overlapping more and more, literature uses the term **information and communication technologies (ICT)** to describe this trend (Peppard and Ward, 2016, p. 3). ICT is nothing new, but advancements of the technologies involved created new possibilities for companies to approach customers or shape their value proposition (Bharadwaj et al., 2013, p. 471). Digitalisation therefore acts as a trigger for innovation in society and industry (Weber, 2017c, p. 16).

It is further possible to subdivide **digitalisation into two phases** (Hirsch-Kreinsen and Hompel, 2017, p. 359). The first phase started in the 1990s, when the value proposition of certain industry sectors was starting to be based on intangible products (e.g., data or digital information). A core technology was the internet, which became widespread during this time (Châlons and Dufft, 2017, p. 13). The internet changed the communication within a company and with external stakeholders, which created novel networks and links. The second phase now involves especially the digitalisation of physical objects (Gimpel and Röglinger, 2015, p. 5; Hirsch-Kreinsen and Hompel, 2017, p. 359). This increase in connectivity allows companies to create new business models and business processes. At first, digitalisation impacted companies with goods or products that were easy to digitize (e.g., music, videos, or news) (Kaeser, 2017, p. 143). However, technological developments in recent years has accelerated digitalisation further (Brynjolfsson and McAfee, 2014, pp. 39–41; Kaeser, 2017, pp. 142–143). Microprocessors, for example, have not only become more powerful, but also cheaper. At the same time, networks (broadband and mobile networks) have become more widespread and faster, which further improved the functionalities of connected products.

2.1.2 Impact of digitalisation on companies and competition

Some publications use the term **digital revolution**, which aims to indicate how comprehensive the effects of digitalisation are (Linz et al., 2017, p. 9; Münnich and Zwick, 2016, p. 73). In general, digitalisation influences many different areas of the economy and society (Schallmo and Williams, 2018, p. 1). Digitalisation affects many economic activities, which creates completely new possibilities for business activities and interactions between stakeholders (Hirsch-Kreinsen and Hompel, 2017, p. 359).

In general, digitalisation affects every part of the **value chain in industry** (Bloching et al., 2015, p. 6). The digitalisation changes the manufacturing process and the machines that companies use to produce their goods (Kaeser, 2017, p. 143). The term Industry 4.0 is often used to describe the changes in manufacturing due to progressing digitalisation. Section 2.3.1 provides a discussion of the term. Furthermore, digitalisation changes the way in which companies develop products (Kaeser, 2017, p. 143). Engineers often use multiple tools to derive virtual representations of products or their components before a first physical prototype even exists. Simulations allow for the testing of different designs without requiring a test rig (Albers, 2016, pp. 548–549). Therefore, companies can test products or components early on during the development process. Nevertheless, companies need to ensure that the simulation considers all relevant factors in order to ensure high quality results.

Altogether, digitalisation allows companies to change their internal **business processes**. These changes become more visible for internal stakeholders. Moreover, digitalisation also has a strong impact on the products that companies offer and produce. A main observation is that digitalisation leads to the replacement or extension of the tangible product with a digital product (Linz et al., 2017, p. 16). Digitalisation impacts traditional products like aircraft engines (Peppard and Ward, 2016, pp. 13–14; Roth, 2017, p. 1). Modern engines constantly produce data and transmit it to the manufacturer, which enables the manufacturer to monitor the health status of the engine in order to prevent failure. Section 2.2 provides a detailed discussion of connected products. Changing their products by using digitalisation-driven opportunities allows companies to offer new business models and change their value creation (Rachinger et al., 2018, p. 14). These new possibilities are positive outcomes for traditional companies because they might be able to generate new turnover. However, digitalisation also allows new competitors to enter the market because it removes the clear separation between industries (Linz et al., 2017, p. 6). From a customer perspective, digitalisation helps to improve the customer experience, for instance by simplifying their access to information or offering additional services (Westerman et al., 2011, p. 16). At the same time, digitalisation leads to the empowerment of customers because it allows them, for example, to review products or services online (Gimpel and Röglinger, 2015, p. 5).

Furthermore, digitalisation also has an **organisational impact** on companies. As discussed earlier, IT is a key enabler and accelerator for digitalisation. In the past, the IT strategy of a company was often a functional strategy that provided an infrastructure for the business (Bharadwaj et al., 2013, p. 472; Weinrich, 2017, p. 652). Due to the importance of IT for the competitiveness of a company, the IT that a company uses becomes a key asset. Therefore, companies need to formulate an IT strategy that drives innovation based on the possibilities that digitalisation offers (Yoo et al., 2010, p. 731). Companies need to build up new competencies in order to compete successfully within the digitalisation environment (Linz et al., 2017, p. 8). Therefore, managers need to build up an understanding about how their company can take advantage of digitalisation (Kane et al., 2015, p. 15).

Nevertheless, the previous examples only highlight some areas that are impacted by digitalisation. The overall impact of digitalisation is way more far reaching and influences many aspects, for instance the working environment, communication, hierarchy, or job content (Hirsch-Kreinsen and Hompel, 2017, p. 363; Kane et al., 2015, p. 4)

2.1.3 Digital transformation

The adoption of these new technologies requires a **change process** in order to benefit from digitalisation. Accordingly, the term digital transformation describes the change process that companies need to undergo in order to increase their level of digital maturity (Wolf and Strohschen, p. 64). It is important to assess the **digital maturity** of a company with a combination of different factors in order to take the multiple and diverse aspects of digitalisation into account (Kane et al., 2015, p. 15; Wolf and Strohschen, p. 61). A central aspect for assessing the maturity of a company is the IT because it provides the technological foundation for digitalisation. However, it is possible to further subdivide the IT into layers: software, data management, governance, and infrastructure (Wolf and Strohschen, p. 61). It is important to understand to which degree the company incorporates digitalisation into its own products and value chain. Kane et al. (2015, p. 15) suggest further taking the leadership of the company into consideration when assessing the maturity of a company. Overall, the variety of dimensions of digital maturity highlights the complexity of this topic. The importance of the individual factors, however, depends on the context of the company (Wolf and Strohschen, p. 61).

Westerman et al. (2012, pp. 3–4) suggest to distinguish four **digital maturity levels** based on the two dimensions digital intensity and transformation management intensity. The first dimension describes for what a company uses the digitalisation (e.g., new product functionalities, additional digital services, or improvement of business processes). The second dimension captures how a company approaches the digital transformation from an organisational and management perspective in order to create a suitable environment (e.g., development of vision or adjustment of the organisational structure). The adoption of these new technologies requires a **change process** in order to benefit from digitalisation. Accordingly, the term ‘digital transformation’ describes the change process that companies need to undergo in order to increase their level of digital maturity (Wolf and Strohschen, p. 61). It is important to assess the **digital maturity** of a company with a combination of different factors in order to take the multiple and diverse aspects of digitalisation into account (Kane et al., 2015, p. 15; Wolf and Strohschen, p. 61). A central aspect for assessing the maturity of a company is its IT because this provides the technological foundation for digitalisation. However, it is possible to further subdivide the IT into layers: software, data management, governance, and infrastructure (Wolf and Strohschen, p. 61). It is important to understand to which degree the company incorporates digitalisation into its own products and value chain. Kane et al. (2015, p. 15) suggest further taking the leadership of the company into consideration when assessing its maturity. Overall, the variety of dimensions of digital maturity highlights the complexity of this topic. The importance of the individual factors, however, depends on the context of the company (Wolf and Strohschen, p. 61).

Table 2-1 provides an overview of the four maturity levels and describes the main characteristics of each level. It is not only important to take advantage of the digitalisation, for example, by offering new products or improving business processes. At the same time, it is important how a company approach digitalisation from an organisational and management perspective in order to take advantage of the opportunities that the digitalisation offers

Table 2-1: Four levels of digital maturity (based on Westerman et al. (2012, p. 4))

Maturity level	Short description of the characteristics
Digital beginners	• Limited capabilities to take advantage of digitalisation • Missing understanding of the opportunities that investments would provide
Digital fashionistas	• Completion of a limited number of initiatives for a digital transformation • Unclear strategy for the transformation and missing synergies between initiatives
Digital conservatives	• Good understanding of the importance of a vision and strategy for a transformation • Risk aversion hinders the company from driving innovation based on digitalisation
Digirati	• Implementation of changes in order to extract value from digitalisation • Clear strategy and coordination of the investments in order to drive the transformation

There are different **drivers for the digital transformation** of companies. The main stakeholders that act as drivers are customers, employees, and competitors (Rachinger et al., 2018, p. 14; Westerman et al., 2011, p. 9). Therefore, companies need to understand and manage the internal and external expectations. The digital transformation is more far reaching than a nice to have feature. Thus, companies believe that a digital transformation is crucial in order to stay competitive in the future (Fitzgerald et al., 2014, p. 2). A central impact of the digitalisation is that new competitors are able to access the market and at the same time, new networks of stakeholders occur. Customers demand more than just physical products because they ask for additional functionalities or services explicitly. At the same time, employees want to benefit from the digitalisation when developing products or collaborating with other departments. The pressure on companies is not only high, companies further believe that the transformation speed will further increase in the future (Westerman et al., 2011, p. 9). The speed is mainly driven by technological advances, but also by the solutions that other companies offer (Kaeser, 2017, p. 142). A competitor that starts to offer, for example, a monitoring service for the products, will most likely change the expectations of customers.

The central task is the **combination of digital and physical technologies** in order to take advantage of the new opportunities (Weber, 2017a, p. 54). However, digital technologies (e.g., smartphones or social media) work as enablers and do not automatically provide additional value (Kane et al., 2015, p. 5; Westerman et al., 2011, p. 5). The main challenge is therefore to integrate digital technologies into the business process or business model. Companies should not believe that, for example, investing in a new IT infrastructure is a guarantee for a successful digital transformation. At the same time, existing technologies for physical products do not become obsolete (Weber, 2017a, p. 55). Companies need to understand how digital technology complements existing products while maintaining their core competencies.

A common mistake of companies is that they only focus on adopting digital technologies (Berman and Bell, 2011, p. 2; Kane et al., 2015, p. 6). Thus companies need to **develop a strategy** that describes how digital and physical technology should work together in order to benefit from the digitalisation (Châlons and Dufft, 2017, p. 19; Fitzgerald et al., 2014, p. 12).

Nevertheless, companies are also required to stay innovative in their core business in order to avoid losing important skills by neglecting their core competencies (Svahn et al., 2017, p. 16). Due the technological and organisation complexity of the digital transformation, it is important that companies follow a structured approach for embracing the opportunities related to the digitalisation (Fitzgerald et al., 2014, p. 12). Companies should thus follow a stepwise approach in order to learn from the experience and identify promising links between the physical and the digital world.

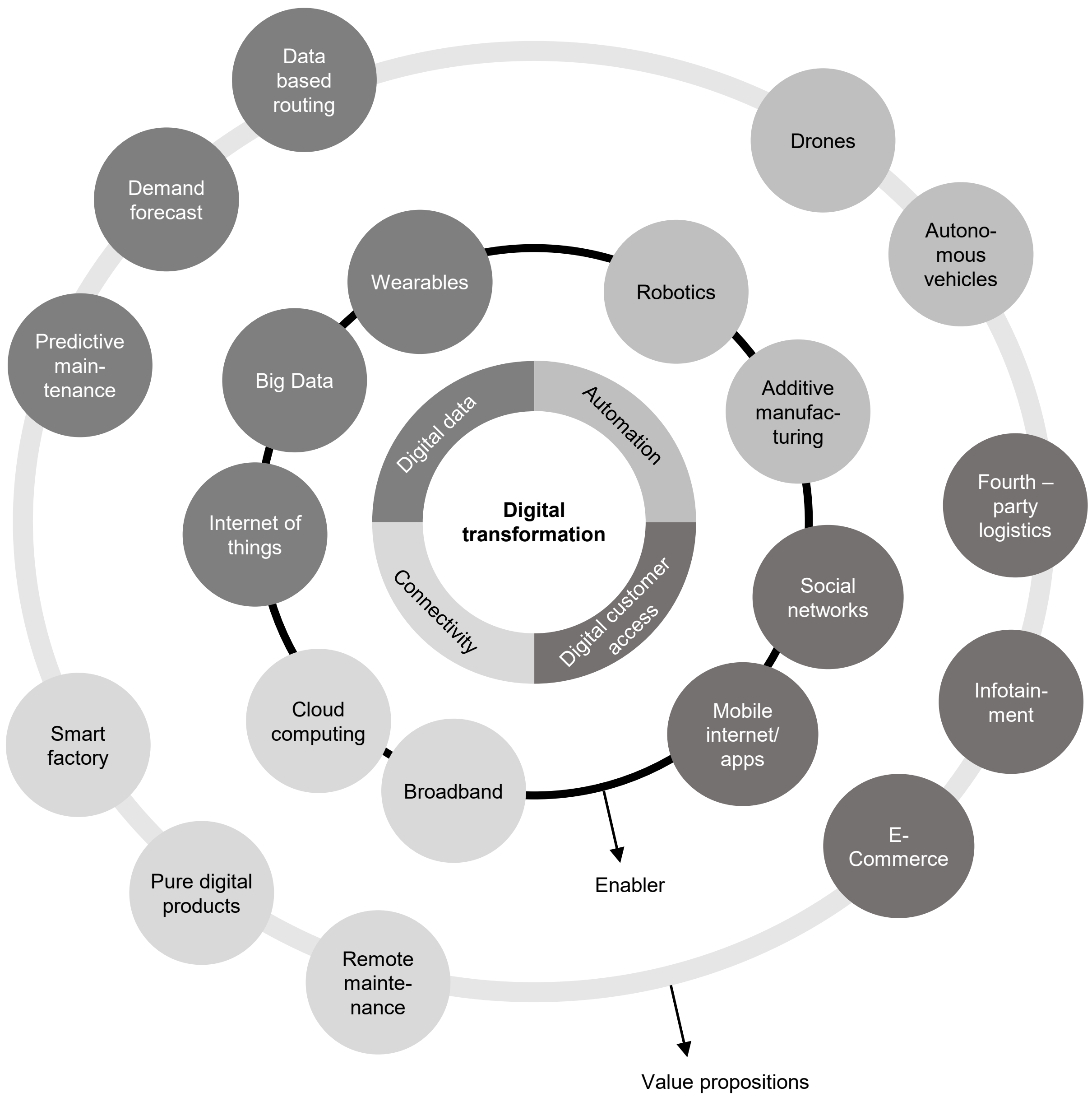

Figure 2-1: Levers, enablers, and possible value propositions based on digitalisation (derived from Bloching et al. (2015, p. 20))

In order to take advantage of digitalisation, the companies need to gain an **understanding of the underlying technologies** (Rachinger et al., 2018, p. 13). The challenge here is that digitalisation is driven by multiple technologies and at the same time leads to new technologies and products (Bloching et al., 2015, pp. 17–19; Collin et al., 2015, p. 29; Gimpel and Röglinger, 2015, p. 6). In addition, the technology landscape is constantly involving with new technologies occurring and others disappearing (Olleros and Zhegu, 2016, p. 9). Bloching et al. (2015, pp. 16–19) suggest that digitalisation is mainly driven by four levers: digital data, atomisation, connectivity, and digital customer access. Figure 2-1 illustrates how the levers can be combined with enabling technologies in order to provide value based on digitalisation. The value proposition can be based on a product or a service. Sections 2.2 and 2.3 discuss the enablers Big Data and Internet of Things on a detailed level.

2.1.4 Benefits and challenges

Benefiting from digitalisation requires that companies need to rethink, for instance, how they organize their business processes or which services they offer (Svahn et al., 2017, p. 16). A study that was initiated by the Federation of German Industries (Bundesverband der Deutschen Industrie – BDI) estimates that digitalisation is able to create additional value worth 450 billion Euro by 2025 (Bloching et al., 2015, p. 7). Therefore, companies need to overcome the barriers occurring during the digital transformation in order to be successful.

The range of possible **benefits** related to digitalisation covers internal and external aspects. From a high-level perspective, digitalisation can help to improve customer experience and engagement, streamline operations, or define new businesses and business models (Fitzgerald et al., 2014, p. 5). Therefore, companies are able to increase their turnover (Fitzgerald et al., 2014, p. 6; Rachinger et al., 2018, p. 12). Digitisation, for example, enables GE to use a new business model when selling aircraft engines (Allmendinger and Lombreglia, 2005, p. 133). Instead of selling the engine to the airlines, the company sells operating time of the engine to the airlines. Therefore, the company uses digitalisation to monitor the engines and coordinate their required maintenance. Customers benefit from digitalisation because companies are able to enhance their products or even develop new ones (Svahn et al., 2017, p. 16). Digitalisation further helps to improve the operations within a company (Fitzgerald et al., 2014, p. 6). A main benefit is that digital technology allows for the automation of internal processes, which reduces the time that employees spend on administrative work. In general, companies see high potential in increasing the productivity of workers by using digital technology. Altogether, Berman and Bell (2011, p. 5) state that digitalisation either changes the way that a company provides its value or the value proposition itself (product or service).

In contrast, digitalisation also creates new **challenges** for companies. Similar to the benefits, the barriers strongly depend on the company. An understanding of the barriers to a digital transformation is important because it enables companies to actively address or avoid them (Herbert, 2017, pp. 75–76). The challenges are not only technology-related but also include management and social ones (Westerman et al., 2011, p. 5). It is possible to divide the challenges into the following four categories: people, processes, platform, and partnership (Herbert, 2017, pp. 76–77). The first aspect involves, for example, employees needing to take over new responsibilities. Furthermore, transforming the company might also require defining new roles in order to create innovative products that combine physical and digital technology. Another challenge within this domain is that employees need to have additional skills (Rachinger et al., 2018, p. 13). Looking at the processes, digitalisation requires companies to rethink their operation processes and to foster collaboration between stakeholders that have not worked together before (Herbert, 2017, p. 76). Data is an enabler for digitalisation and, therefore, a central effect of digitalisation is that the amount of data is constantly increasing (Rogers, 2017, pp. 16–17). However, a key challenge for companies is to extract value from the data. A company's lack of experience hinders them from deriving ways in which to extract value from the digital transformation, constituting another important barrier (Fitzgerald et al., 2014, p. 6).

Nevertheless, research findings indicate that the challenges differ based on the digital maturity of a company (Kane et al., 2015, p. 5). Companies with little experience mention that lacking a strategy for incorporating digital technologies is their main challenge because no clear vision exists. More mature companies, in contrast, struggle because they have too many or competing priorities. The findings of another research study show that challenges differ over the course of the digital transformation process (Westerman et al., 2011, pp. 35–42). During the initiation, companies struggle to identify a business case that clearly describes the benefits of a digital transformation. During the execution phase, companies often have skill-, culture-, and IT-related issues. In the end, the main challenges are a limited vision and problems with coordination among the stakeholders. From a process perspective, a problem is that companies start different initiatives without coordinating them (Châlons and Dufft, 2017, p. 19).

2.2 Big Data and data analytics – Exploitation of data

A key takeaway from the previous section is that digitalisation leads to a steep increase in available data. Estimations state that every day 2.5 quintillion bytes of data are generated (Jacobson, 2013). The data stems from different sources, for example, social media or connected products (Wamba et al., 2015, p. 235). The term Big Data is often used in this context to describe the large amount of data that is available (Katal et al., 2013, p. 404). Big Data is of interest for many different research fields and industry sectors (e.g., physic, engineering, or finance) (Yin and Kaynak, 2015, p. 143).

In the following, the terms 'data analytics' and 'Big Data' will be used interchangeably to describe tasks and activities along the entire value chain when exploiting (Big) data. This section provides a characterisation for data, introduces data analytics approaches, discusses benefits and challenges, and derives suggestions for initiatives for exploiting data.

2.2.1 Sources of data and characterisation of Big Data

On an abstract level, one can describe data as syntactic entities, which means that data itself has no meaning and little value (Aamodt and Nygårdb, 1995, p. 197; Stafford, 2009, p. 180). Therefore, data needs to undergo an **interpretation process** in order to turn data into information. This information then provides important input for the decision-making process.

Almost every company nowadays possesses large amounts of data, but there differences among industry sectors (Gandomi and Haider, 2015, p. 138). Available data stems from a large variety of **different sources** (Barrera and Pachitariu, 2018, p. 19; George et al., 2014, p. 321). The internet is one main source of data. At the same time, machines, products, sensors, business transactions, health care, medical devices, and engineering process are among the additional sources that have led to a rise in data. Companies thus collect data stemming from internal and external sources. On a general level, it is possible to divide data into two categories: **human-generated** and **system-generated data** (Sicari et al., 2016, p. 669; Zheng et al., 2018, p. 659). Human-generated data includes all data that stems from sources such as online reviews, videos, or texts. In contrast, system-generated data stems, for instance, from products, production machines, or wearables. Coleman et al. (2016, p. 2158) suggests separating data into human, process, and machine-generated data . However, different possibilities exist to categorize data based on its origin.

Another common way to describe data is based on its **structure** (EMC Education Services, 2015, pp. 5–6). Structured data contains data in defined formats and data types (e.g., CSV files or spreadsheets). Unstructured data, in contrast, has no structure and is therefore more difficult to analyse. Examples of unstructured data are text documents, audio files, or videos. An in-between category is semi-structured data, which contains defined patterns but within which the data is unstructured (e.g., XML files). Estimations however state that only five percent of all data is structured (Cukier, 2010). The challenge with unstructured data is that it is more difficult to handle (Markham et al., 2015, p. 31). To analyse failures of machines, for example, it is helpful to combine structured and unstructured data in order to identify the cause for machine failure (Abramovici et al., 2017, p. 329).

During the last few years the term **Big Data** became popular to describe the increasing amount of data, which mainly consists of unstructured data (Chen et al., 2014, p. 171; McAfee and Brynjolfsson, 2012, p. 63). The definition developed by Laney (2001) for Big Data is among the most used ones. The definition states that Big Data compromises of three characteristics: volume, velocity, and variety. The term **volume** describes the size of data. However, there is no definition of which size of data is considered as Big Data (Wierse and Riedel, 2017, p. 26). The second term **velocity** characterises the speed of the data generation and processing. Lastly, the term **variety** highlights the differences in data types and data sources that Big Data comprises. Besides these three V's, other publications suggested including additional characteristics in the definition of Big Data. Schroeck et al. (2012, p. 5) argue that a fourth dimension should be the **veracity** of data in order to highlight the importance of dealing with the uncertainty that data constitutes. Another suggestion is to include **value** as an additional dimension in the definition (Gantz and Reinsel, 2011, p. 6). However, the discussion highlights a general problem with the term Big Data. Different definitions exist in research and industry, which underlines the different perspectives on this topic (Chen et al., 2014, p. 173; Ward and Barker, 2013, p. 1). Despite the different perspectives, it is important to highlight that the term Big Data describes more than just the data itself, but also includes technologies for storing, processing, and analysing data (Mauro et al., 2015, p. 103; Wamba et al., 2015, p. 235). Therefore, Big Data represents a comprehensive topic that includes more than just data.

2.2.2 Approaches, processes, and technologies

The analysis of data already existed as a topic of interest for research and industry before the Big Data era. An overview of existing approaches is thus important. In general, Big Data analytics consists of different analytics techniques that comprise of novel and traditional approaches that help companies to deal with large, diverse, and fast growing data sets (Chen et al., 2014, p. 190). The term analytics represents the intention of the different approaches, because it indicates that data is analysed in order to derive insights from it (Cooper, 2012, p. 3; Dorschel et al., 2015, p. 55). In the following, the concepts of data mining, knowledge discovery in databases (KDD), business intelligence (BI), and Big Data analytics are introduced and compared.

Data mining itself describes the identification of patterns and relationships in data sets (Che et al., 2013, p. 3; Runkler, 2016, p. 2). However, the focus of data mining activities is always driven by the application context. Data mining compromises of visual analytics methods and algorithms (e.g., correlation, cluster analysis, or classification) in order to identify patterns (Runkler, 2016, p. 3). Due to the diversity of approaches, a central task is to identify suitable approaches for the data-mining problem. Figure 2-2 provides an overview of common analytics tasks in data mining.

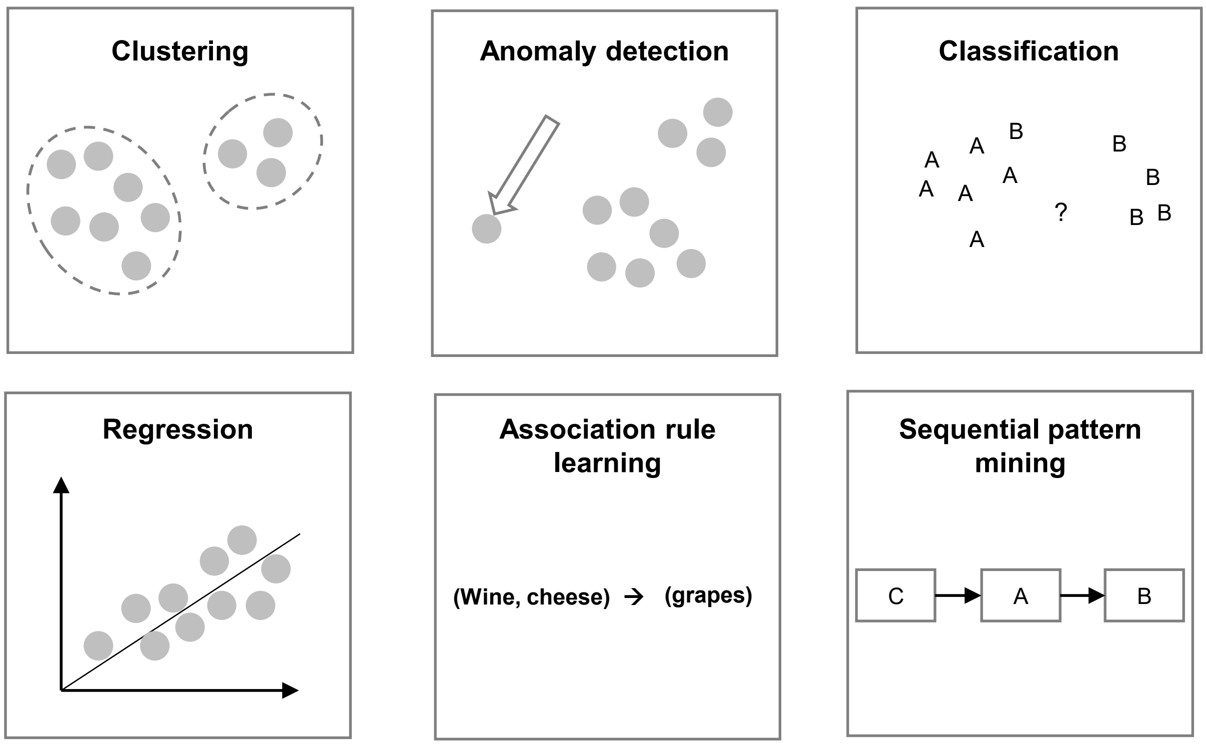

Figure 2-2: Overview of data mining tasks (based on Müller and Lenz (2013, p. 80))

Another term in the area of data mining is **knowledge discovery in databases (KDD)**. Fayyad et al. (1996a, p. 39) state that "… KDD refers to the overall process of discovering useful knowledge from data, and data mining refers to a particular step in this process." Accordingly, the definition highlights that value extraction involves additional tasks besides data mining.

Deriving valuable insights from data involves, for example, data preparation, data selection, data cleaning, and interpretation (Fayyad et al., 1996a, p. 39). Figure 2-3 illustrates the entire KDD process with its nine process steps. The first step of the KDD process is to gain an understanding of the application domain in order to identify a problem that should be addressed (Fayyad et al., 1996b, p. 30). The second step is then afterwards to create a target data set for the subsequent analysis. The figure shows that actual data mining is the seventh step in the process. The last step is the application of the knowledge gained in order to incorporate improvements. Nevertheless, KDD originated during a time when data was mainly stored in a structured way in databases (Fayyad et al., 1996b, p. 27). The KDD process was the starting point for the development of other process models (Mariscal et al., 2010, p. 142). Another important process model for data mining is the CRISP-DM (Cross-Industry Standard Process for Data Mining) (Chapman et al., 2000), which is depicted in Appendix A3.

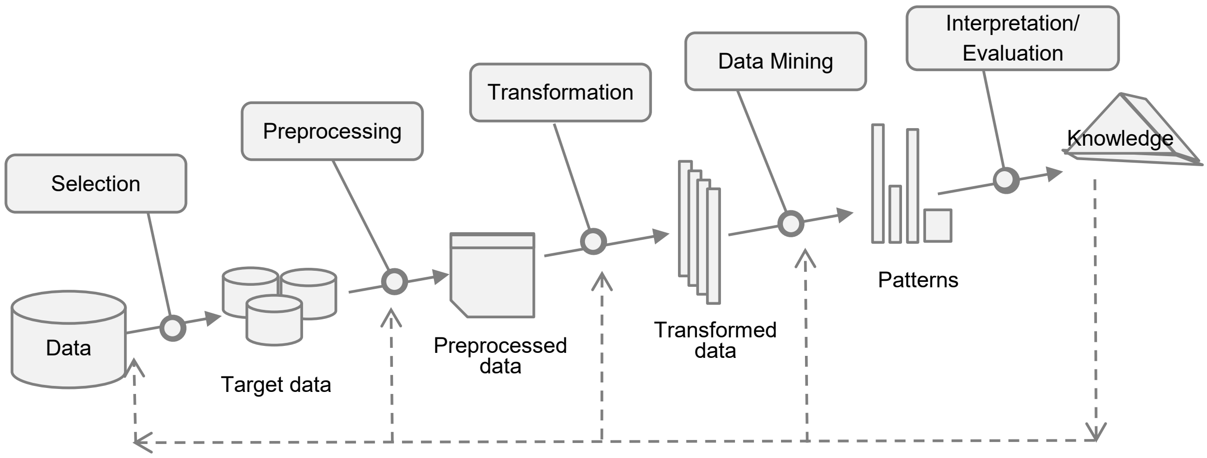

Figure 2-3: Depiction of the KDD process (derived from Fayyad et al. (1996b, p. 29))

Another term commonly used when discussing data analytics is **business intelligence (BI)**. According to Negash (2004, p. 178), a system for business intelligence has the following tasks: to gather data, store data, and derive insights from data analytics. The description of the tasks highlights the similarities with the previous two topics. However, the main objective of business intelligence is to support planners and decision makers within companies. Thus, insights gained through business intelligence should support the planning, coordination and controlling activities of managers in companies (Chamoni and Gluchowski, 2004, p. 119). In order to analyse data, business intelligence also applies data mining approaches (Chen et al., 2012, p. 1166; Negash, 2004, p. 178). Altogether, the intention is to enable better-informed decision-making processes within companies. The Big Data trend also has an impact on business intelligence research because it provides novel analytics approaches (Chen et al., 2012, p. 1166). However, business intelligence approaches are mainly developed for structured data and therefore are only partly suitable for data analytics problems involving Big Data (Fels et al., 2015, p. 263).

The term Big Data does not only describe the data itself, but also the tools and methods for handling Big Data. In literature, different terms such as **Big Data analytics** or **Big Data mining** are used to describe data analytics approaches for Big Data (Che et al., 2013, p. 6; Russom, 2011, p. 4; Sathi, 2012, p. 1). Therefore, Big Data analytics includes approaches that address the special characteristics of Big Data, which does not exclude traditional approaches like data mining (Chen et al., 2014, p. 190). Due to the characteristics of Big Data, the approaches need to handle heterogeneity, size, and velocity, which goes beyond identifying patterns or relationships in the data (Che et al., 2013, p. 6). Due to the complexity of the analytics tasks related to Big Data, the portfolio covers many different approaches, for example data mining, artificial intelligence, natural language processing, machine learning, social network analysis, visualization, and optimization methods (Russom, 2011, p. 4; Yaqoob et al., 2016, p. 1241). Due to the complexity of the different approaches and the focus of this work, the reader is asked to consult publications that provide in-depth descriptions of the various approaches for Big Data analytics.

However, it is possible to further **characterize Big Data analytics**. From a time perspective, it is possible to distinguish between a real-time analysis and an offline analysis (Chen et al., 2014, p. 192). It is further possible to cluster analytics approaches, based on the answer that they provide, into descriptive, diagnostics, predictive, or prescriptive approaches (Erwin et al., 2015, p. 29; Mousannif et al., 2014, p. 376). Descriptive analytics is often the starting point when analysis data because approaches like segmentation or clustering help to first provide an understanding of the data (Shi-Nash and Hardoon, 2017, p. 331). The next level is diagnostics analytics, which focuses on understanding the reasons for events and therefore helps to identify correlations. The objective of predictive analytics is to provide forecasts for the future based on data from the past. It is possible to separate the approaches into regression techniques and machine learning techniques (Gandomi and Haider, 2015, p. 143). Lastly, prescriptive analytics aims to support the decision making process by evaluating options and suggesting which actions to take in order to reach a desired outcome (Shi-Nash and Hardoon, 2017, p. 331). The complexity of the analytics task increases with each level, but at the same time the potential value of results increases as well.

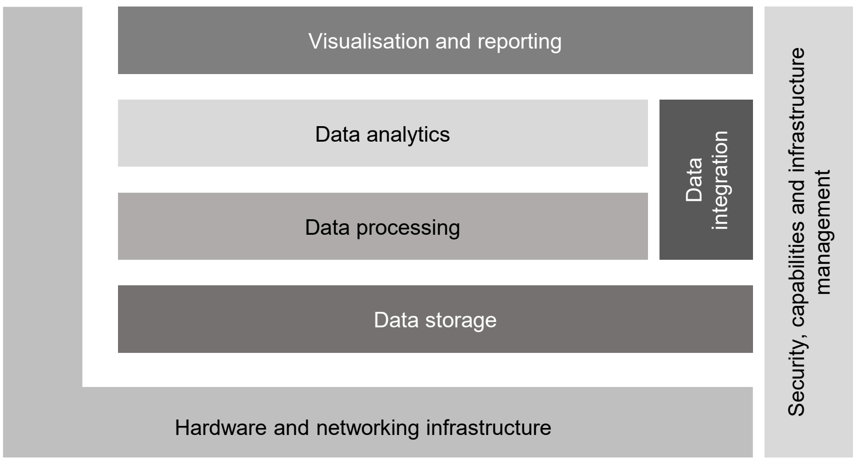

Figure 2-4: Structure of an IT infrastructure for Big Data (Coleman et al., 2016, p. 2155)

However, handling Big Data requires more than just analytics approaches. The entire **Big Data value chain** consists of the following four steps: data generation, data acquisition, data storage, and data analysis (Chen et al., 2014, p. 171). With the presence of Big Data, additional challenges arise during each step of the value chain (Chen and Zhang, 2014, pp. 318–321). A central challenge is storage, due to the size, speed, and variety of Big Data. Traditional database systems reach their limits when it comes to storing the mostly unstructured data (Mousannif et al., 2014, p. 373). The demand for new approaches led to the development of NoSQL, which aims to enable the handling of Big Data in a more suitable way (Chen and Zhang, 2014, pp. 319–320). The NoSQL approach was implemented in tools like Hadoop or MapReduce. Nevertheless, there are a lot of different tools that enable organizations to deal with Big Data. Having suitable Big Data architecture is therefore important in order to turn the data into value (Chen and Zhang, 2014, p. 331). Figure 2-4 depicts the seven main levels of an infrastructure for Big Data.

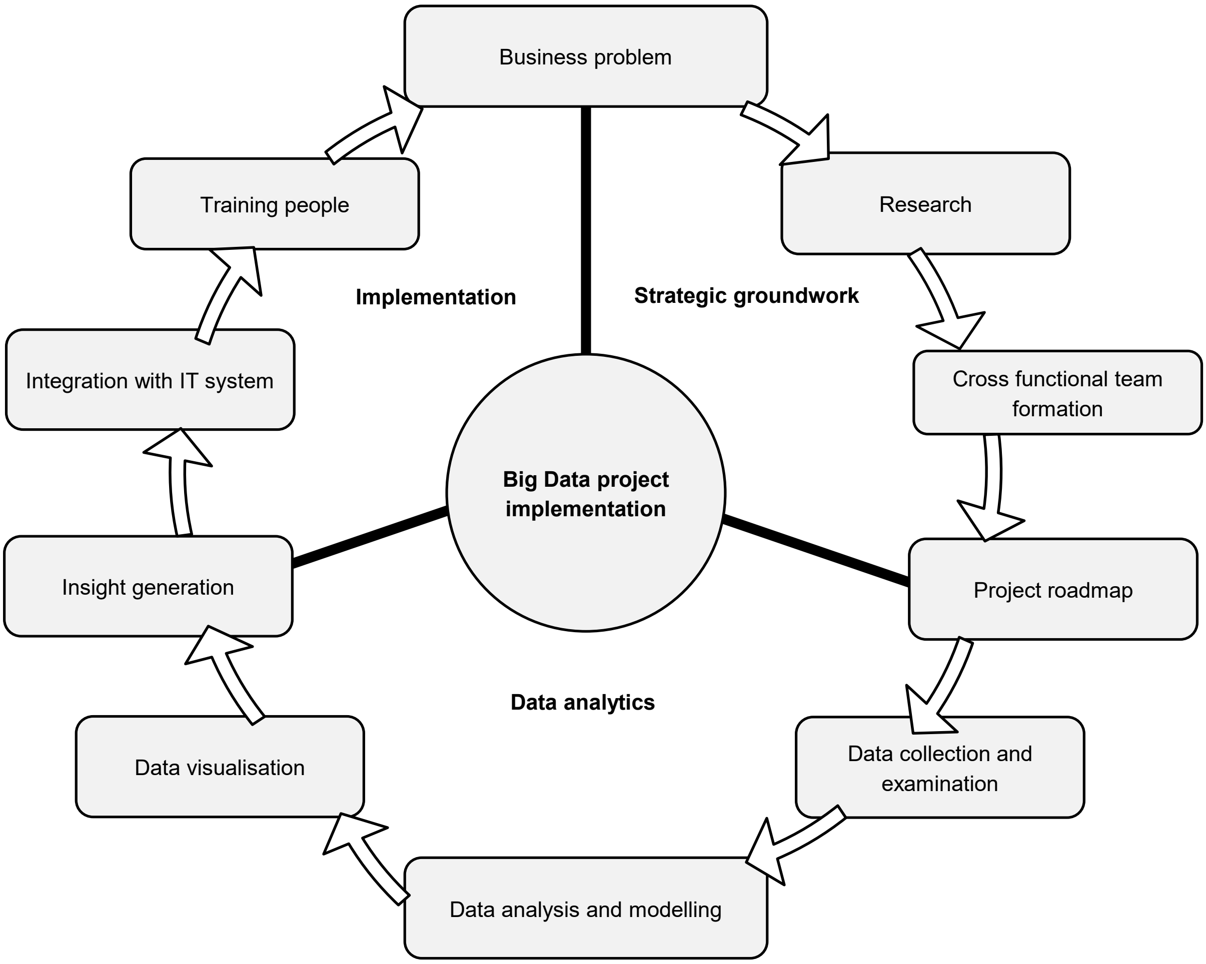

Figure 2-5: Process model for Big Data projects (Dutta and Bose, 2015, p. 295)

Due to the characteristics of Big Data, new approaches have arisen because Big Data impacts the way in which companies address analytics problems (Dutta and Bose, 2015, p. 294; Saltz, 2015, pp. 2066–2067). Therefore, tasks and activities for projects working with Big Data differ.

In general, Saltz et al. (2017, pp. 188–189) suggest characterising Big Data projects based on the data context, analytical context, team context, and organisational context, which highlights the diverse facets that need to be taken into account. In addition, Figure 2-5 illustrates a process model for Big Data projects. The depiction shows that strategic and organisational aspects also play an important role when working with Big Data. A comparison with the KDD process model indicates that extracting value from Big Data goes beyond technical questions.

2.2.3 Application areas

Big Data enables all types of organisations to exploit data and is therefore suitable for all kinds of application areas (Palem, 2014, p. 25). However, besides the general applicability for different organisations, research findings indicate that the distribution of data analytics **differs across industry sectors**. From a historical perspective, supermarkets and banks were early users of Big Data (Coleman et al., 2016, p. 2152).

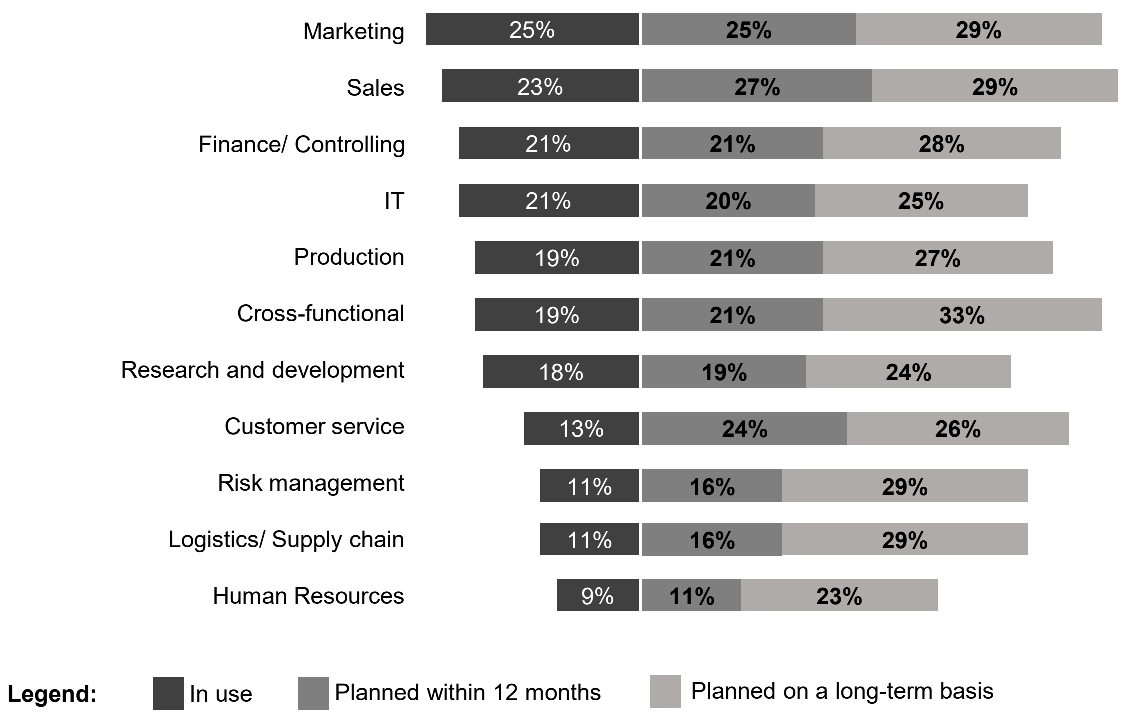

Figure 2-6: Application areas within a company for Big Data (Bange et al., 2015, p. 17)

A study among companies from Europe and North America highlighted that the retail and IT sector are at the forefront when it comes to applying Big Data (Bange et al., 2015, p. 11). Even though fewer participants from the mechanical engineering sector confirmed that Big Data is a crucial part of their business processes, many confirmed that they had carried out pilot projects. Another study asked German companies about the ways in which they incorporate data analytics (Erwin et al., 2016). The findings indicated that companies from the automotive and machine and plant engineering sectors apply data analytics mostly to aid decision-making. The results also indicated that companies from these two sectors believe that the outcome of the analysis provides additional value. Besides separating companies based on industry sector, another study indicated that small and medium-sized enterprises (SME) are lagging behind when it comes to the application of data analytics (Coleman et al., 2016, p. 2152).

However, there are not only differences concerning the application of data analytics among companies, but also between the different departments **within a company**. Figure 2-6 illustrates the findings of a study about the application of Big Data within a company. The findings indicate that the marketing and sales department are among the most frequent adopters. Nevertheless, other departments like R&D and production are planning to incorporate Big Data in the future.

2.2.4 Benefits and challenges

Due to the diversity in application areas, the specific benefits and challenges differ between the industry sectors, but also among the companies (Yin and Kaynak, 2015, p. 145). On a high-level, data analytics can provide additional **benefits** for internal and external stakeholders (Schüritz et al., 2017, p. 3). Thus, data analytics can help to support the engineering department, but at the same time, it might also be possible to provide suggestions for customers, which help them, for example, to use products more efficiently. However, in literature different approaches exist for categorising the benefits related to Big Data and data analytics. Davenport (2014, p. 22) suggests that the main benefits are cost reduction, decision improvement, and improvement of products and services. Data analytics and the increasing availability of data thus allow for the identification of patterns and the prediction of outcomes. Therefore, it is possible to make decisions with less uncertainty. Furthermore, the improvement of products and services is relevant for traditional engineering companies as well as tech companies (e.g., Netflix or Google) (Davenport, 2014, p. 24). Palem (2014, p. 26) agrees that a main benefit is cost reduction, but at the same time Big Data can also generate new revenue. A structured literature review led to the definition of five benefit categories related to Big Data (Wamba et al., 2015, p. 239):

- Creating transparency
- Enabling experimentation in order to discover needs, expose variability, and improve performance
- Segmenting populations to customize actions
- Replacing/supporting human decision making with automated algorithms
- Innovating new business models, products, and services

Urbinati et al. (2018, p. 4) suggest similar benefit clusters from a provider's perspective: customer need identification, risk management and decision-making, data-driven knowledge, product and service design, quality management, and opportunity recognition and creation. Altogether, it becomes clear that improved decision-making and a better understanding of patterns are key benefits. At the same, Big Data also enables companies to derive new products and services that take advantage of insights gained from data.

However, publications also discuss benefits in a more specific manner. For **service development**, data analytics can help to set up an optimised service delivery process, adjust service offerings in real-time, or even develop completely new services (Troilo et al., 2017,

p. 624). Big Data especially enables service providers to understand their customers better, which allows for the provision of more tailored service offerings. Algorithms do not only help companies to understand customer preferences, but they also allow them to predict such preferences (BITKOM, 2014, p. 61). Furthermore, Big Data can help service providers to make their own delivery process more efficient by automating it (Troilo et al., 2017, pp. 624–625). It is also possible to develop completely new services, which address special customer needs and solve related problems.

For **engineering**, Big Data can also lead to a number of benefits. As mentioned earlier, a variety of technical products are sold in combination with a service (PSS or smart PSS). Therefore, the benefits for service providers also apply to engineering companies. Within the context of production, Big Data can help, for example, to increase the quality or improve the process flow (Bange and Janoschek, 2014, pp. 32–33; Brown et al., 2011, p. 9). Within the production environment, the term Industry 4.0 is often used to describe the advances based on data analytics and connectivity (Lee et al., 2014, pp. 4–5). Section 2.3.1 provides a brief elaboration of the term Industry 4.0. Big Data further enables engineering companies to predict failures of machines and products (van der Vegte, 2016, p. 3). A main advantage of Big Data for engineering companies is that it can help to provide a detailed understanding of the customer, which can lead to an improved product design (Yin and Kaynak, 2015, p. 146). In general, data analytics is often used in combination with connected products, which is discussed in Section 2.3.4 on a detailed level.

Another important benefit within the context of Big Data is that it enables companies to enhance existing **business models** or even derive new ones (Muhtaroğlu et al., 2013, pp. 32–33; Schüritz and Satzger, 2016, p. 140). According to Osterwalder and Pigneur (2013, p. 14) a business model "… describes the rationale of how an organisation creates, delivers and captures value." A review of existing literature indicated that data analytics impacts the value creation, value capturing, or value proposition of a business model (Schüritz and Satzger, 2016, p. 136). Research findings further highlight that a combination of these three elements is possible in order to come up with a data analytics-based business model. An example of a data-infused value proposition via value creation is the service that Rolls Royse offers to airlines in combination with their engines, which enables airlines to monitor the fuel consumption (Schüritz and Satzger, 2016, p. 138). From a customer's perspective it is possible to distinguish four benefit categories related to data-driven business models (Kaeser, 2017, pp. 144–145). Firstly, a main benefit is enhanced product performance due to, for example, higher flexibility or individualized products. Secondly, a data-driven business model can help to reduce costs by increasing the process efficiency. A third benefit is that such business models allow for increased energy and resource efficiency. Lastly, it is possible to reduce or even avoid certain risks, which helps to increase the security of systems.

Overall, the discussion of the benefits highlights the potential that Big Data offers for companies. Table 2-2 provides an overview of potential benefits for different industry sectors. The number and variety of examples indicates the ability of Big Data to trigger innovations that were not possible before (Vanauer et al., 2015, p. 910).

After reviewing the benefits that Big Data can offer to companies, it is also important to discuss the **challenges** that arise when working with Big Data. In general, it is important to highlight that the exploitation of Big Data is not a simple task for an organisation and its stakeholders (Coleman et al., 2016, p. 2152). Therefore, it is important to understand the related challenges in order to take suitable measures to avoid them. Findings indicate that only a mere third of companies evaluate their Big Data projects as successful (Colas et al., 2014, p. 3).

Table 2-2: Overview of benefits for different industries based on Big Data (Palem, 2014, p. 30)

Industry	Solution
Automotive	Fleet management • Predictive maintenance • Optimal workforce scheduling and inventory control Eco-routing • Sensor-based traffic monitoring • Emergency response and passenger safety
Healthcare	Public health • Real-time disease progression monitoring and epidemic outbreak detection • Healthcare cost predictions based on living conditions and dietary habits Clinical decisions support • Health information exchange with electronic health records • Diagnostic assistance
Retail	Real-time asset tracking Supply chain monitoring
Finance	Usage based insurance Real-time fraud detection Credit-score modelling
Energy/ Utilities	Smart-grid usage prediction and dynamic load based on smart sensors Real-time monitoring of operational metrics for failure prediction

In literature, different suggestions for **categorising challenges** exist. When focusing on internal challenges when working with Big Data, it is possible to divide them into three categories: people, process, and technology (Gao et al., 2015, pp. 2–4). These three categories include different individual problems and it is crucial that companies do not only focus on one category because all three are equally important for successful Big Data projects. King (2014) conducted a literature review on barriers within Big Data. The scope of the analysis is wide and includes the social context of a company. The work suggests the following categories: data, ethics, society and culture, organisation, legal aspects, and technology (King, 2014, pp. 121–122). Table 2-3 provides an overview of the categories and lists barriers that each category contains. Overall, the range of barriers highlighted that the challenges related to Big Data go beyond technical ones. Legislation and data privacy are also important topics for companies (Sagiroglu and Sinanc, 2013, pp. 45–46). Further, the list of barriers also indicates that organisational aspects play an important role (Henke et al., 2016, p. 30). In the following, the main barriers are discussed from a technical and organisational perspective. It is important to highlight that literature provides various perspectives on the challenges with Big Data, which makes it difficult to provide a complete overview.

From a **technical** perspective, a variety of challenges occurs when companies work with Big Data. A main consequence of digitalisation is the steady increase in available data. Companies therefore nowadays state that they have more data than they can actually handle (Davenport et al., 2012, p. 22; LaValle et al., 2011, p. 22). Thus, companies need to apply advanced tools in order to analyse their data and extract insights from it. At the same time, having large data sets does not automatically mean that companies are able to extract value from it (Coleman et al., 2016, p. 2158). Companies need to be aware that data might be very noisy or only exist in an unstructured way. Therefore, comprehensive preparation and pre-processing of the data might be required before the actual analysis can even start. An important challenge within this context is also data quality (Erwin et al., 2017, p. 55). The findings of the study of Erwin et al. (2017, p. 55) indicate that data quality is an important challenge for engineering companies. Companies should not count on analytics tools to deal with insufficient data quality because the value of the results strongly depends on the input quality (Bose, 2009, pp. 166–167).

Table 2-3: Challenges connected with the application of Big Data (based on King (2014, pp. 121–122))

Category	Barriers
Data	• Availability • Access • Filtration • Representativeness and usefulness • Quality
Ethics	• Conflict of interests • Property rights • Control of guidelines • Missing notions • Reference systems and values
Society/Culture	• Sensibility and privacy • Trust in stakeholders
Organisation	• Competence of management team • Acceptance of management • Waiting times through insufficient decision-making authority • Budget restrictions • Resistance of business units or employees • Insufficient cross-functional cooperation • Organisational culture • Expectations • Strategy • Lack of staff/know-how
Legal situation	• Inconsistent legal situation • EU “data protection regulation” • US “consumer privacy bill of rights” • Data rights of purchase and sale
Technology	• Filtration • Structuring/Consolidation • Administration • Storage • Data security • Visualisation/Data preparation • Incompatible or insufficient hard- and software • Choice of Technology • Sentiment analysis

Even though data collection is fairly easy, companies need to think about the storage and maintenance of the data (Morabito, 2015, p. 97). Depending on the industry sector and the application area, the amount of data might increase quite fast. Certain applications might also require data to be stored for a long time. Therefore, companies need to be aware of the related issues and costs. Another important challenge is data security (Yaqoob et al., 2016, p. 1244). Due to the increase in available data, companies often store data in a scattered way because IT systems evolve independently within companies, which can lead to unconnected data silos (Colas et al., 2014, p. 3; Huby et al., 2013, p. 50). Further, Big Data often uses real-time data as an input and, at the same time, the data might contain sensitive information. Therefore, companies need to strike a balance between data access and security measures. Nevertheless, these are only a few technical challenges and the reader is referred to other publications for more details (e.g., Jagadish et al. (2014) or Katal et al. (2013)).

Organisational challenges also play an important role when working with Big Data. Different publications even indicate that these challenges are the main obstacles for companies (LaValle et al., 2011, p. 23; McAfee and Brynjolfsson, 2012, p. 65; Wirth and Wirth, 2017, p. 32). In general, the introduction of Big Data involves a comprehensive transformation process that impacts organisational processes, roles, and structures (Troilo et al., 2017, p. 617). Therefore, companies need to undergo a change process that can have a comprehensive impact on the organisation. A company and its stakeholders need to learn to work with data analytics because decisions might be made differently with the support of data (Barton and Court, 2012, p. 82). Prior to using data analytics, decisions might have been driven mainly by intuition, but insights from data reduce uncertainty and also require other processes. In addition, companies need additional skills among their employees. Even though managers are aware of the potential benefits related to Big Data, companies' lack of experience still remains an important challenge because they struggle to address this topic (Palem, 2014, p. 28). A reason why companies struggle to implement Big Data might be the range of possible use cases that Big Data enables (Morabito, 2015, p. 17). The discussion of the application areas revealed the diversity in application areas among industry sectors and within companies. Therefore, a main challenge at the beginning is that decision makers struggle to understand how Big Data can provide additional value for their organisation (Barton and Court, 2012, p. 80; Mazzei and Noble, 2017, p. 406). Therefore, companies need to have a clear understanding about which use cases they want to pursue. In general, internal and external stakeholders play an important role in the overall success of a Big Data project (Urbinati et al., 2018, p. 10). The coordination of Big Data projects is thus a challenge because working with Big Data requires new networks of stakeholders (Saltz, 2015, p. 2068). It is not enough to just hire data scientists that work on the analysis of data (Henke et al., 2016, p. 36). Therefore, companies struggle to set up a team that brings the technical, organisational, and business perspective together. It requires multiple perspectives in order to identify meaningful use cases for Big Data.

Altogether, it is important to highlight that the challenges over the course of a Big Data project change (Schroeck et al., 2012, p. 15). At the beginning, the main challenges are to start a Big Data project and to come up with use cases. Later on, technical issues like data quality or analytics tools become more important. Nevertheless, based on the study by Russom (2011, pp. 12–13), a majority of companies evaluated Big Data as an opportunity rather than an obstacle.

2.2.5 Recommendation for an implementation

Wirth and Wirth (2017, p. 32) state that the way in which companies approach Big Data projects is a central success factor because such projects are complex and therefore require an adequate approach (Dutta and Bose, 2015, p. 303). The list of challenges highlights the complexity on a technical as well as organisational and managerial level. Gao et al. (2015, pp. 6–7) suggest a list of success factors that are categorised into people, process, and technology related ones. In the following, suggestions for each of the three categories are discussed.

Exploiting data goes beyond using tools and algorithms to analyse data. Therefore, **people** play an important role. Due to their focus on data, Big Data analytics projects rely on analytics skills (Davenport et al., 2012, p. 23). In general, three options exists to integrate data scientists into the organisation: single unit, a unit for each business unit, or a combination of the first two options (Coleman et al., 2016, p. 2160). Due to the importance of the data analytics aspect, data scientists should be integrated more centrally into the organisation in order to be closer to products and processes (Davenport et al., 2012, p. 23). Data scientists should not have the role of a service provider anymore but should be actively integrated into the project and the transformation process. At the same time, data scientists will not be able to drive Big Data projects alone because such projects require experts from different areas within an organisation (Dutta and Bose, 2015, p. 303). Therefore, companies should review their current organisational structure in order to decide whether the current structure is suitable for a more data-driven future. In addition, companies need to understand and manage the changes in required skills (Schroeck et al., 2012, p. 16). Big Data demands new skills and capabilities among employees. Thus, companies need to train employees or hire new people with relevant skills. However, the benefits for companies do not occur just from hiring data scientists. In addition, the leadership itself also plays an important role in the success of Big Data projects (McAfee and Brynjolfsson, 2012, p. 66). Leaders must understand the potential value of Big Data for a company and then drive the change in order to ensure that stakeholders work together.

The second success factor is the underlying **process** for data analytics projects. The starting point for data analytics projects should not be to hire a data scientist (Davenport, 2014, p. 59). The business value should be the main driver for data analytics projects. If companies start working without a clear picture of the desired benefits of an analytics project, the risk is quite high that the project will not add any value in the end. In many cases, it is helpful to analyse the needs of customers in order to identify potential use cases for Big Data (Schroeck et al., 2012, p. 15). Another possibility for identifying possible use cases is to review existing data and define how value can be extracted from it (Davenport, 2014, p. 77). Therefore, companies should define clear objectives that a data analytics project should fulfil. Without clear objectives, the risk is quite high that projects will not be completed, which can increase the barriers for future projects (LaValle et al., 2011, p. 25). As discussed in the previous paragraph, stakeholder involvement plays an important role when working on Big Data. Therefore, it is crucial that stakeholders get involved in the ideation process for use cases right from the beginning (Wirth and Wirth, 2017, p. 33). Furthermore, a data analytics project should have a clear sponsor from the management level for the entire process (Schroeck et al., 2012, pp. 16–17). Management support is important to ensure that required resources are accessible and that commitment within the company exists. In order to come up with valuable use cases, the ideation process should be flexible and stakeholders need to think outside of the box in order to come up with innovative ideas (Kampker et al., 2018, p. 5). Nevertheless, it is important that companies follow a structured approach when searching for use cases and during their evaluation (Wirth and Wirth, 2017, p. 34). The selection of suitable use cases should be driven based on the return on investment of each use case (Gao et al., 2015, p. 9). Depending on the experience of a company, it is also helpful to start with a pilot project first in order to learn how to apply data analytics and to demonstrate the benefits (Troilo et al., 2017, p. 631). Due to the complexity, companies should really target their efforts instead of changing the entire company all at once (Barton and Court, 2012, p. 83). Altogether, multiple authors agree that a main task for companies is to derive a clear strategy (BITKOM, 2013, p. 36; Davenport, 2014, p. 59; Mazzei and Noble, 2017, p. 406). The development of a strategy for data analytics ensures the structured development of the required capabilities (e.g., skills, software, or hardware). Furthermore, a data analytics strategy helps to differentiate the company from its competitors (Barton and Court, 2012, p. 79). When working on their strategy, it is crucial that companies also consider potential future scenarios in order to avoid deriving a strategy that only addresses the current situation (Morabito, 2015, p. 18). A roadmap should complement the strategy and should outline the process for the implementation of Big Data (Schroeck et al., 2012, p. 16) .

The last category to discuss is the **technology** required for data analytics. In general, different technologies and tools exist for the different tasks along the Big Data value chain. Even though technology plays an important role when exploiting data, it should not be the starting point (Davenport, 2014, p. 59). Technology is an important enabler, but it is normally not the objective of a data analytics project to buy advanced analytics tools or IT solutions (Mousannif et al., 2014, p. 375). Therefore, it is important that a company first understands which use cases it wants to pursue in order to then derive technological requirements from it (Gao et al., 2015, p. 9). Concerning the data, it is important that companies achieve transparency concerning available and required data (Wirth and Wirth, 2017, p. 33). A company needs to have a clear overview in order to derive measures that help to close the gap between available and required data. A main advantage of Big Data is that it allows companies to derive dependencies within large sets of data. Therefore, it is important that companies ensure that data is stored in a central place in order to be able to connect different data sets (Wirth and Wirth, 2017, pp. 35–36).

2.3 Connected products – Accessing products during the use phase

Digitalisation influences many different domains. The focus of this section is to discuss the impact on physical products and related services. In recent years, more and more physical products have become digital, which means that they consist not only of physical parts, but also of software and sensors (Roth, 2017, p. 1). Due to this development, the boundaries between the physical and digital product disappear because both domains are converging (Linz et al., 2017, p. 7; Peppard and Ward, 2016, p. 13). In the last few years, an increasing number of products have started to be being equipped with the ability to communicate with other products, the user, or the manufacturer (Ellen MacArthur Foundation, 2016, p. 14; Porter and Heppelmann, 2014, p. 69). This new type of product is referred to as a smart, connected product or the Internet of Things (IoT) (Manyika et al., 2015, p. 1; Porter and Heppelmann, 2014, p. 68). Sometimes connected products are also called smart PSS, which highlights the importance of the service component of these connected products (Hagen et al., 2018, p. 87). A main consequence of connected products is the increase in data. Therefore, data analytics is important in order to enable companies to extract value from the large data sets that their products produce during the use phase (Morabito, 2015, p. 76; Ochoa et al., 2017, p. 82). Due to these characteristics, Bloching et al. (2015, p. 17) describe the IoT as an enabler for the digital transformation of industry.

This section, therefore, discusses the concept of connected products and its connection with other concepts within digital transformation (e.g., Industry 4.0 or Cyber-physical system).

2.3.1 Important concepts and functionalities of connected products

An increasing number of physical products contain components for connectivity. These connected products play an important role within the digital transformation. Therefore, this section discusses the technological advances that led to the development of connected products.

In the last decades, microprocessors have become smaller and cheaper and, at the same time, more powerful (Yoo, 2010, p. 215). Therefore, computers are part of many different applications and play an important part in everyone's daily life. The term **ubiquitous computing** describes the concept that computers are now available everywhere and at any time (Marwedel, 2018, p. 1; Poslad, 2009, p. 2). A main driver for the spread of computing power is advances in ICT. Nevertheless, computers do not only exist in the form of personal computers, they have also made their way into products. Nowadays, a wide range of products contains computers that enable their functionalities (e.g., cameras or cars). The shrinking size of microprocessors and the decreasing costs of manufacturing them enabled the integration of information processing into physical products, which led to the development of **embedded systems** (Marwedel, 2018, p. 2). Embedded systems are integrated into technical products without looking like a computer to the users. They consist of hardware and software components (Bender, 2005, p. 368). Furthermore, products with embedded systems also consist of sensors and actuators that enable the system to fulfil monitoring and controlling tasks. Products with embedded systems are also called **smart products** (Rijsdijk and Hultink, 2009, p. 25). Based on the definition of Rijsdijk and Hultink (2009, p. 25) a smart product has at least one of the following functionalities: "autonomy, adaptability, reactivity, multifunctionality, ability to cooperate, humanlike interaction, and personality".

However, products with embedded systems mostly work as enclosed systems without any connection to the outside world (Lee, 2008, p. 366). Enriching embedded systems with communication capabilities brings the embedded system and physical world closer together (Marwedel, 2018, p. 14; Rajkumar et al., 2010, p. 731). Enabling technical products to communicate with other products or with the user facilitates new functionalities and changes the way in which users interact with such products. Due to the fact that such systems bring together the digital (or cyber) and the physical worlds, the term **Cyber-Physical Systems (CPS)** is used to describe them (Lee, 2008, p. 366; Rajkumar et al., 2010, p. 731). Advances in network technology which make it possible to connect embedded systems therefore provide the foundation for CPS (Broy, 2010, pp. 18–19). The internet is a main enabler for CPS because it provides a worldwide communication network for connected products with embedded systems. Examples of CPS are robotic systems or automated factories (Rajkumar et al., 2010, p. 731).

In the last years, the term **Internet of Things (IoT)** became popular in industry and research. Table 2-4 provides an overview of different definitions of IoT derived from literature. The definitions highlight that the connection of products via the internet is a main characteristic. Furthermore, IoT products are not only controlled by human beings, they also directly interact with other products. According to Rayes and Samer (2017, p. 2), products that are part of the IoT consist of the following elements: sensors, identifiers, software for data analysis, and internet connectivity. Due to the similarities between IoT and CPS, both terms are often used synonymously (Gimpel and Röglinger, 2015, p. 6; Marwedel, 2018, p. 3). According to Broy (2010, p. 25), the term IoT presents a certain perspective on CPS that focuses on the connectivity of products which are present in our daily life. Nevertheless, a clear differentiation between both research fields is difficult because they also have a strong overlap with other research domains (Stankovic, 2014, p. 3). Porter and Heppelmann (2014, p. 64) use the term '**smart, connected products**' for physical products that not only consist of sensors, but also have the ability to communicate. In the following, this work will use the term '**connected products**' to describe products with sensors and actuators, as well as the ability to communicate with other products or human beings.

However, there are also other terms in literature that should be discussed within the context of connected products. **Industry 4.0** or the **Industrial Internet of Things (IIoT)** are also often found in literature (Gilchrist, 2016, pp. 2–3). Both terms are used to describe the application of the IoT within an industrial environment, for example manufacturing processes or energy production. The term Industry 4.0 is mainly used in the German speaking area and focuses predominantly on production (Huber and Kaiser, 2017, p. 17). However, this work does not focus in particular on products that are only used within the production environment.

After discussing the main definitions and underlying concepts, the objective is now to discuss the **capabilities of connected products**. In general, the connectivity of products fulfils two main tasks (Porter and Heppelmann, 2014, p. 69). First, it enables the exchange of information between the product and its environment, user, or manufacture. On a high-level, connected products are able to transmit data concerning location, conditions, and availability (Ellen MacArthur Foundation, 2016, p. 31). Information about the location enables companies to track products in real-time or at defined checkpoints. Knowledge about their condition is helpful to predict failure or schedule maintenance. Information about the availability is important for sharing concepts for connected products. Secondly, it allows for additional functionalities outside the product (e.g., mobile apps). Furthermore, it is possible to categorize connected products based on their functionalities (Porter and Heppelmann, 2014, pp. 70–72):

- Monitoring: knowledge of the condition, operation, or external environment of a connected product through sensors.
- Control: bidirectional data transmission enables users or manufacturers to remotely control the connect product. Furthermore, it is possible for products to be controlled automatically using algorithms.

- Optimization: based on the possibility to control the product, it is also possible for the user or manufacturer to optimize the product's performance during the use phase. Data analytics helps to improve the output, utilisation, and efficiency of a connected product.
- Autonomy: the combination of the other three functionalities in order to enable autonomous operations of the connected product. Autonomous product is able to communicate with other products and operate in harmony with them.

Overall, it is possible to use these four functionalities to design connected products with different capabilities. Section 2.3.3 discusses the wide range of application areas and highlights how the different functionalities can be helpful, for example, within the context of a smart home.

Table 2-4: Overview of definitions for the Internet of Things

Author	Definition
Koreshoff et al. (2013, p. 335)	"The Internet of Things (IoT) refers to a broad vision whereby 'things' such as everyday objects, places and environments are interconnected with one another via the Internet. […] Efforts within pervasive, ubiquitous, tangible and wearable computing to date often consist of only one device connecting to one data source, whereas the IoT promotes the concept of an ecosystem where one device is speaking to many things."
Manyika et al. (2015, p. 1)	"We define the Internet of Things as sensors and actuators connected by networks to computing systems. […] Connected sensors can also monitor the natural world, people, and animals. […] The ability to monitor and manage objects in the physical world electronically makes it possible to bring data-driven decision-making to new realms of human activity – to optimize the performance of systems and processes, save time for people and businesses and improve quality of life.""
Xia et al. (2012, p. 1101)	"The networked interconnection of everyday objects, which are often equipped with ubiquitous intelligence."
Mattern and Flörkemeier (2010, p. 107)	"The Internet of Things represents a vision in which the Internet extends into the real world embracing everyday objects. Physical items are no longer disconnected from the virtual world, but can be controlled remotely and can act as physical access points to Internet services."
Miessler (2014, p. 1)	"The Internet of Things refers to the unique identification and Internetization of everyday objects. This allows for human interaction and control of these "things" from anywhere in the world, as well as device to device interaction without the need for human involvement."

2.3.2 Architecture and technologies

Different technologies are the main enablers for connected products and IoT. Therefore, connected products require a new infrastructure in order to enable the desired functionalities (Porter and Heppelmann, 2014, p. 69). According to Rayes and Samer (2017, p. 2) connected products within the IoT domain have four components: sensors, identifiers, software and internet connectivity. The previous discussion highlighted that IoT is bringing the physical and digital world closer together. Figure 2-7 illustrates how both worlds work together in order to provide additional value based on a digital service. The link between the physical and digital world is facilitated through the connectivity module that can use different technologies (e.g., wireless LAN or mobile network) to transmit data. The additional value occurs due to the interplay of both worlds. Consequently, this means that solutions for connected products build upon technologies from different domains (e.g., engineering, data science, or IT) (Weyrich and Ebert, 2016, p. 113). In literature, some sources use the term technology stack in order to describe the mix of different technologies which are required for IoT and connected products (Porter and Heppelmann, 2014, p. 70; Weyrich and Ebert, 2016, p. 113). Architectures for IoT describe a general layout for a technical implementation, including the basic elements of the necessary architecture. However, a key challenge is that there is no singular agreed upon architecture within literature (Sethi and Sarangi, 2017, p. 2). In general, architecture models provide different layers for the design of a solution for IoT. Models for IoT that were published at the beginning of the research activities often propose three layers, whereas more recent models propose five layers (Sethi and Sarangi, 2017, pp. 2–3). Figure 2-8 illustrates an architecture model for IoT with five layers. IoT architecture models with five layers are commonly used (Al-Fuqaha et al., 2015, p. 2349).

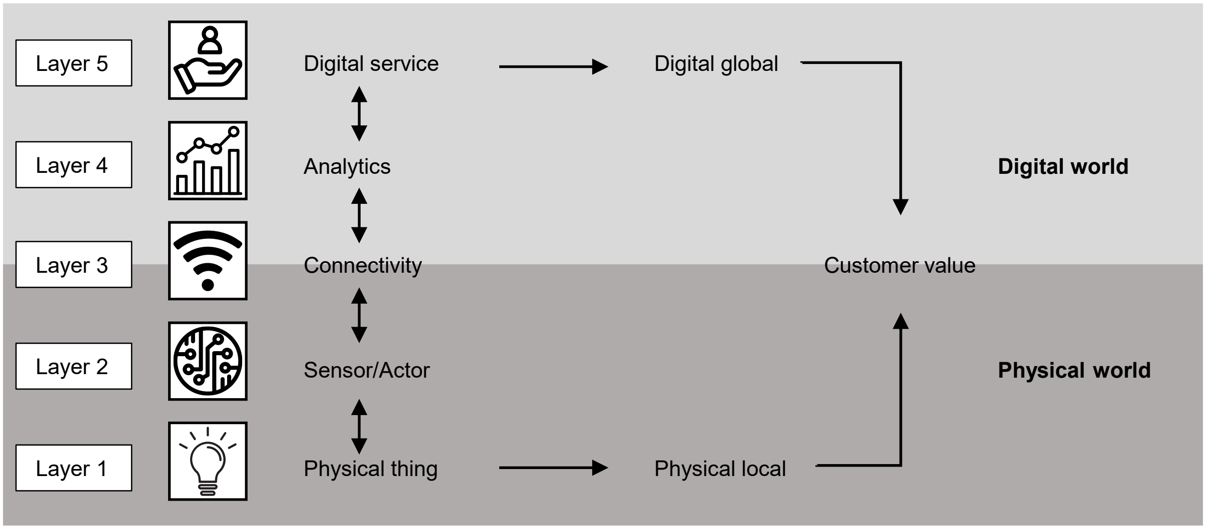

Figure 2-7: Interplay of the physical and digital world to create value for IoT (Fleisch et al., 2017, p. 7)[4]

The first layer is the **perception layer**, which contains the physical device itself and its sensors (Khan et al., 2012, p. 2). Within this context, sensors can also be RFID technologies (radio-frequency identification) or barcodes. Sensors are very important for connected products because they collect information about the environment that the product is working in (Tan and Wang, 2010, 377). In general, a broad range of possible sensors exist for products (Popović and Vlacic, 1999, p. 5). On an abstract level, it is possible to separate sensors based on their application (e.g., temperature or pressure sensing) or the operation principle (e.g., optical or

[4] This figure and further figures use third party icons. The sources for the icons can be found in Section 11.3.

capacitive sensing). Sensors therefore help to collect data that describes the operational context of the connected product. The embedded system uses such data to control the actions of the connected product.

Afterwards, this data is transmitted through the **network layer** (Khan et al., 2012, p. 2). The main task is to ensure a secure transmission of the data using a wired or wireless medium. This layer therefore establishes the connection between the product and a relevant communication partner (e.g., other connected products or the manufacturer) (Sethi and Sarangi, 2017, p. 2). The network layer can use different technologies to transmit the data (e.g., 4G, LAN, or Bluetooth).

The third layer within the IoT infrastructure is the **middleware layer** (Khan et al., 2012, p. 2). This layer is responsible for processing the data that is coming in from the network layer (Sethi and Sarangi, 2017, p. 2). Thus, the main tasks of this layer are to store, analyse and manage the incoming data. In order to do this, the layer uses cloud technology, database systems, or data analytics. Furthermore, the layer provides different services to the next layer. The fourth layer is the **application layer** (Khan et al., 2012, pp. 2–3). This layer is responsible for providing the value for the user of the system based on the application area (Sethi and Sarangi, 2017, p. 2). The layer thus also makes the information generated on the middleware layer accessible.

The last layer is the **business layer** (Khan et al., 2012, p. 3). First, the layer includes the underlying business model and visualization of the data. Therefore, this layer ensures that value is generated from IoT. Furthermore, the management of the IoT infrastructure and establishment of suitable measures to ensure secure operations should span across all layers (Porter and Heppelmann, 2014, p. 70; Weyrich and Ebert, 2016, p. 115).

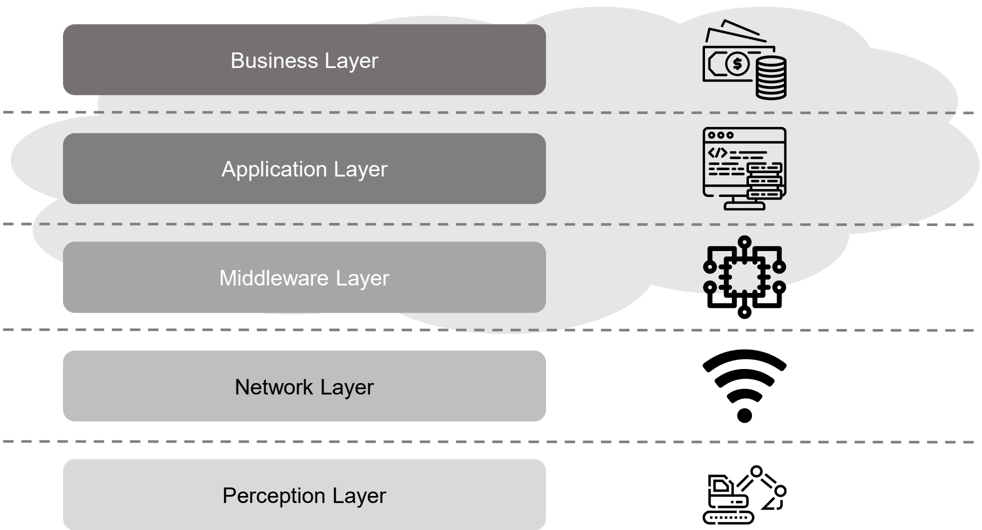

Figure 2-8: General architecture for IoT (based on Khan et al. (2012, pp. 258–259))

Overall, the discussion of the five layers highlights the complexity of the different technologies that need to interlink when developing solutions for connected products. The discussion only provides an overview and the reader is asked to consult other publications for detailed insights about the technologies enabling IoT (e.g., Al-Fuqaha et al. (2015) or Bassi et al. (2013)).

2.3.3 Application areas

The definitions for connected products and IoT highlight its wide applicability within different domains. Therefore, available publications present different perspectives on possible application areas for connected products. It is thus difficult to provide a complete overview of all possibilities. Furthermore, it is important to highlight that the number of connected products will further increase within the next few years. At the same time, there are many possible application areas that still have the status of just an idea because they have not been implemented yet (Atzori et al., 2010, p. 2793; Sethi and Sarangi, 2017, p. 16). In general, offering connected products can provide additional benefits for various industry sectors (e.g., manufacturing, energy, or logistics) (Ellen MacArthur Foundation, 2016, p. 13). Figure 2-9 provides an overview of how to describe and cluster possible application areas for IoT. The figure outlines the diversity of possible application areas and shows that connected products can affect the industrial environment as well as daily life.

According to Hunke et al. (2017, pp. 2–4), ten use cases will mainly drive IoT within the next years: predictive maintenance, self-optimizing production, automated inventory management, remote patient monitoring, smart meters, track and trace, distributed generation and storage, connected cars, fleet management, and demand response. A literature review compiled by van der Vegte (2016, p. 3) confirms that **maintenance** is the main focus of many publications that discuss the possible advantages of connected products. The main idea of this application is that connectivity allows for better monitoring of the product's condition. This can help to better plan maintenance or replace parts before they even break.

Another application domain is **healthcare** because connected products enable the monitoring and support of patients (Al-Fuqaha et al., 2015, p. 2352). Knowing the blood pressure or heart rate of a patient can help to identify critical situations and to automatically trigger suitable measures.

Within the **manufacturing** domain, connected machines can also provide different benefits that result, for example, in the higher quality of the produced good (Hunke et al., 2017, p. 2). Furthermore, connectivity of production machines can enable the machines to automatically adjust themselves in order to react to the current situation.

Another possible application area is a **smart home** (Al-Fuqaha et al., 2015, pp. 2351–2352). The objective of an application within this area is to make daily life easier. A possible use case is that the light switches off automatically when it is no longer required because there is nobody in the room anymore (Atzori et al., 2010, p. 2795).

Nevertheless, possible application areas do not only exist for users or customers. Data stemming from connected products can also support **product design** (van der Vegte, 2016, p. 4). Such data can help the company to better understand their customers. Therefore, companies have the chance to better design future product generations (Ellen MacArthur Foundation, 2016, p. 39). However, these application areas represent only a small sample of possibilities. The next section therefore, discusses the general benefits of connected products.

Setting	Examples
Human	Devices (wearables and ingestibles) to monitor and maintain human health and wellness; disease management, increased fitness, higher productivity
Home	Home controllers and security systems
Retail environments	Stores, banks, restaurants, arenas – anywhere consumers consider to buy; self-checkout, in-store offers, inventory optimization
Offices	Energy management and security in office buildings; improved productivity, including for mobile employees
Factories	Places with repetitive work routines, including hospitals and farms; operating efficiencies, optimizing equipment use and inventory
Worksites	Mining, oil and gas, construction; operating efficiencies, predictive maintenance, health and safety
Vehicles	Vehicles including cars, trucks, ships, aircrafts, and trains; condition-based maintenance, usage-based design, pre-sales analytics
Cities	Public spaces and infrastructure in urban settings; adaptive traffic control, smart meters, environmental monitoring, resource management
Outside	Outside uses include railroad tracks, autonomous vehicles (outside urban locations), and flight navigation; real-time routing, connected navigation, shipment tracking

Figure 2-9: Overview of possible application areas for IoT (based on Manyika et al. (2015, p. 19))

2.3.4 Benefits and challenges

The discussion of possible application areas revealed how many options exist for taking advantage of connected products. Therefore, the goal is to structure the possible **benefits** that companies could gain from connecting their products. In general, it is important to highlight that both internal and external stakeholders can benefit from offering connected products (Golovatchev et al., 2016, p. 2). At the same time, benefits can be financial and non-financial (Uckelmann and Scholz-Reiter, 2011, p. 229). However, it is also possible to further cluster possible benefits related to connected products. Chui et al. (2010, p. 3) suggest the two clusters of information and analysis, and automation and control. The first category uses data from connected products, for instance to better understand the user's behaviour or the environment in which the product is used. The second category empowers machines or products to adjust to current circumstances.

From a **customer's perspective**, a main benefit is that connected products can improve the customer experience during the use phase (Troilo et al., 2017, p. 624). A connected product enables the manufacturer to design a tailorable value proposition that takes the context of the customer into account. Having knowledge about the specific customer that uses a connected product allows the company to design individualized services, which can increase customer acceptance because customers are treated more individually (Valencia et al., 2015, p. 19). Enabling companies to offer data-driven services is a main benefit of connected products (Kampker et al., 2018, p. 1). Offering such services does not only provide value for customers, but also for companies because they also have the chance to differentiate themselves from competitors and gain competitive advantages. In general, the connectivity of products can have a positive impact on the relationships between a company and its customers (Valencia et al., 2015, p. 14). Without connected products, the responsibility of the manufacturer often ends after the product is sold. Connectivity creates, however, new touchpoints during the use phase because users and the manufacturer continue to interact. At the same time, services become a combination of physical and digital services (Troilo et al., 2017, p. 620). Consequently, the connection between both parties gets stronger and more intense, which provides additional opportunities, but at the same time also responsibilities. A frequently discussed example of a data-driven service is predictive maintenance (Palem, 2014, p. 26; van der Vegte, 2016, p. 3). Offering such a service can reduce the risk that products fail during the use phase, which can avoid customer frustration. Furthermore, companies are able to better schedule service jobs, which can lead to smoother operations (Kaeser, 2017, p. 143). Besides offering data-driven services, connected products also enable companies to integrate innovative functions into their connected products (Porter and Heppelmann, 2014, p. 67). The connectivity of technical products enables companies not only to collect data, but also to feed it back after the data has been analysed (Chui et al., 2010, p. 6). This feedback can enable a product to adjust its settings in order to improve, for instance, its resource consumption.

Besides the benefits that are mainly visible for external stakeholders, offering connected products also provides advantages for the **manufacturer** itself. Receiving data from connected products provides valuable insights into the actual usage of the product (Allmendinger and Lombreglia, 2005, p. 132). Therefore, companies can better understand the actual needs of their customers, which provides additional insights that would not have been possible without connected products. A better understanding of the product's usage can also help to reduce over engineering and to develop products that have a better fit with their actual application (Manyika et al., 2015, p. 85). In addition, insights gained form data can also help to shorten product development cycles due to increased transparency about the usage of a product (Kammerl et al., 2016, p. 379). Altogether, data from connected products therefore empowers companies to improve or better design future product generations (Abramovici and Lindner, 2011, p. 214; Kaeser, 2017, p. 144). This benefit is especially important for engineering companies because most of their development projects lead to new product generations rather than entirely new products (Albers et al., 2015, p. 4; Albers et al., 2017a, p. 1). Survey results indicate that product generation development represents a majority of cases in product development (Albers et al., 2017b, pp. 16–17). Companies can use data from connected products to decrease uncertainty about the design of future products and their functionalities (Manyika et al., 2015, p. 85). Therefore, insights gained through connected products help to reduce costs and improve business processes (Kranz, 2017, p. 78).

In addition, the connectivity of products also enables companies to offer **new business models** (Bartolomeo, 2014, p. 2; Bughin et al., 2015, p. 92). Therefore, companies have the chance to create additional revenue streams based on their connected products and services. Offering connected products provides insights about the usage of a product, which makes, for example, usage based pricing possible (Bughin et al., 2015, p. 96). Being able to collect and analyse data from multiple products empowers the manufacturer to provide services to its customers that help them to operate the products more efficiently. New business models for connected products might also lower the importance of the actual ownership of a product because manufacturers can take over more responsibility for their operation (Porter and Heppelmann, 2014, pp. 64–65). However, connectivity does not only provide business opportunities for manufacturers, but also for third parties. A manufacturer, for example, can sell data to other companies that offer services based on the insights gained from analysing the data (e.g., tailored advertisements or offers of repair services).

Besides the wide range of benefits, connected products also create a list of additional **challenges** that companies need to overcome in order to benefit. In general, challenges arise from a technical and organisational perspective (Atzori et al., 2010, p. 2788). Findings from a survey, however, indicate that companies consider organisational challenges to present greater obstacles than technical ones (Pureswaran et al., 2015, p. 2). Based on a literature review, Al-Fuqaha et al. (2015, p. 2362) derived the following eight challenges: architecture, availability, reliability, mobility, performance, management, scalability, interoperability, and security and privacy. Similar to the challenges relating to the exploitation of data, the following paragraphs discuss challenges from a technical and organisational perspective.

The number of **technical challenges** occurring together with connected products are diverse. Interoperability is especially crucial for connected products because additional value arises particularly when connected products from different manufactures can communicate and interact (Al-Fuqaha et al., 2015, pp. 2363–2364). However, many different communication protocols and platforms exist. Companies therefore need to ensure that their products fit to the environment in which they are supposed to operate. Other important challenges for companies are security and privacy (Porter and Heppelmann, 2014, p. 84). Application areas like healthcare are especially sensitive in terms of privacy and confidentiality because such products transmit very sensitive data that shows the health status of a person (Manyika et al., 2015, p. 105). Data from production machinery can also contain confidential information because it might include information about process parameters or production rates. At the same time, data security is a main technical challenge for connected products (Al-Fuqaha et al., 2015, p. 2364). In general, every connected product is a potential entry point for cyberattacks (Manyika et al., 2015, p. 105). Therefore, companies need to make sure that products are not, for example, controlled by attackers. Trust is another challenge within this domain because connected products can enable companies to track the activities or movements of individuals (Atzori et al., 2010, p. 2793). Accordingly, it is important to ensure that customers see the benefit in sharing their data because otherwise concerns about data privacy might lead to the refusal of customers to share their data, which would make adding connectivity unnecessary (Mohr et al., 2016, p. 6).

Another central challenge linked with connected products is data. Without transmitting data, connected products would not provide additional value because of the missing feedback loop between the manufacturer and user. However, companies struggle to deal with the large amounts of data that connected products produce (Golovatchev et al., 2016, p. 3; Huber and Kaiser, 2017, p. 24).

Organisational challenges also occur when companies offer connected products. Companies struggle to turn the collected data into value for them or its customers (van der Vegte, 2016, p. 7). Similar findings were already presented in Section 2.2.4. The value extraction from data seems to be especially challenging for engineering companies because they often have less experience with exploiting data (Fleisch et al., 2017, p. 14). However, companies not only struggle to extract value from data for themselves, they also have difficulties to develop data-driven services that take advantage of available data (Valencia Cardona et al., 2014, p. 9). Within this context, the ownership of the data stemming from connected products is also critical (Roy et al., 2016, p. 668). Data from production machinery might be of value for the user as well as the manufacturer. Therefore, a clear agreement about its ownership is required.

Another challenge for companies is the development process for connected products. Connected products combine the physical and digital world (Fleisch et al., 2017, p. 13; Roth, 2017, p. 4). Successful solutions require that both worlds work together. However, both domains use different development approaches. Engineering departments often use sequential approaches and informatics departments rather than applying agile approaches. This leads to conflicting perspectives on the development process. The development of connected products also requires new skills and a collaboration between different disciplines (Roth, 2017, p. 4).

The design of connected products and services itself also creates new challenges. It is not enough to just equip products with connectivity because the sheer integration of connectivity does not provide any value for the company (Fleisch et al., 2017, p. 7). Companies often lack a vision of how they want to benefit from connectivity. Managers thus need to understand the value of connected products because without this understanding required changes might get overlooked (Kranz, 2017, p. 164). In general, offering connected products further increases the complexity for companies because companies need to align the physical product, service and data in order to create a successful offering (Schüritz et al., 2017, p. 12; Valencia Cardona et al., 2014, p. 8). This includes developing new business models that enable companies to create new revenue streams (George et al., 2014, p. 324). Besides the large variety of possible benefits, a challenge for the company is to select the right use cases and define the value proposition for the customer (Valencia Cardona et al., 2014, p. 9).

However, offering connected products and services comes at a price. Adding additional sensors for products increases the costs even though the company is able to collect valuable data (Schüritz et al., 2017, p. 11). Therefore, companies need to evaluate the costs and benefits when connecting their products. For products with a long lifecycle, companies might need to consider updating them in order to equip them with connectivity (Manyika et al., 2015, p. 86). In general, offering connected products requires companies to change their development process and services in order to address the additional requirements that are linked to connected products (Bartolomeo, 2014, p. 3).

2.3.5 Recommendations for introducing connected products

The previous section outlined the various challenges that occur within different domains when companies introduce and operate connected products and services. Subsequently, this section provides an overview of recommendations.

The first set of recommendations lie within the **ideation** domain. The technology available for connected products should not be the starting point for the search for possible ideas and use cases because companies need to keep in mind that solving a defined problem is the objective (Kranz, 2017, p. 95). Therefore, it is crucial for companies to develop a clear understanding of the underlying benefits that they want to achieve by connecting their products (Hunke et al., 2017, pp. 1–2). The previous section showed that a broad range of potential benefits exist (e.g., cost reduction, improved quality, or new business opportunities). Based on this understanding, companies need to derive specific use cases that help to achieve the desired benefits (Hunke et al., 2017, p. 2). For the identification of possible use cases, companies should use both internal and external sources in order to ensure that different perspectives are covered (Kampker et al., 2018, p. 4; Valencia et al., 2015, p. 25). The discussion of the benefits revealed that both internal and external stakeholders could benefit from connected products and services. However, during the ideation it is important that companies gain a clear understanding of their customers when developing use cases for them (Troilo et al., 2017, p. 630). Another starting point for the ideation can be an analysis of the product lifecycle in order to identify current pain points of stakeholders (Allmendinger and Lombreglia, 2005, p. 133). Overall, companies should use multiple sources to derive use cases because this helps to obtain a comprehensive overview of the possibilities (Kampker et al., 2018, p. 4).

The **organisational setup** is also important. Offering connected products often requires a comprehensive change process, for instance because new processes are needed. Therefore, it is important that the C-level supports the transition and change process in order to ensure that the project can trigger the required changes (Kranz, 2017, p. 39). The team that is working on ideas should bring together the different perspectives in order to come up with a suitable solution (Manyika et al., 2015, p. 12). The development process should also involve decision makers in order to ensure that all disciplines are represented and balanced (Kampker et al., 2018, p. 4).

Companies must further be aware that they may need to develop new skills among their employees or hire new ones in order to implement the ideas (Manyika et al., 2015, p. 107). Using prototypes at the beginning helps companies to reduce the risk of developing unsuitable solutions because they provide initial insights about the feasibility of a project (Wixom et al., 2017, p. 22). Furthermore, companies should also try to gain initial experience with less advanced solutions before getting lost in complexity (Kampker et al., 2018, p. 4). The term 'minimum viable product' is often used to describe products, which contain just enough functionalities to address the customer needs. Lastly, companies should be aware that offering connected products necessitates a step-by-step approach rather than a revolutionary approach (Porter and Heppelmann, 2015, p. 70). This means that connected and unconnected products might exist at the same time.

Lastly, recommendations exist for addressing **technical** challenges. In general, connected products are more complex than previous unconnected products and therefore companies need to revise their current product design (Porter and Heppelmann, 2015, p. 59). In order to take full advantage of connected products, it is crucial that companies develop comprehensive solutions that bring together both the technical and the digital world (Fleisch et al., 2017, p. 1). If a company wants to offer a data-driven service, it is essential, that the product is equipped with the right sensor and that the data is transmitted in the right quality. Therefore, the required data should drive the design of the connectivity solution and not the other way around (Kranz, 2017, p. 175). Based on the current product, companies need to evaluate whether they want to enhance the existing product or develop an entirely new one (Burkitt, 2014, p. 12). The discussion of challenges revealed that security is a main concern because connectivity creates additional potential entry points for attackers. Companies should therefore perform a structured risk assessment in order to identify potential threats and to define suitable measures (Kranz, 2017, pp. 184–187). An additional challenge related to connected products is the amount of data that companies need to handle. Using a cloud-based solution can help companies in storing and analysing data from connected products and services (Al-Fuqaha et al., 2015, p. 2364).

Based on the list of possible ideas for connected products and services, it is important that companies develop a comprehensive **strategy** in order to ensure that they gain competitive advantages from connectivity (Porter and Heppelmann, 2014, p. 67). Offering connected products often requires comprehensive changes within the organisation (Kranz, 2017, p. 39). Deriving a strategy therefore enables companies to lay the foundation for the change process. Due to the fact that data plays a central role in connected products, the strategy should define how a company wants to access and analyse data (Schüritz et al., 2017, p. 9). Nevertheless, a strategy for connected products should not be detached from the company's overall strategy and it is important that a link between both exists (Manyika et al., 2015, p. 107). Companies might even be required to rethink their overall strategy.

2.3.6 Use phase data and use phase data strategy

The examples of data that are generated by connected products and the recommendations for an exploitation of data highlight the importance of a structured approach. Section 2.2.1 describes different possibilities for clustering data in order to distinguish the different types. However, within the context of connected products additional terms for the data exists

(Kammerl, 2018, pp. 24–25). A commonly used term is ‘usage data’ (Lachmayer et al., 2013, p. 685; Porter and Heppelmann, 2014, p. 68), but rarely used terms like ‘IoT data’ (Bughin et al., 2015, p. 95) or ‘system-in-use data’ (Hussain et al., 2012, p. 319) also exist. Nevertheless, many publications just use the term ‘data’. However, due to the large diversity of data, the author’s belief is that a term other than data is needed to clearly define the data that is within the scope of this thesis. ‘Usage data’ often only describes data stemming from connected products, but connectivity also enables users to interact with their products using, for instance, an app on smart phones or tablets (Porter and Heppelmann, 2015, p. 60). Such services that complement connected products are an additional source of data (Zheng et al., 2018, p. 660).

Therefore, this thesis employs the term ‘**use phase data**’ to highlight the special value that data, which connected products and related services generate during the use phase of a product, contains. Accordingly, this thesis understands use phase data in the following way (Wilberg et al., 2017b, p. 2):

> “… use phase data is the data that is generated during the use phase by the product itself (e.g., by sensors or microprocessors) or by related services (e.g., Apps, maintenance reports, or repair reports). The data might be transmitted constantly or at discrete events (e.g., maintenance or failures).”

Figure 2-10 illustrates the definition of use phase data and depicts the exploitation process of use phase data. The discussion in Sections 2.2.4 and 2.3.4 highlighted the large variety of possibilities for exploiting data. As discussed earlier, within thus thesis the term ‘**use case**’ describes the process of exploiting use phase data in a certain way in order to provide value for internal or external stakeholders. Therefore, a use case represents one possibility out of a broad spectrum of possible ways to exploit use phase data (e.g., predictive maintenance, reduction of over-engineering, or adjustment of the product based on the user’s preferences). Furthermore, the exploitation of use phase data might require consideration of additional data sources, for example context data (e.g., user data or weather), production data (e.g., end-of-line test), or product development data (e.g., requirements, or simulation models).

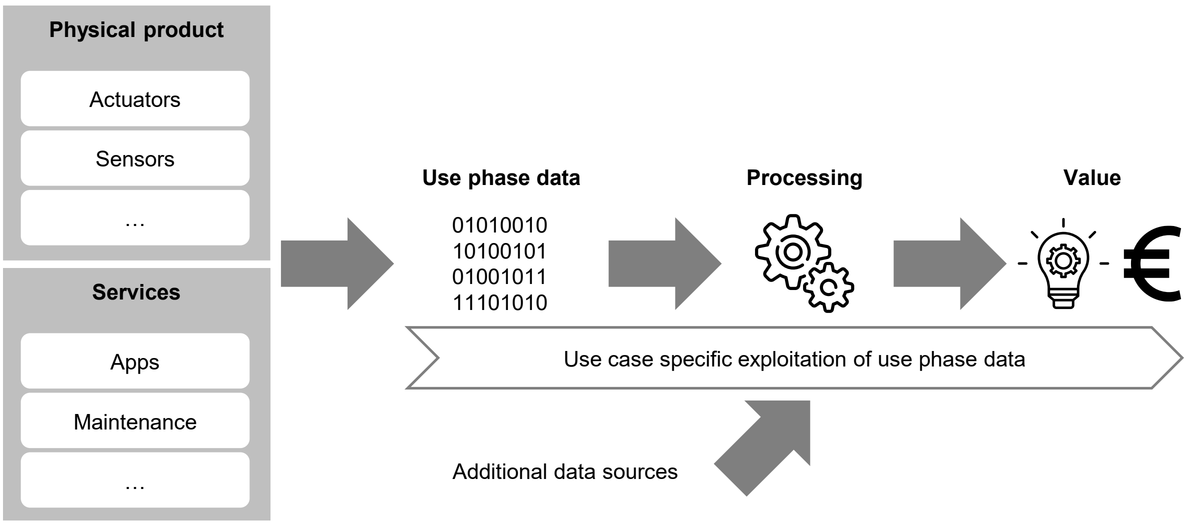

Figure 2-10: Depiction of the exploitation process for use phase data

The review of the recommendations for digitalisation (see Section 2.1.3), data analytics (see Section 2.2.5), and connected products (see Section 2.3.5) highlighted the importance of a strategy in order to take advantage of the new possibilities that use phase data offers for companies. A number of publications highlighted that companies need to have their own **data strategy** due to the importance of data for competitive success (Gao et al., 2015, p. 9; Mazzei and Noble, 2017, p. 411; Schüritz et al., 2017, p. 15).

In general the term '**strategy**' is used within many different context and therefore covers a broad spectrum of application areas (e.g., business, politics, or sports) (Kotler et al., 2016, p. 5). Having a strategy helps companies to define clear objectives and allocate required resources accordingly (Kotler et al., 2016, p. 10). Furthermore, a strategy is also important to communicate the objectives to internal and external stakeholders. Critical for the success of a strategy is its implementation, because otherwise a strategy will not trigger any changes (Hubbard et al., 2015, pp. 4–5). According to Hussey (1997, p. 332), three additional success factors for strategy development are: analysis, creative thinking, and the decision process. In general, strategies exist on different levels (Hubbard et al., 2015, pp. 20–22; Nilsson and Rapp, 2005, p. 47). Strategies can exist on a corporate level (strategy of the entire company), business level (e.g., strategy of a certain business unit), and a functional level (e.g., strategy of the R&D department). It is important that the strategies on all levels are consistent in order to avoid, for instance conflicting objectives.

Based on the previous discussion, a data strategy will most likely complement strategies on the functional level. Due to the focus of this thesis on use phase data, the term '**use phase data strategy**' is used. The term is defined in the following way (Wilberg et al., 2017b, p. 7):

> "A use phase data strategy defines which use cases a company plans to implement in order to create additional value for internal stakeholders (e.g., product development or service department) and/or external stakeholders (e.g., customers). The strategy also determines which data sources are used and what data quality requirements exist for the individual use cases. Furthermore, the data strategy includes a roadmap describing the timeline for the implementation of the different use cases and required tasks of the involved stakeholders. The strategy also describes the responsibilities of the stakeholders involved."

Based on the previous definition, Figure 2-11 depicts the elements of a use phase data strategy and highlights its connection with use cases. Overall, a use phase data strategy presents the organisational framework and use cases describe the technical process of exploiting use phase data.

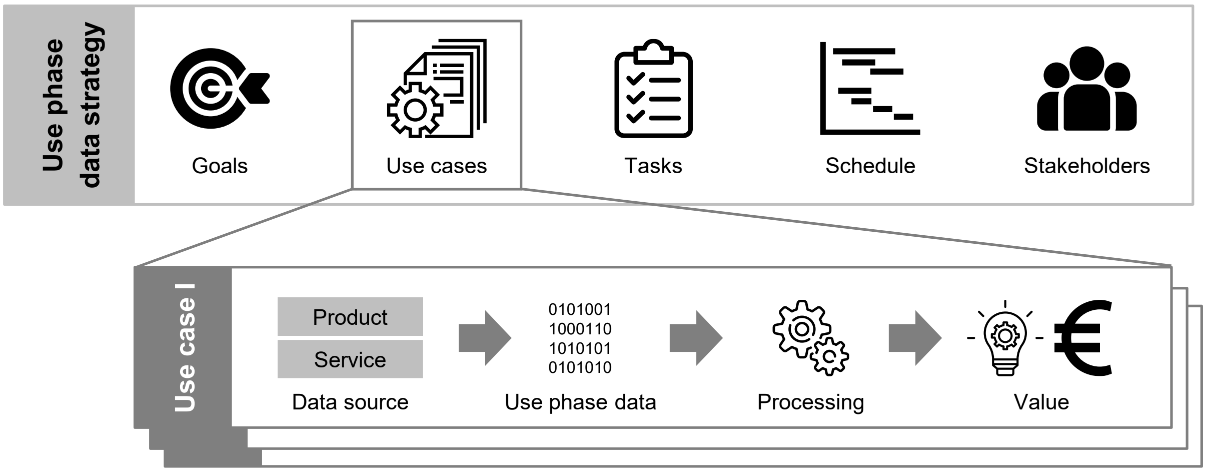

Figure 2-11: Depiction of the elements of a use phase data strategy

2.4 Summary of the findings

The technological environment that engineering and other companies operate in is changing at a fast pace. Advances in information and communication technologies (ICT) are a main driver for new opportunities, but also additional challenges. The discussion of the three topics digitalisation, data analytics, and connectivity highlighted the central role that data plays.

Transforming information into a digital format marks the technical starting point of **digitalisation**, which affects companies, organisations, and society in many ways. Currently, companies are undergoing a digital transformation in order to take advantage of the novel opportunities that digitalisation offers (e.g., business process improvement, development of new products and services, or improved decision-making). However, this transformation also confronts companies with new challenges (e.g., new competitors, higher customer expectations, or demand for new product offerings). Suggestions for achieving a successful digital transformation show that companies need to proceed in a structured way, addressing both technical and organisational topics.

Data analytics is a topic that is driven by digitalisation, because an increasing amount of available data is one of the main effects of digitalisation. Nowadays, research and industry often use the term ‘Big Data’ to describe the phenomena of a swiftly increasing and diverse set of data. However, without any processing and analysis, data does not provide any value. Advances in data analytics approaches therefore enable companies to exploit data stemming from various sources (e.g., business transactions, social media, or connected products). Besides the many benefits that a successful exploitation of data offers, it also introduces new technological, and organisational and managerial challenges. Overall, the suggestions for an implementation of Big Data show how important it is to follow a structured approach. Companies need to define a clear strategy in order to ensure that people-, process-, and technology-related changes go hand in hand in order to ensure that it is possible to extract the desired value from the data.

The product portfolio of many engineering companies nowadays often includes **connected products and services**. The rise in connected products is one main source for data, which data analytics helps to exploit. Having built-in connectivity enables products to exchange data with their manufacturer, user, or other products. At the same time, products are often complemented by services (e.g., mobile apps or monitoring platforms). The IoT field provides the crucial technical foundation (e.g., communication protocols or system architectures) that enables the interaction between connected products and services. Having a communication link with connected products during the use phase is the central innovation that enables, for example, detailed insights into actual product usage or customer preferences. Being able to access data from connected products opens up new possibilities, for example additional product functionalities, data-driven services, or new business models. However, these opportunities come at a price because companies face new technical and organisational challenges. The review of recommendations shows that companies need to follow a comprehensive approach to make possible use cases and organisational changes visible. Companies thus need to develop a use phase data strategy in order to have clear objectives.

Altogether, offering connected products and services enables engineering companies to collect and analyse use phase data that can be of great value for internal and external stakeholders. The IoT technology stack provides a technological foundation for operating connected products and data analytics approaches help to exploit use phase data. However, these technologies are just enablers, which only deliver value when companies collect suitable and relevant use phase data. Therefore, companies need to explore the opportunities that an exploitation can provide for them in a structured way. Deriving a **use phase data strategy** is important in order to align the organisational and technical elements. Overall, a critical success factor for companies is how they approach these new opportunities that use phase data from connected products and services can offer them.

3 Empirical studies on value extraction from use phase data

After introducing the theoretical foundation of this work, this chapter analyses empirical data in order to better understand the challenges that engineering companies faces when aiming to exploit use phase data. In addition, the objective of this chapter is also to deduct an understanding of the potential that use phase data from connected products can provide. Therefore, Section 3.1 presents the findings from four industrial case studies that focused on the exploitation of use phase data. Afterwards, Section 3.2 summarizes the findings of an interview study that focused on the application of data analytics in product development. Then, Section 3.3 outlines the results of an industry workshop that was conducted in order to discuss the role of a use phase data strategy within a successful exploitation of use phase data. Lastly, Section 3.4 presents overall conclusions derived from the analysis of the empirical data.

3.1 Insights from initial case studies on the exploitation of use phase data

Before presenting the findings of the initial cases studies, it is important to discuss why case studies in general can provide valuable insights for the development of a solution approach that supports companies in exploiting use phase data. Besides the theoretical input that existing research publications provide, case studies are an important research method to gather additional insights from industry in order to link the theoretical understanding with the needs of industry (Eisenhardt and Graebner, 2007, pp. 25–26). Case studies are especially helpful in novel research fields (Eisenhardt, 1989, p. 534). Connected products is a research field that currently concerns academia and industry at the same time. From a theoretical standpoint, the main objective of case study research is threefold, as case studies help to describe situations, test theories, or generate theories (Eisenhardt, 1989, p. 537).

The intention of conducting cases studies was to prepare for the development of the solution approach by understanding how mechanical engineering companies currently exploit and want to exploit use phase data. The goal was also to uncover challenges that companies face when planning to exploit use phase data. The empirical data stemming from the case studies should therefore help to derive need for further research and requirements the solution approach.

In order to obtain the required empirical data, it was possible to conduct four initial cases, which focused on the exploitation of use phase data in mechanical engineering companies. Table 3-1 lists the four cases studies that provide the empirical data for this work. The first three case studies took place in an industrial context while collaborating with a company. Due to confidentially reasons, the names of the companies are not provided. The fourth case study was a student project that was conducted at the university. All four case studies were part of a student project. Appendix A1 provides a detailed description of each of the cases studies, which includes a summary of the case execution and the main learning from the cases studies. The following paragraph briefly describes each case study before all of them are compared.

The **first case study** took place in collaboration with a manufacturer for additive manufacturing machines (see Appendix A1.1). The objective was first to identify possible use cases in order to explore how use phase data could provide additional value for the company and its customers. Furthermore, the company wanted to derive a strategy that helps to collect the right use phase data in the future. Over the course of the case study, it was possible to derive a number of use cases that can increase the efficiency of the machines during the production process. Furthermore, it was possible to identify the required data for the use cases and to formulate an implementation roadmap for selected use cases. Nevertheless, the results showed that the company needs to change its products (e.g., add sensors) in order to obtain the desired use phase data.

Table 3-1: Overview of the four initial case studies

Characteristics	Initial case study 1	Initial case study 2	Initial case study 3	Initial case study 4
Scope	Identification of use cases	Use cases to reduce machine failure and improve maintenance	Use cases to support cost management	Development of a data-driven business model
Industry sector	Additive manufacturing	Workout devices	Packaging machines	Automotive
Case study format	Industrial	Industrial	Industrial	Academic
Company size	~700 employees	~ 300 employees	~ 500 employees	-

A collaboration with a company for connected workout devices served as the **second case study** (see Appendix A1.2). The company already had some use phase data due to the fact that it already offered connected products and services. The company's belief at the beginning of the case study was that the available data was suitable to reduce the number of machine failures and to improve maintenance. The development of such an approach was therefore the objective. Understanding the failure modes of machines and the corresponding root causes was the starting point of the case study. Afterwards, the analysis of available use phase data showed that it was possible to identify three out of five root causes for failure. However, it was not possible to predict failure or improve maintenance due to insufficient data quality.

The **third case study** with a manufacturer for thermoforming machines was only two months long and was part of a research project that focused on supporting the cost management in engineering design (see Appendix A1.3). Therefore, the objective was to identify use cases that support the cost management of the company's products. The company had no experience in exploiting use phase data and therefore wanted a strategy for collecting the right data in the future. The first task was creating transparency concerning available data, which highlighted that no use phase data from the machines was available and only service reports were accessible. Afterwards, the cost structure of the product was assessed. Based on this, interviews outlined how use phase data could potentially help to improve functionality-to-cost ratio of certain components. The case study results provided the company with suggestions about which use phase data the company should start collecting in the future.

The **fourth case** studies differ from the previous three because the case study was part of an academic development project at the university (see Appendix A1.4). Despite the different environment, the case study also provides relevant input because the project focused on the development of a use phase data-based business model for a device that plays personalised music and can be integrated into an existing car. First, customer needs concerning the product's functionalities were identified. Afterwards, a data map for the use phase data of a car was derived, which was then used to show how use phase data could enable certain functionalities. Lastly, the product idea was translated into a data-driven business model.

Without any doubt, all case studies confirmed that the exploitation of use phase data could provide benefits for the company and its customers. However, the case studies also revealed a number of challenges that the companies encountered when planning to exploit use phase data. Understanding these challenges provides important input in order to derive a suitable solution approach that enables companies to exploit use phase data more successfully. Therefore, Table 3-2 presents an overview of the challenges that were identified during the case studies. The comparison highlights that various challenges occurred in different case studies, but none were found in all four of them. However, four challenges were present in three case studies. The identification of possible use cases was one main problem during the case studies. Another common related problem was that the companies had a rather traditional perspective of their products and did not think about use phase data. In addition, it became clear that a broad range of use cases are possible, which makes identification more challenging. The second challenge was the quality of available use phase data. The case studies showed that data was stored in formats that make analysis difficult or that data points needed for specific use cases were missing. The third aspect that became visible was the lack of internal transparency. The case studies showed that the companies collected use phase data, but a complete overview was often missing. The last important challenge was that the companies were aware of the potential that use phase data has, but at the same time did not assign any resources to work on this topic.

Table 3-2: Comparison of the cases studies in terms of identified challenges

Challenges	Case study 1	Case study 2	Case study 3	Case study 4
Missing experience in analysing data	X			X
Difficulties in identification of use cases	X		X	X
Insufficient data quality	X	X	X	
Unclear organisational responsibilities	X	X		
Lack of internal transparency		X	X	X
Fragmented data silos		X		
Limited resource allocation	X	X	X	

Besides the different challenges, the case studies showed that the companies required methodological support in order to identify, detail, and select suitable use cases. A main input from a research perspective was to guide companies through this process when working with use phase data. The case studies further revealed that a clear strategy and plan for the exploitation of use phase data supports companies in working towards a defined goal, which includes collecting the required data for implementing the desired use cases.

3.2 Interview study on data analytics in product development

The empirical data from the four case studies helps in better understanding the challenges that engineering companies face when planning to exploit use phase data. It is important to mention that the all four case studies involved companies that had less than 1,000 employees and that had little experience working with use phase data. Therefore, the objective was to conduct an interview study in order to obtain a broader understanding of the current practice of engineering companies in terms of data analytics in product development. The literature review highlighted, that existing publications on data analytics and Big Data discuss results from interview studies, but these studies do not focus in particular on opportunities and challenges in engineering companies and rather present a cross-industry perspective (Wilberg et al., 2017a, p. 819).

In order to obtain a detailed understanding about the needs of mechanical engineering companies, additional empirical data is needed. A qualitative interview study can help to collect such empirical data and to obtain an in-depth understanding of the topic in focus (Turner III, 2010, p. 754). Thus, the decision was to conduct an interview study to investigate the current practices of engineering companies and discuss future scenarios in terms of data analytics. The interview study used the term Big Data. The discussion in Section 2.2.2 showed that data analytics approaches are also used for Big Data. Therefore, the assumption is that both terms can be used comparably.

The interview study was conducted partially as a student project (Schäfer, 2017) and selected results are published in Wilberg et al. (2017a). The following section briefly describes the research design of the interview study. However, the interview study included topics that are not relevant for the development of the solution approach. Thus, Section 3.2.2 only discusses the relevant findings for supporting companies in exploiting use phase data.

3.2.1 Research design of the interview study

There are a number of ways to conduct interviews. The decision was to use a semi-structured questionnaire for the interview study. The advantage of a semi-structured questionnaire is that interviewees have the room to share their experience, ideas, and options (Bryman and Bell, 2011, p. 467). However, depending on the interview partners (IPs) and the answers given, the more open character of a semi-structured questionnaire can introduce additional challenges when comparing different answers. Despite this disadvantage, semi-structured questionnaires are still adequate to collect different perspectives and compare them (Bryman and Bell, 2011, p. 473).

The main objective of the interview study was to understand how engineering companies already apply Big Data in general and in product development. In addition, the intention was to explore future use cases for Big Data in product development. To ensure a matching understanding, basic terms (e.g., Big Data) were provided and discussed. The questionnaire for the interviews consisted of 13 different questions and is attached in Appendix A2.1.

Figure 3-1 illustrates the structure of the questionnaire on a detailed level and highlights the topics of the 13 questions. The questionnaire was divided into the following three parts:

- Big Data and the product development process
- Current practice in using Big Data in the company
- Future application of Big Data in product development

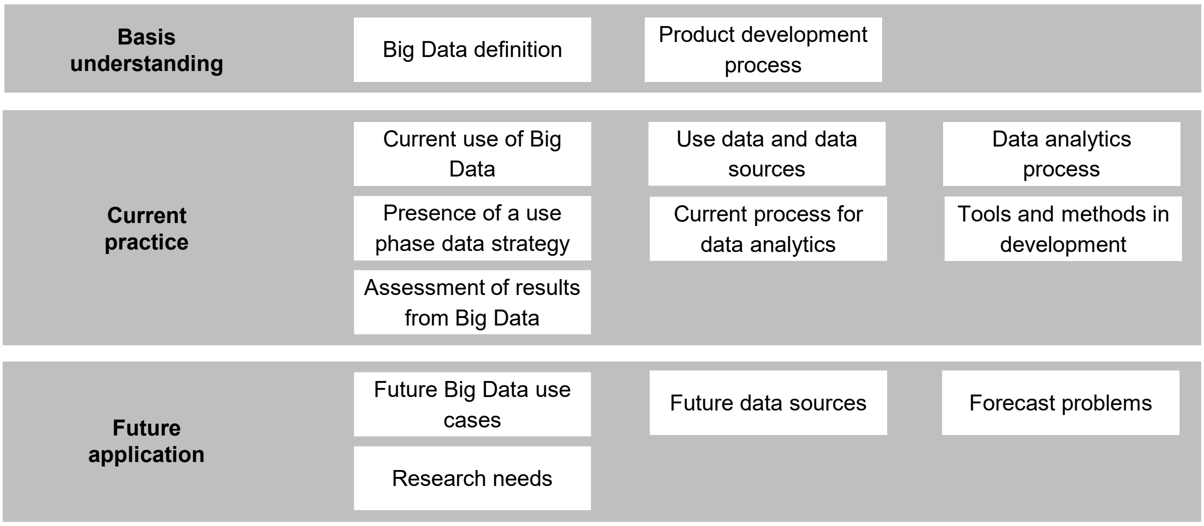

Figure 3-1: Overview of the structure of the questionnaire for the interview study

For the identification of potential interview partners, different methods were used: online career platforms (e.g., Xing or LinkedIn), personal contacts, and cold calling at fairs. Therefore, employees in different functions were contacted at the beginning of the interview study. The objective was to talk to employees that were either involved in Big Data analytics initiatives themselves or at least have a detailed understanding about the activities within the company. Another requirement was that the interview partner was either in an engineering department or worked closely together with such a department. The final assessment concerning the suitability of a suggested interview partner has to be done by the researcher (Kaiser, 2014, p. 39). Therefore, the potential interviewee was provided with the questionnaire prior to the interview.

During the preparation of the interviews, more than 50 engineering companies were contacted. It turned out that Big Data is a strategic topic and thus handled confidentially, which made it quite challenging to find interview partners. In the end, it was possible to conduct 15 interviews in total. Appendix A2.2 provides a list of all interview partners. Out of the 15 interviews, nine were conducted face-to-face and six via telephone. It was not possible to conduct all interviews face-to-face due to the required travel effort. One company sent two interview partners. Overall, each interview lasted between 30 and 70 minutes. The experience after the first three interviews showed that minor adjustments to the questionnaire were needed because at first the interviewees did not evaluate the results obtained through Big Data. Gläser and Laudel (2010, p. 151) mention that an adjustment of a questionnaire is feasible when it increases the quality of the study results, which was assumed to happen in this interview study.

The list with the interview partners shows that it was possible to talk with domain experts (e.g., product manager, head of R&D, IoT program manager, in-house consultant) from different-sized companies and value chain positions. In addition, a fair amount of interview partners had senior positions, which often entails a good knowledge of the product and current activities within the company. Looking at the value chain position of the interviewed companies shows that 80 percent of all interview partners worked for original equipment manufacturers (OEMs). Due to confidentially reasons, it is not possible to provide company names in the following.

In order to ensure the comparability of all interviews and to avoid missing information, 14 out of 15 interviews were audio recorded. Each interview was transcribed afterwards using bullet points to prepare the qualitative content analysis. This allowed for a reduction of information and its systematic extraction and categorization based on the three main topics of the interview study. This approach makes it possible to structure the content more precisely, identify interdependencies and to interpret the results (Gläser and Laudel, 2010, p. 200). In addition, the frequency of the experts' common responses between interviews (e.g. characteristics of Big Data) was measured by a quantitative content analysis to evaluate the importance of these.

3.2.2 Findings of the interview study

Due to the wide range of topics covered by the survey, this section only summarizes the findings related to the exploitation of use phase data using data analytics approaches. Therefore, the two questions focussing on the product development and the use of methods are not discussed. Furthermore, the following sections thematically group the results of the individual questions in order to derive meaningful insights for the development of the methodological support.

Big Data and data sources

The study started with the discussion of the term 'Big Data'. Only two interview partners confirmed that their company has an internal definition. The discussion about the five V's of Big Data showed that volume was seen as the main characteristic (mentioned by 13 interviewees). Value was mentioned five times during the interviews. A common understanding among the practitioners was that data alone does not present any value because only the application of data analytics tools helps to exploit value from data. One interview partner especially highlighted that domain knowledge is crucial to analyse data in a meaningful way.

The interviews confirmed that data stemming from sensors embedded in their products is a main data source (13 mentions). Two interviewees from Tier-1 companies highlighted that they have no sensors in their products. One main obstacle is the cost pressure and the other is accessibility because the OEMs must be willing to forward the data. Out of the 13 companies that use sensor data, another eight stated that they collect data stemming from mobile apps, maintenance, repair or services. Such data is especially interesting for companies because it provides insights about the actual usage and failures of the products. However, two practitioners mentioned that their apps also require sensor data for certain functionalities. The data from both sources therefore seem to complement each other, which supports the fact that the definition of the term 'use phase data' is eligible. Five interview partners also stated that their company uses social media data, for instance, in order to see initial reactions concerning a new product.

Data analytics process

An important research objective was to better understand the data analytics process and the importance of the different process steps. During the interviews, each participant had to evaluate the importance of the four basic process steps: Development of a data strategy, collection of data, correlation and analysis of data, and derivation of findings. The question used the term ‘data strategy’ for the use phase data strategy. Each step was ranked on a five-point scale from “very unimportant (-2)”, “unimportant (-1)”, “neutral (0)”, “important (1)” to “very important (+2)”. Table 3-3 summarizes the results of the process assessment. The results show that the step ‘correlation and analysis of data’ was rated as the most important one. The first and fourth steps were both ranked as the second most important ones. The standard deviation indicates a disagreement about the importance of the first and second step especially. However, the sample size is limited, which means that the results can only provide indications.

Table 3-3: Evaluation results concerning the importance of the steps of the data analytics process

Step	Development of a data strategy	Collection of data	Correlation and analysis of data	Derivation of findings
Rating of the importance	1.13	0.67	1.6	1.13
Standard deviation	1.09	1.32	0.50	0.90

During the interviews, some experts mentioned that they see the development of a data strategy as the most important step because without clear objectives it is difficult to collect the required data. Two interview partners said that the collection of data happens automatically and therefore no planning is required. However, the results indicate that no consensus existed on this matter.

Concerning the importance of the other steps, the interviewees highlighted the following aspects. Six of the interviewees stated that the collection is very important, but the other ones assessed its related importance rather at a lower level. One interview partner highlighted that data quality is a central issue to ensure that insights can be deduced. The discussion about the correlation and analysis of data showed that the selection of a suitable analysis approach (e.g., algorithm) and employees with data analytics skills are very important. Finally, the discussion about the importance of the last step revealed that companies currently have little experience in deriving findings from data. The comments made clear that many analysis tasks are currently done manually and that the interview partners believed that this would change in the future.

Use phase data strategy

Another main topic was the relevance of a use phase data strategy for a successful exploitation of data. The discussion about the importance of the first process step of the data analytics process revealed the variation in opinions among the interview partners. Two interviewees mentioned that a use phase data is very important in order to have a clear understanding about the objectives and use cases that a company wants to pursue. From their point of view, companies need to decide beforehand which sensors and data points are needed. Equipping products with sensors is a cost driver, which entails that investments should match the benefits.

The two interview partners stated that a use phase data strategy should be developed in an iterative way because companies will build experience while working with use phase data, which leads to new use cases and increasing capabilities. Another interviewee highlighted that a strategy is not only important to determine the required use phase data, but also to identify necessary context data (e.g., size of the household the product is used at) in order to interpret use phase data.

In contrast, two interview partners stated that a use phase data strategy is not necessary, because they would start working with available use phase data instead of spending time thinking about use cases. It is important to mention that one company that made this comment has not worked with use phase data before, which might have influenced the opinion. Two participants mentioned that a use phase data strategy was rated unnecessary until the company failed to analyse use phase data and to implement desired use cases.

During the interviews, the participants had to evaluate the current status of the use phase data strategy at their company. Seven companies confirmed that they already have a strategy. In addition, two companies stated that they are currently developing a use phase data strategy and another two plans to develop one. Four interview partners mentioned that their company does not plan to develop a use phase data strategy in the future. Figure 3-2 illustrates the dependency between the evaluated importance of the strategy and the status of the use phase data strategy. The figures indicate that companies with a use phase data strategy especially confirmed the importance of strategy. Overall, the conclusion of the discussion is that most interview partners confirmed the need for a use phase data strategy in order to successfully exploit use phase data.

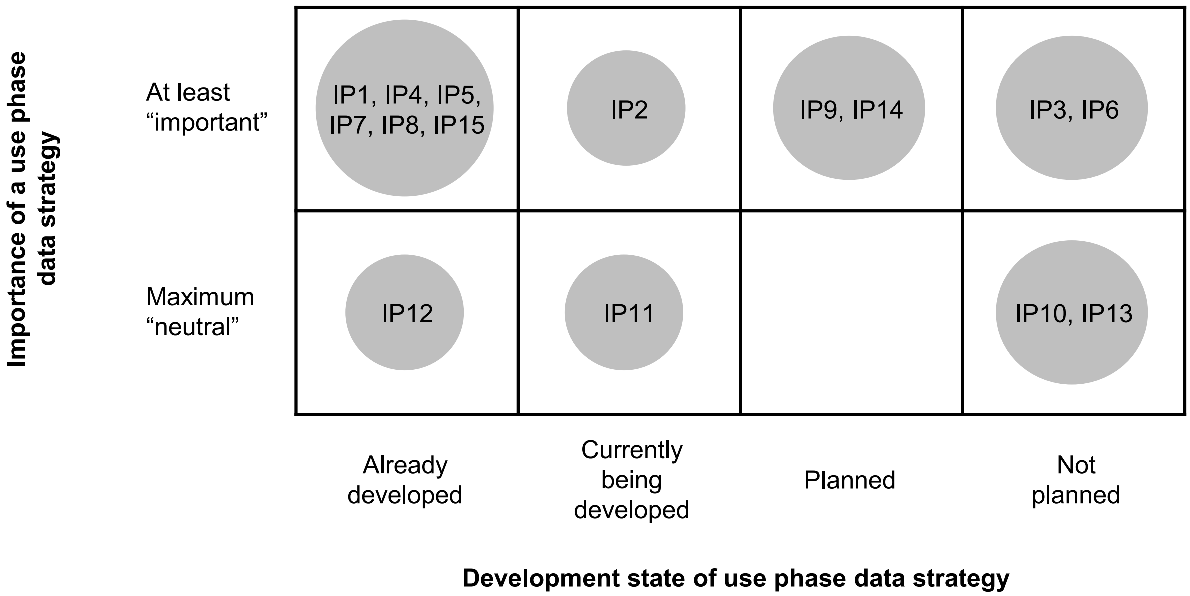

Figure 3-2: Comparison of the use phase data strategy status and the rating of its importance

The interview partners further shared their thoughts about the development process for a use phase data strategy. One interviewee highlighted that the service department began the development of a strategy. However, different departments (IT, R&D, and others) got involved in the process, which helped to derive a sound strategy for the entire company. Based on their own experience, one participant revealed that management plays a crucial role when developing and implementing a use phase data strategy. Besides the organizational aspects, two interviewees highlighted that it is important to define which products should transmit use phase data and if it is worth it to equip products already in use with connectivity. Another participant stated that a clear definition of the data format and the backend is important to transmit the data required. In addition, the interviews highlighted that a use phase data strategy is important for mechanical engineering companies because development cycles often take a few years and therefore companies need to decide during the development phase which data points and sensors are needed. The discussion also revealed it is crucial to ensure during strategy development that the product provides the required data for a data-driven service. Concerning the content of a use phase data strategy, the interviews indicated that a strategy should describe the intended use cases and contain a clear roadmap for implementation.

Use cases in product development

During the interviews, the participants also talked about current and future use cases for Big Data in product development. Many of the use cases either involved support for idea generation or requirements analysis. Two participants highlighted that use phase data is a great opportunity to better understand customer needs and the way products are used. Currently, interviews with customers provide a main input for product development. However, it is often uncertain which functionalities customers really use and what the actual application of the product looks like. The second category of possible use cases addresses requirements engineering. Two interview partners mentioned that they believe that use phase data and Big Data can help to derive specifications for a product and to validate customer requirements. Another three interviewees stated that use phase data could be very useful to reduce over-engineering because companies can better understand the real loads that a product sees.

Problems and solutions

The discussion about problems that companies face when aiming to exploit use phase data was very helpful for this research. Three interview partners highlighted that interdisciplinary teamwork is a main challenge because stakeholders with domain knowledge (e.g., engineering or service) must work together with IT and data analytics experts, which was often not done before and therefore needs to be established. It is not enough to hire data analytics experts and provide them with use phase data. Another challenge for companies is to ensure that context data is available in order to interpret use phase data. Two experts stated that a use phase data strategy helps to reach a clear understanding about data needs. Customer acceptance is another problem that hinders the collection of use phase data because equipping products with connectivity does not automatically ensure that customers also connect their products. Companies thus need to convince customers that connectivity provides additional benefits.

Formulated research needs

The last part of the interview study was to talk about additional support that research could provide to industry in order to improve the value extraction from use phase data. The comments indicate that technical, but also methodological support is requested by the industry. First, industry would like to have additional algorithms and tools that make it easier to analyse unstructured data. Two interviews partners mentioned that a definition of data standards and interfaces would help to improve the transmission of data.

Secondly, the interview partners highlighted that methodological support would be very helpful. Industry would like to have a process model that allows for the identification and implementation of use cases in a systematic way. A key task is to design a roadmap that matches products and services. Three interview partners mention that industry also requires additional support to explore the wide range of possible use cases and to understand the related implications concerning models and algorithms.

3.3 Industry workshop on use phase data integration

The interview study overall highlights the potential that use phase data offers for industry, but at the same time it also became clear that some unsolved problems exist. The interview study confirmed the importance of a use phase data strategy, but some individual comments of interview partners left some open questions in this matter. In addition, the interview study highlighted the need for additional support in terms of strategy development. Therefore, the decision was to conduct an industry workshop that discussed these findings.

Thus, a four-hour long workshop with six practitioners was performed. Three of the workshop participants took part in the interview study and the other three were contacted based on previous collaborations. Overall, it was possible to bring participants from different industry sectors (e.g., construction equipment or heating systems) and sizes (e.g., more than 50,000 employees and less than 1,000 employees) together. The workshop included a discussion about the content of a use phase data strategy, its importance, and the requirements for a methodological support for the development of a use phase data strategy. Overall, the workshop was a combination of a presentation, open discussion and tasks that the participants had to fulfil.

The workshop started with a discussion about the importance of a use phase data strategy. The participants confirmed that a use phase data strategy is an important aspect for competitive differentiation, but at the same time, their comments indicated that their company's strategy requires more maturity. It also became clear that a strategy could help to increase customer acceptance of sharing use phase data by describing clear incentives to customers. The conclusion was that a use phase data strategy is important to define use cases and describe the intended value a company wants to provide by exploiting use phase data.

Afterwards, the intention was to discuss the content of a use phase data strategy and the process leading towards it. The comments of the participants showed that a use phase data strategy should provide boundaries for iterations when identifying and implementing use cases. Due to the fact that the connectivity of products often causes extra costs, companies should know which data they want to collect. At the same time, it should be possible to develop a strategy, starting with objectives for an exploitation of use phase data (top-down approach) and starting with available resources, for instance, collected use phase data from which to derive possible use cases (bottom-up). Nevertheless, besides the technical focus, a use phase data strategy should also outline for the management why investments and changes to the products, for collecting and analysing use phase data, provide an additional value for the company.

The workshop also included a discussion about the requirements for methodological support for the development of a use phase data strategy. The comments during the interview study showed that companies would like to have more support. The discussion during the workshop revealed that the support should help to identify and detail use cases. Furthermore, the participants stated a support should provide a guideline for the user and suggest methods to carry out the required tasks. On a more general level, the support should not be too abstract and high-level. Overall, the discussion showed that a structured approach reduces the risk that companies lose their focus. Some participants however also mentioned that they would prefer an agile approach, which fosters a more dynamic development of a use phase data strategy.

Another relevant part of the workshop discussed the opportunities and problems that companies already encountered or expect to encounter in the future. Participants mentioned that they already offer new services, support the requirements engineering, or support the sales department by exploiting use phase data. For the future, they believe that use phase data will lead to new business models or self-adapting machines. The practitioners stated that main problems involve the lacking acceptance of customers to share data because the value for the customer is not clear. Another obstacle is the missing experience of employees when working with use phase data.

3.4 Conclusions drawn from the empirical studies

The previous sections provide an overview of the empirical data that was gathered to support the development of a methodological support. Such data is important to derive the need for additional research and to formulate requirements for a solution approach. The **four case studies** revealed the potential that use phase data offers in order to improve products and processes, or to offer new services. At the same time, the case studies helped to identify the challenges that hinder companies' exploitation of use phase data. A comparison of the challenges showed that organisational and technical ones occurred when companies planned to exploit use phase data. Furthermore, none of the challenges occurred at every case study, but some occurred at three of the four cases studies (e.g., difficulties in identifying use cases or insufficient data quality). Another main finding of the case studies was that companies needed comprehensive methodological support because they struggled to identify promising use cases. In general, it was difficult for the companies to link their engineering perspective with the use phase data perspective. Thus, companies had limited experience in how to approach the development process of a use phase data strategy. After providing processual support, the case studies showed that companies benefit from a clear strategy because it enables them to plan the exploitation of use phase data and to define use cases that they want to achieve.

The **interview study** and **workshop** helped to further detail the understanding of the challenges in industry and the required support needed to overcome them. First, the interview study confirmed that the term use phase data covers the data that is of special interest for engineering companies because sensor and service data are the main sources. Furthermore, the interviews and the workshop confirmed the importance of a use phase data strategy because companies need to plan the integration of sensors and other data sources in order to ensure that the promising use cases can be implemented. The participants further stated that a structured process would help them to exploit use phase data in a more systematic way. During the workshop, it was further possible to discuss the design of a possible solution approach that supports companies in developing a use phase data strategy.

Overall, the empirical data clearly shows the opportunities that use phase data can cause, but at the same time the struggle that companies have. Therefore, the task of the following chapter is to merge the findings from the literature review and the empirical data in order to analyse how research can support companies in turning use phase data into value more successfully.

4 Necessity for the development of a solution approach

After analysing literature and empirical studies concerning the benefits and challenges linked to the exploitation of use phase data, the objective of this chapter is to prepare for the development of the solution approach. The objectives are to outline the need for a solution approach and to derive requirements that must be met when developing the solution approach. First, Section 4.1 compares findings from literature and empirical data concerning the challenges that hinder companies from exploiting use phase data. The section then outlines the importance of planning and managerial challenges, which results in the refinement of the research scope. These insights serve as input for Section 4.2 in order to derive requirements for the solution approach. Based on these requirements, Section 4.3 then analyses existing process models for data analytics projects. Afterwards, Section 4.4 describes the resulting research gap for methodological support and the need for an additional solution approach.

4.1 Challenges hindering companies from exploiting use phase data

The first task to prepare for the development of a support is a clear description of the need for additional research and the problems that a solution approach should address (Blessing and Chakrabarti, 2014, p. 145). This section therefore combines findings from literature (see Chapter 2) and empirical data (see Chapter 3). The intention is to obtain a clear understanding of the scope of the solution approach in order to overcome the identified challenges.

4.1.1 Synthesis of challenges hindering the exploitation of use phase data

Based on the findings from literature and empirical data, being able to collect use phase data can, without a doubt, provide many financial and non-financial benefits for internal and external stakeholders. However, companies need to overcome technical and organisational challenges before being able to benefit fully from the exploitation of use phase data. It is thus important to compare the challenges derived from literature and empirical data. The four initial case studies especially provide valuable insights about the challenges because they offer a good overview of the process of exploiting use phase data.

The review of **existing literature** on challenges related to data analytics in Section 2.2.4 (e.g., Wamba et al. (2015) or King (2014)) and connected products in Section 2.3.4 (e.g., Al-Fuqaha et al. (2015) or Fleisch et al. (2017)) listed a variety of potential challenges. For data analytics, technical challenges involve the processing and storage of data, which is becoming even more challenging in the era of Big Data. Even though companies possess large data sets, collecting data of the right quality is becoming an important issue. Nevertheless, the review also showed that various organisational challenges arise within the context of data analytics. An overall finding was that introducing data analytics often requires a comprehensive change process because using data analytics in many cases requires new processes and skills. The review also highlighted that companies struggle to approach data analytics projects. A key challenge for companies is to identify possible use cases and to identify objectives that they want to pursue.

Furthermore, the review highlighted that companies find it challenging to foster collaboration between the different disciplines required when exploiting use phase data.

The review of literature focusing on connected products highlighted similar challenges for companies. Equipping products with connectivity creates novel technical challenges related to security, data privacy, and confidentiality. The transmission of data in general creates new entry points for cyber-attacks and data breaches. Because connected products also lead to an increase in available data, a central challenge for companies is the storage and processing of the data. Therefore, the technical challenges overlap with those identified for data analytics. Concerning the organisational challenges, literature indicates that the identification and selection of use cases in order to take advantage of connected products is a central challenge as well. Companies struggle to derive starting points and a vision for connecting their products and services. Furthermore, engineering companies need to plan ahead in relation to which data points they need because it is often difficult and costly to integrate sensors later on. It is thus necessary that companies align the data, product, and service in order to come up with a coherent concept.

Overall, findings from literature indicate that organisational challenges are a main cause for problems when exploiting use phase data perspective (LaValle et al., 2011, p. 23; McAfee and Brynjolfsson, 2012, p. 65; Pureswaran et al., 2015, p. 2). Whilst the technology for data analytics and IoT constitutes an important enabler, companies do not obtain any direct value from just buying expensive data analytics software, hiring data scientists, or connecting all of their products (Davenport, 2014, p. 59; Henke et al., 2016, p. 36).

The insights from **empirical data** mostly stem from the four initial case studies. Section 3.1 summarizes the central challenges that arose during the case studies. The overview also highlights that technical and organisational challenges hindered the exploitation of use phase data. The most significant technical obstacle was that companies had insufficient data quality, which made implementing certain use cases impossible. The second company had many different places for data storage, which hindered the synthesis of different data sets. Nevertheless, a majority of challenges stemmed from the organisational domain. The case studies highlighted that companies struggle to come up with use cases that they want to implement. Individual stakeholders often had some ideas in mind, but these ideas only existed in a fragmented way and a high-level format. Another obstacle was that the organisational structure and responsibilities did not provide a suitable foundation for the exploitation of use phase data. Even though the case study companies saw high potential in use phase data, nobody was responsible for these topics because the companies' organisational structures did not reflect the increasing importance of connected products and their data. After supporting companies in identifying relevant use cases, the challenge that arose was the mismatch between available and required data because no coherent strategic concept existed.

The interview study and workshop confirmed the significance of organisational challenges to the successful exploitation of use phase data. From a technical perspective, the workshop participants would have liked to have an automated analysis and handling of the data in order to gain insights with less effort. However, a key finding was that companies struggle to exploit use phase data because of missing experience and lack of cooperation among the different disciplines. The companies pointed out how important it is to convince customers to share their data, which requires the company to have clear objectives and to provide benefits for customers.

Overall, the **comparison of insights from literature and empirical data** highlights the significance of organisational challenges when companies plan to exploit use phase data. The empirical data shows that companies with less experience especially face organisational challenges at the beginning of a data analytics project, whereas technical challenges play a less important role at the start. Companies first need to derive use cases before discussing technical requirements. Organisational and technical challenges can occur during the entire exploitation process, but at the beginning companies need to define use cases and related objectives before collecting data and buying analytics tools that do not fit to the objectives.

4.1.2 Deduction of the scope of the solution approach

Through connecting the understanding of the challenges that companies face when exploiting data with the suggestions from literature and empirical data for approaching such projects, the objective of this section is to derive the scope of the solution approach. The overall objective of this work is to enable engineering companies to exploit use phase data successfully, which still presents a topic that is too far-reaching for one research project.

The learnings of the previous section highlighted how significant **organisational challenges** can be to a successful exploitation of use phase data. For technical challenges, a variety of solutions for connected products and data analytics already exists (see Sections 2.2.2 and 2.3.2). However, different literature sources confirmed that organisational challenges are a main obstacle also from a company's perspective (LaValle et al., 2011, p. 23; McAfee and Brynjolfsson, 2012, p. 65; Pureswaran et al., 2015, p. 2). A main characteristic of these challenges is not only their significance, but also that companies are in fact able to address them through their own actions (King, 2014, p. 163). Therefore, the research objective of this work is to address organisational challenges. It is important to mention that these organisational challenges consist of many different kinds of challenges, which is also underlined by the findings of the literature review. Therefore, it is necessary to subdivide the area of organisational challenges. Schneider (2018, p. 826) suggests differentiating six types of Industry 4.0 related challenges within the domain of non-technology related challenges (analysis and strategy, human resource, change and leadership, and other aspects). Due to the discussion in Section 2.3.1, the assumption is that connected products and Industry 4.0 share certain challenges.

The previous discussion showed that the general data analytics process consists of different process steps (see Section 2.2.2). As in most projects, the **planning phase** at the beginning plays an important role in data analytics projects because companies often make important decisions during this phase which have a significant impact on the subsequent phases (King, 2014, p. 163; Wilberg et al., 2017b, p. 6). The findings of the empirical data also confirmed the importance of this phase and the case studies showed that many organisational challenges occur right at the beginning. This research work focuses on supporting engineering companies because planning is very important due to the following reasons. The exploitation of use phase data can only be successful if relevant use phase data of a suitable quality is available. Companies can only collect certain data points if the required data sources (e.g., sensors or actuators) are integrated into the product or service. Adding sensors, in many cases, increases the cost of a product and an integration of data sources is often difficult after a product has been released. Engineering companies therefore need a coherent concept of product, service, and use phase data, therefore making the planning phase crucial.

During the planning phase, the findings from literature and empirical data show that companies face both **planning and managerial challenges**. The planning-related challenges arise due to the activities that companies need to carry out right at the beginning of the exploitation process. When planning to exploit use phase data, the first step should not be to collect large amounts of data or hire people with data analytics skills (Chen et al., 2014, p. 175; Davenport, 2014, p. 59). Companies should start with the discovery and evaluation of possible use cases that provide value for them or their customers (Hunke et al., 2017, pp. 1–2; Wirth and Wirth, 2017, pp. 32–33). However, findings from literature and empirical data highlighted that companies struggle to come up with suitable use cases. One reason might be their lack of experience with exploiting data.

Managerial challenges also play an important role, not only during the planning phase, because the findings indicate that the way in which companies approach and manage projects working on the exploitation of use phase data is crucial (Wirth and Wirth, 2017, p. 32). Deriving use cases requires that different disciplines (e.g., IT, R&D, and service) work together in order to derive coherent use cases (Dutta and Bose, 2015, p. 303; Manyika et al., 2015, p. 12). The empirical data indicates that companies struggle to bring the relevant people together. Furthermore, the insights from literature showed that management plays an important role because data analytics projects need to have access to relevant resources (McAfee and Brynjolfsson, 2012, p. 66). At the same time, it is important that companies have realistic expectations concerning the intended value that an exploitation of use phase data can provide. The findings of empirical studies confirm that companies have difficulties with managing projects working on the exploitation of use phase data because they struggle to define clear responsibilities, define objectives, and bring the different disciplines together.

Understanding the planning and managerial challenges provides central input for deriving a solution approach that helps companies to overcome such challenges. The reviews of suggestions for data analytics projects and the development of connected products in Sections 2.2.5 and 2.3.5 indicated that companies need to develop a **use phase data strategy** (see Section 2.3.6) in order to successfully exploit data from connected products and services (Mazzei and Noble, 2017, p. 406; Schüritz et al., 2017, p. 9). Porter and Heppelmann (2014, p. 79) highlight that the development of a suitable strategy lays the foundations for the competitive advantages that a company can gain through offering connected products. Davenport (2014, pp. 59–60) states that the most important step at the beginning of a data analytics project is that companies develop a strategy. The results of the empirical studies confirm the importance of a strategy in order to ensure that companies have clear objectives and are aware of the benefits that they want to achieve. Based on the discussion during the workshop, a strategy also helps to ensure competitive differentiation.

During the four initial case studies, it became clear that companies required comprehensive **guidance** in form of methodological support throughout the process of developing a suitable use phase data strategy. Assessing the background of the four companies indicated that their lack of experience with the exploitation of use phase data might have been a reason for the lack of understanding about how to develop a strategy. During the interview study and the workshop, participants also emphasized that that methodological support is missing (see Section 3.4). Survey findings of Colas et al. (2014, p. 7) also indicate that a structured and systematic approach helps to increase the success rate of implementation projects. In addition, different publications also mention that additional methodologies and tools are required in order to tackle the new challenges that arise during the exploitation of data (Hagen et al., 2018, pp. 94–95; Porter and Heppelmann, 2015, pp. 59–60; Saltz, 2015, p. 2067).

Accordingly, the **scope of the solution approach** is on supporting engineering companies from a methodological perspective in order to enable them to derive a suitable and coherent use phase data strategy. The previous discussion outlined the importance of a strategy for overcoming the planning and managerial challenges that hinder companies from exploiting use phase data. The next section subsequently derives the requirements of a solution approach.

4.2 Requirements for the solution approach

The previous section highlighted that companies require support in order to enable them to turn use phase data into value. Based on these findings, supporting the development of a use phase data strategy is a promising starting point because such a strategy provides a clear direction for companies and addresses thus relevant planning and managerial challenges. Therefore, the crucial task is now to understand how a suitable solution approach should look like in order to support companies is exploiting use phase data. The related research task is accordingly to formulate requirements for the intended solution approach because this allows describing the desired situation based on the identified problems (Blessing and Chakrabarti, 2014, p. 148).

Table 4-1: List of requirements for the solution approach

Categories of requirements	Specification of the requirements
Formal requirements	• Foster a structured development of a use phase data strategy • Guide the development of a use phase data strategy on a step-based level • Support a use case-driven and data-driven development approach • Overcome managerial and planning challenges during strategy development
Functional requirements	• Build up the understanding of the company context and competitive environment • Foster the structured collection, elaboration, and selection of use cases for internal and external stakeholders • Compile available and required use phase data • Provide a comprehensive use phase data strategy and related implementation concept
Application requirements	• Be applicable to different engineering companies • Facilitate a tailorable approach for different application contexts • Integrate and balance relevant stakeholders across different disciplines • Provide an efficient approach for strategy development

Within the context of this work, the requirements fulfil three different purposes. First of all, requirements help to assess existing approaches and support for the development of a use phase data strategy. Based on this, it is possible to derive the corresponding research gap. Secondly, the requirements help to develop a solution approach that addresses research and industry needs at the same time. Thirdly, the list of requirements helps to evaluate the developed solution approach in order to identify its shortcomings and to derive opportunities for improvement. Table 4-1 summarizes the requirements that were derived from the literature review and the empirical data. The requirements focus on planning and managerial challenges. They are grouped into three categories (formal requirements, functional requirements, and application requirements) and will be further elaborated in the next sections. The categories were derived from the work of Langer (2017, pp. 237–241). Prior to elaborating the requirements, the application context for the solution approach is defined in order to understand the presumed application context of the solution approach.

4.2.1 Intended context for the application of the solution approach

The approach is meant to support engineering companies that offer already connected products including services or plan to offer them in the future. In the context of this thesis, a product can also include a combination of a physical product and a service, which is often referred to as a product-service system (PSS). Sometimes the term smart PSS is used to highlight the additional functionalities based on connectivity. The solution approach is meant for companies that already have a use phase data strategy or have decided to develop one in order to exploit use phase data. Therefore, the assumption is that the company and its management already verified the need for a use phase data strategy.

The user of the solution approach can be one person or an entire team. The user or users can have different roles in a company, for instance, product manager, development engineer, IoT manager, or (in-house) consultant. Overall, the user of the solution approach will have responsibility for data analytics, IoT, or connectivity. Due to the cross-disciplinary nature of a use phase data strategy, it is hard to exactly define the user.

4.2.2 Formal requirements

The first block of requirements are formal requirements, which define the boundaries and focus of the solution approach. Based on the previous sections four formal requirements were derived. The solution approach should **foster a structured development of a use phase data strategy**. The previous discussion showed that companies face multiple problems when exploiting use phase data. Exploiting use phase data is a complex task and should therefore happen in a structured way (Vanauer et al., 2015, p. 916). The literature review pointed out that the planning phase at the beginning is a key factor for success. Thus, companies should derive a clear strategy (Barton and Court, 2012, p. 80; Mazzei and Noble, 2017, p. 406; Schüritz et al., 2017, p. 15). Furthermore, it became clear that a strategy is a very important cornerstone in order to ensure that clear objectives are defined and that all stakeholders work together towards similar objectives. Research findings indicate that strategy development should be a combination of a planned and emergent approach (Titus et al., 2011, p. 452). Due to the complexity of integrating use cases, the belief is that a strategy should be developed in a structured and holistic way in order to ensure that all relevant aspects (e.g., technology, human skills, or competitive environment) are taken into account (Wirth and Wirth, 2017, p. 34). Methods take a central role for a structured development because they allow to conduct tasks in a goal oriented and efficient manner (Lindemann, 2009, p. 57). The previous discussion also highlighted that a strategy is especially important for engineering companies because their products often have long development cycles and data sources cannot be added instantaneously.

The solution approach should provide **step-based guidance for the development of a use phase data strategy** in order to support the development of a use phase data strategy. Support for the development process exists on different abstraction levels (Lindemann, 2009, p. 38). The granularity level on which development processes are supported ranges from micro logic to a macro logic. Solution approaches on a micro level, for instance, describe cycles of a creative process that take only a few minutes or even less. On a macro level, support looks at project in its entirety, which might include all activities that span years. These are the two extremes of how development processes can be supported. The objective is to provide a solution approach on a step level because the assumption based on the empirical data is that the development of a use phase data strategy takes a few months. Therefore, taking a micro perspective is impossible due to the increased complexity. Supporting development of a use phase data strategy development on a macro level bears the risk, especially for less experienced companies of obtaining too little guidance and therefore no sufficient support is provided.

The solution approach should also **support a use case driven and data-driven approach** when developing a use phase data strategy. On a high-level two principle options exist to derive use cases (Wilberg et al., 2018a, p. 1446). Following a use case driven approach (top-down) means that the user of the solution approach already has one or multiple use cases in mind that should be implemented. Therefore, the main objective is to detail these use cases, identify the data needs, and prepare the implementation. In contrast, the data-driven approach (bottom-up) starts the search for use cases with the available use phase data. Therefore, the user wants to explore which use cases are possible with available use phase data. A main objective is accordingly to make use of available data instead of adjusting the product or service in order to collect additional use phase data. However, it is clear that in industry a combination of both approaches is possible because many companies already collect use phase data and therefore want to take advantage of it. At the same time, companies might have an idea of which use cases they want to implement. Thus, the solution approach should support both approaches. Furthermore, taking advantage of available use phase data can help to reduce implementation effort and thus realize a strategy with a shorter planning and implementation horizon.

Furthermore, the solution approach should help to **overcome managerial and planning challenges during strategy development**. The exploitation of use phase data includes a range of challenges and the same accounts for the development of a use phase data strategy (Saltz, 2015, pp. 2069–2070). Companies need to identify suitable use cases that provide value for internal and external stakeholders. However, implementing use cases often requires comprehensive changes, for instance, to the processes or IT infrastructure (Vanauer et al., 2015, p. 914). Therefore, addressing managerial and planning challenges is important when working on a use phase data strategy. However, legal and data security issues also often arise when data analytics and connectivity are discussed (Manyika et al., 2011, p. 11; Schüritz et al., 2017, p. 17; Wielki, 2013, p. 988). Use phase data often contains sensitive information about users or processes. Connected products in industry in contrast maybe transmit confidential process parameters or machine settings. Ensuring that data is protected and data privacy is ensured is thus a central task as well as challenge when developing connected products (Bertino, 2016, pp. 1–2). However, the related issues open up an entire research field. The solution approach therefore should focus on planning and managerial challenges in order to ensure a clear scope. The solution approach should thus point the user towards involving additional stakeholders to address legal and data security issues but cannot provide support in assessing whether laws are violated or data security is not ensured.

4.2.3 Functional requirements

The next block of requirements addresses the core functions of the intended solution approach. Deriving functional requirements is important to prepare the conceptual development of a solution approach (Blessing and Chakrabarti, 2014, p. 153). These requirements therefore define the capabilities that a solution approach should have in order to enable companies to develop a use phase data strategy in a structured manner.

The solution approach should support the user in building up **an understanding concerning the company context and competition environment** when developing a use phase data strategy. Due to the fact that a use phase data strategy must fit to the organisational context, it is crucial that framing conditions become clear because the user should, for instance, understand which internal and extern stakeholders could benefit from exploiting use phase data (Valencia et al., 2015, p. 25). At the same time it is important to know, which use phase data is already available (Wirth and Wirth, 2017, p. 33). The approach should also entail an external perspective in order to avoid that use phase data strategies of competitors are overlooked (Grant, 1991, pp. 5–6). In the end, the approach should lead towards a strategy that fits to the organisational context, customers, and products.

A central element of a use phase data strategy are the use cases and therefore the solution approach should **ensure a structured collection, elaboration, and selection of use cases for internal and external stakeholders**. A broad range of potential use cases exists thus requiring that companies obtain an overview first. The analysis of obstacles revealed that the diversity of use cases is an opportunity and a burden at the same time because companies often struggle to derive use cases (Barton and Court, 2012, p. 80; Mazzei and Noble, 2017, p. 406). Therefore, it is important that companies gain an understanding of the range of possibilities (Palem, 2014, p. 29). Due to the number of different stakeholders and departments, use cases can provide value in different areas. Thus, collecting use cases in a structured way ensures that the attention is not drawn too fast towards a certain area (Wirth and Wirth, 2017, p. 34). Furthermore, due to the diversity of the stakeholders, ideas for use cases exist in a fragmented way in an organisation, which requires a structured collection. In addition, different stakeholders can benefit from use phase data. The solution approach should accordingly provide use cases for internal as well as external stakeholders. Thus, no stakeholder is excluded from the search for use cases. Due to complexity reasons, the user might decide, however, to focus only on a certain group of stakeholders. Thus, the solution approach should provide tools and methods to identify and elaborate use cases that, for instance, support engineers during product development or integrate new product functions into the product. Understanding the needs of stakeholders ensures that synergies for internal and external stakeholders are not overlooked. The solution approach should further ensure that relevant use cases are detailed and relevant information is available in order to assess use cases. Reaching a suitable level of detail enables companies to make informed decisions about their use phase data strategy. The solution approach accordingly should also support the user in selecting suitable use cases that lead to a sound use phase data strategy.

Use phase data is the foundation for every use case and therefore the solution approach needs to **compile available and required use phase data**. The previous case studies clearly showed that the companies experienced problems to implement desired use cases because of insufficient data quality. Therefore, it is not only important to support companies in identifying use cases, but at the same time also provide support to define the required use phase data and related quality (Morabito, 2015, p. 89). Understanding the needs for use phase data also is a prerequisite to identify adjustments to product or service design. At the same time, companies already collect use phase data, but sometimes machines generate data, which the machine currently does not transmit. Obtaining an overview of available use phase data is therefore important to make use of available data (Wirth and Wirth, 2017, p. 33). Due to fast increase in available data, companies often have different silos for data, which are not connected (Huby et al., 2013, p. 50). Therefore, the solution approach should also help to reach transparency about available use phase data in order to take advantage of it and to enable a data-driven approach for the development of the use phase data strategy.

The overall objective is to obtain a sound use phase data strategy. Therefore, the solution approach **should provide a comprehensive use phase data strategy and related implementation concept**. The use phase data strategy should not only describe the objectives concerning the exploitation of use phase data but should also indicate the path leading towards an implementation. Strategy development can only be successful if the implementation is done correctly (Grant, 2016, pp. 8–10; Paulus-Rohmer et al., 2016, p. 12). The implementation itself is very context-specific and therefore, the solution approach can only provide support in order to facilitate companies to identify tasks for an upcoming implementation. The requirements thus also ensure that the use phase data strategy is imbedded in the organisation framework of the company. A strategy and an organisation are closely linked, which means that a change in strategy also influences the organisation.

4.2.4 Application requirements

The third block covers all requirements related to the application of the solution approach. Therefore, these requirements rather address the design of the solution approach. First of all, the solution approach should be **applicable in different settings of engineering companies**. Therefore, the solution approach should work independent from the size of a company, age of the company, or industry sector. It further should be possible to support the development of a use phase data strategy for companies that operate in a B2B or B2C environment. Besides, a use phase data strategy can be implemented at different levels (e.g., business unit or department level) in a company. However, the support is intended for engineering companies that already offer or plan to offer connected products.

The solution should be a **tailorable approach for different application contexts**. As mentioned earlier, one requirement for the solution approach is that it can be applied in different settings. Companies benefit from a strategy development that combines a formal process with a flexible planning so that companies can react to changing circumstances (Dibrell et al., 2014, p. 2006). The solution approach must therefore be flexible enough in order to enable the user to adjust the approach to the application context and the framing conditions. The same accounts for methods supporting the strategy development process. Thus, the user of the solution approach is responsible for deciding on how much time a step or task requires. In order to ensure that use phase data strategies can always be adjusted to changing circumstances or objectives, the solution approach should allow for an iterative application. Especially when companies start working with data analytics and exploit use phase data, the capabilities will get better with every iteration (Gao et al., 2015, p. 13). The approach should not only enable the development of a strategy but also to review an existing strategy. Changing objectives or competitive environment might also force a company to adjust their use phase data strategy even before finalizing the development. Thus, allowing for an iterative application helps to derive a strategy that addresses the new circumstances.

The solution approach should **integrate and balance relevant stakeholders across different disciplines**. The literature review and case studies highlighted the importance of a collaboration between different disciplines (Dutta and Bose, 2015, p. 295; Roth, 2017, p. 1). Offering connected products and exploiting use phase data requires that stakeholder from different departments work together in order to extract value from data. It is not enough to just hire data scientists and let them analyse use phase data (Fitzgerald et al., 2014, p. 12). On one hand, exploiting use phase data requires business understanding to derive use cases (Coleman et al., 2016, p. 2158). One the other hand, technical knowledge is important to implement and operationalise use cases. Therefore, the solution approach should ensure that all relevant stakeholders work together when developing a use phase data strategy in order to integrate the required skills into the process.

Lastly, the support should foster an **efficient approach for strategy development**. The development process only prepares the implementation of a use phase data strategy and its use cases. Efficiency means that the process consumes limited amount of resources, but at the same time provides a high-quality use phase data strategy. Due to the fact that the strategy development only prepares the implementation of a strategy and its use cases, the crucial factor that determines the resource consumption will be the time investment of involved stakeholders. Therefore, the solution approach should make use of information and data that is already available within a company. However, developing a use phase data strategy requires also generating new information. Overall, the solution approach should help to obtain results whose value exceeds the invested resources for the development.

4.3 Analysis of existing support for data analytics projects

The previous section outlines the requirements that a support for the development of a use phase data strategy should fulfil. The consequential task is to assess existing solution approaches from literature and compare them with the requirements defined afore. At the same time the intention is to also identify elements and aspects of existing work that can be integrated in the novel solution approach (Blessing and Chakrabarti, 2014, p. 148). Blessing and Chakrabarti (2014, p. 149) suggest to use the following evaluation dimensions: scope, functionality, application areas, underlying concept, and assumptions. The focus of the following analysis will be to assess the functionality of existing approaches from literature in order to outline shortcomings of available solution approaches.

The first step to prepare the assessment was a **comprehensive literature search** for existing process models for data analytics projects. The decision was to focus on process models because they provide users with guidance in order to plan and control processes (Lindemann, 2009, p. 36). Thus, supporting the process leading towards a use phase data strategy is important, which the requirements also reflect. The idea was to focus on process models for data analytics projects in general because the assumption was that working with different types of data (e.g., use phase data or sales data) requires on a high-level similar activity. Furthermore, the decision was to also include process models that were published before the Big Data became a topic of concern because data analytics is a research field with a longer history. The process models of Fayyad et al. (1996a) for knowledge discovery in databases (KDD) and the CRISP-DM process of Chapman et al. (2000) are examples for such process models. These process models were considered during the analysis because they are still popular with data analysist (Dutta and Bose, 2015, p. 294). Overall, thirteen process models were identified and analysed in detail in order to evaluate how they support the development of a use phase data strategy. The search highlighted that both academia and industry propose process models for data analytics projects. The conducted analysis considers both types in order to respect a theoretical and industry perspective on this topic. A depiction of each process model can be found in the Appendix A3.

Table 4-2 provides a **brief overview of the process models** that were identified during the literature search. A more detailed discussion of nine of the process model can be found in Wilberg et al. (2017b, p. 4). The table shows that only two of the process models are older than five years. Many of the novel process models aim to support companies in particular to implement Big Data analytics. The increase of process models also indicates the emerging importance of data analytics for companies and the related need for processual support to analyse data. The analysis revealed that the two process models of Rajpurohit (2013) and Morabito (2015) mostly build upon the KDD process of Fayyad et al. (1996a), which highlights the relevance of the KDD process, but also reduces the number of unique process models by two. The two process models differ in the number of steps and links between the steps, but the activities are similar. Table 4-2 further highlights that the process models aim to cover all process steps required for a data analytics project. However, a main difference is that some process models start with analysing data and others propose to define objectives or to derive a strategy first. The fact that some process models mention strategy development as a main process task at the beginning supports the finding that a use phase data strategy is important for data analytics projects. In addition, many process models highlight the iterative manner of data analytics projects, which correspond with the requirement to have a tailorable approach. When conducting data analytics projects, companies often gain new skills, which will increase with each iteration (EMC Education Services, 2015, p. 28; Morabito, 2015, p. 106). Dutta and Bose (2015, p. 296) mention, that traditional process models (e.g., CRISP-DM) focus too much on data analytics without looking at the organisational aspects that are connected with a Big Data project. Overall, the analysis showed that the scope of all process models is similar. Furthermore, the comparison shows that the abstracted process for data analytics projects consists of the following steps: define goals, analyse data, derive insights, and improve data analytics skills (Wilberg et al., 2017b, p. 4).

Table 4-2: Overview of the analysed process models for data analytics projects

Author	Short description of the process model
Almquist et al. (2015)	• Scope: Process model for the implementation of advanced analytics • Structure: Six steps (*frame opportunity* until *iteration*) – Three phases
BITKOM (2013)	• Scope: Guideline for the management of Big Data Projects • Structure: Eight steps (*assessment - planning of a Big Data Strategy* until *optimization*)
Chapman et al. (2000)	• Scope: Lifecycle of data mining projects • Structure: Six steps (*business understanding* until *deployment*)
Dutta and Bose (2015)	• Scope: Framework for implementation of Big Data projects in firms • Structure: Ten steps (*business problems* until *training people*) – Three phases (*strategic groundwork*, *data analytics*, and *implementation*)
EMC Education Services (2015)	• Scope: Data analytics lifecycle • Structure: Six phases (*discovery* until *operationalize*)
Fayyad et al. (1996)	• Scope: Knowledge extraction from data in databases • Structure: Five steps (*understanding of the application domain* until *acting on the discovered knowledge*)
Gao et al. (2015)	• Scope: Business analytics process • Structure: Six steps (*business phase* until *learning*)
Jagadish et al. (2014)	• Scope: Big Data analysis pipeline • Structure: Five steps (*data acquisition* until *interpretation*)
Köhler and Meir-Hubert (2014)	• Scope: Process model for Big Data projects • Structure: Eight steps (*evaluation and strategy* until *holistic nature optimisation*)
Miller and Mork (2013)	• Scope: Value chain for Big Data • Structure: Seven steps (*collect and annotate* until *make decisions*) – Three phases (*data discovery* until *data exploitation*)
Morabito (2015)	• Scope: Big Data analytics process (based on Rajpurohit (2013)) • Structure: Six steps (*define goals of the analysis* until *visualisation and feedback*)
Rajpurohit (2013)	• Scope: Analytics process for Big Data (based on Fayyad et al. (1996)) • Structure: Seven steps (*domain understanding & KDD Goals* until *visualisation and feedback*)
Vanauer et al. (2015)	• Scope: Methodology for ideation, assessment and implementation for Big Data • Structure: Six steps (*Objectives decision and challenge identification, and key resource identification* until *enterprise transformation*) – Two phases (*ideation* and *implementation*)

The next step is to conduct a **detailed assessment of the functionalities** that existing process models offer when it comes to developing a use phase data strategy. For this analysis, the textural descriptions of the process models were assessed as well. Each process model was evaluated using the following four criteria, which were derived based on the requirements for the solution approach:

- Step for the development of a use phase data strategy
- Support for structured collection, elaboration, and selection of use cases
- Methods supporting the development of a use phase data strategy
- Support to derive an implementation concept of a use phase data strategy

The four criteria represent a condensed set of all criteria that focus on the main challenges that companies face when planning to exploit use phase data. The first criterion is important to evaluate whether the process model considers the development of a use phase data strategy as a relevant task. Use cases are a core part of a use phase data strategy and companies especially struggle to come up with use cases. Therefore, the second criterion evaluates the provided support for collecting, elaborating, and selecting use cases. The third criterion assesses whether the process models provide any methods that help to develop a use phase data strategy. The last criterion evaluates the support that the process model provides in order to come up with an implementation concept for a use phase data strategy because the previous discussion highlighted the importance of the implementation step for the success of a strategy development. Engineering companies need to especially link use phase data strategy and product strategy in order to ensure that required data sources get integrated into products and services.

The **evaluation results** for each process model are summarized in Table 4-3, which are also based on previous publications (Wilberg et al., 2017b; Wilberg et al., 2018a). Each process model was assessed using the same four criteria. Furthermore, a three-point scale was used for the evaluation of each process model. The main finding is that only three process models contain a distinct step for the development of a use phase data strategy. In addition, four process models do not fulfil any criteria. Gao et al. (2015) and Almquist et al. (2015) only provide a visual representation of their process model without further describing any tasks.

Two process models follow a data first approach and suggest to start with an analysis of data without defining any objectives or use cases (Jagadish et al., 2014; Miller and Mork, 2013). The KDD process model and the two related ones are very similar. Thus, the rating for all three process models is similar. Fayyad et al. (1996a, p. 42) only mentions for the first step that the user of the process model should define objectives. Defining objectives is rated as a pre-stage for strategy development, but it must be highlighted that a use phase data strategy is more comprehensive than a set of objectives.

The CRISP-DM process model also mentions that a project plan should be defined and objectives should be formulated (Chapman et al., 2000, pp. 13–14). In addition, the process model highlights the importance of an implementation, but without providing further details (Chapman et al., 2000, pp. 28–29).

Nevertheless, the analysis also revealed that five process models provide limited support for the development of a use phase data strategy. The process model of BITKOM (2013) has an individual step for strategy development and highlights the importance of strategy when analysing data. The process model further suggests a structured collection and evaluation of possible use cases. However, the process model offers suggestions and support only on a very abstract level without providing any methods. The same accounts for the implementation of the strategy because the process model only mentions that an implementation roadmap is important.

Dutta and Bose (2015) propose a comprehensive framework for Big Data projects that starts with a strategic groundwork phase. However, a detailed description of how use cases can be identified and elaborated is missing. The previous research findings show that this task is however very critical for a successful exploitation of use phase data. The process model also does not provide any methods that support the development of a use phase data strategy.

Limited support for the implementation is however provided because the process model suggests the development of a project roadmap that aligns people, activities, and milestones related to the implementation (Dutta and Bose, 2015, p. 295).

Table 4-3: Assessment of the process models for data analytics projects

Author	Step for the development of a use phase data strategy	Support for structured collection, elaboration, and selection of use cases	Methods supporting the development of a use phase data strategy	Support for deriving an implementation concept of a use phase data strategy
Almquist et al. (2015)	not existing	not existing	not existing	not existing
BITKOM (2013)	existing	partially existing	not existing	partially existing
Chapman et al. (2000)	partially existing	not existing	not existing	partially existing
Dutta and Bose (2015)	existing	not existing	not existing	partially existing
EMC Education Services (2015)	partially existing	partially existing	not existing	partially existing
Fayyad et al. (1996)	partially existing	not existing	not existing	not existing
Gao et al. (2015)	not existing	not existing	not existing	not existing
Jagadish et al. (2014)	not existing	not existing	not existing	not existing
Köhler and Meir-Hubert (2014)	existing	partially existing	partially existing	not existing
Miller and Mork (2013)	not existing	not existing	not existing	not existing
Morabito (2015)	partially existing	not existing	not existing	not existing
Rajpurohit (2013)	partially existing	not existing	not existing	not existing
Vanauer et al. (2015)	partially existing	existing	not existing	partially existing

Legend: ○ : not existing ◑ : partially existing ● : existing

EMC Education Services (2015) suggests a process model without a distinct step for the development of a use phase data strategy. The process model suggests the identification of objectives and provides a list of questions that helps to discover possible use cases. In order to prepare an evaluation, the process model proposes to derive an analytic plan.

The process model of Köhler and Meir-Huber (2014) highlights the importance of a strategy. Different activities for the development of a strategy are mentioned, but without suggesting any methods that would help to conduct the activities. Maturity models are suggested to assess the current situation of a company and to derive possible directions. The process model in addition suggests conducting workshops for the development of a use phase data strategy. Nevertheless, the support for the development of an implementation concept does not exist because it only mentions that a company needs to work on closing the gap between the current and desired state.

The process model of Vanauer et al. (2015) is the last one to discuss. The evaluation results show that the process model at least fulfils three requirements partially. The process model mentions the importance of a strategy but does not provide any further details about the related tasks besides the definition of objectives. The process model distinguishes between a data first (available data as a starting point) and business first (business objectives as a starting point) approach (Vanauer et al., 2015, pp. 910–911). However, the main advantage of this process model is the support for the identification, collection, and elaboration of use cases. The authors suggest various methods that provide support for the related tasks. In addition, the business model canvas is the only method related to the development of a strategy that is included in the process model. Overall, this process models mentions many tasks for the ideation and selection of use cases, but the development of an implementation concept is covered only on an abstract level.

Overall, the evaluation results highlight the differences among the process models because each process model takes a different perspective on data analytics projects. Some of the process models confirmed that it is important for a company to develop a use phase data strategy before collecting data and entering the data analytics domain. Nevertheless, the evaluation revealed that none of the process models offers sufficient support for the development of a use phase data strategy. A main problem is that all of the process models cover all of the steps of data analytics projects. Therefore, the development of a use phase data strategy does not play a central role. At the same time no process model exists that covers just the development of a use phase data strategy. Considering the importance of a use phase data strategy, the provided support is very abstract and only discusses required tasks on a general level. Based on the experience gained during the first two initial case studies, developing a use phase data strategy takes a few months and therefore involves a variety of tasks. Overall, the conclusion is that none of the process models guides a user through the development on a step-based level and therefore offers sufficient support.

The second finding of the analysis is that very little methodical support is provided by all process models. Some mention a few general methods like the business model canvas, which can support strategy development. Concerning the identification of possible use cases, only two process models make general suggestions about the actual execution by mentioning that interviews and workshops could be helpful. Nevertheless, highlighting the central role that use cases play for the development of a use phase data strategy, the existing support is not sufficient. The analysis even highlights that even less methodical support is provided for the actual development of a use phase data strategy. The process models neither refer to common methods in strategy development nor introduce methods that address the specific needs of a use phase data strategy. The last important finding is that none of the process models seems to address the special characteristics of engineering companies when it comes to exploiting use phase data. Companies with technical products must coordinate their product strategy with their use phase data strategy because use cases only work when use phase data is available, which might require to add a connectivity module or sensors to the product. Furthermore, companies with technical products and related services have a large variety of different data sources, which must be aligned in order to implement use cases. These are just some examples for the special characteristics of engineering companies that make the development of a strategy more challenging and require sufficient planning.

The **overall conclusion of the analysis** is that a use phase data strategy is important in order to turn data into value. However, available process models provide little guidance because, if at all, they address this topic on an abstract level and do not really describe how a use phase data strategy should actually be developed. None of the existing process models seems eligible to fully address the planning and managerial challenges. Therefore, the main conclusion of this analysis is that additional support is needed in order to better support companies in exploiting use phase data in a structured and systematic way.

4.4 Conclusions for the development of the solution approach

This chapter revealed the broad range of challenges that hinder companies in extracting value from use phase data. Comparing the challenges highlighted that planning and managerial challenges are a main reason why companies fail to exploit use phase data. It became clear that companies struggle to identify suitable use cases and plan their implementation. These challenges often occur early on because companies already struggle to identify use cases before use phase data is even collected and analysed.

However, for a successful exploitation of use phase data, it is important to formulate use cases in order to collect required use phase data. Thus, problems linked to data analytics and other more technical aspects are not the only barriers that companies face. Based on the findings extracted from literature and empirical data, it was possible to formulate formal, functional, and application requirements that a solution approach needs to fulfil in order to support companies in overcoming the challenges connected with the exploitation of use phase data. A central finding was that companies should develop a use phase data strategy that outlines which use cases a company wants to implement in order to achieve desired benefits for internal and external stakeholders. Nevertheless, it is not only important to decide which use cases seem suitable, but also to plan how an implementation should be done and what the overall use phase data strategy is.

The assessment of existing process models revealed that numerous process models for data analytics projects exists. However, none of them has a particular focus on supporting the development of a use phase data strategy, but rather covers the entire data analytics process. Some highlight the importance of such a strategy and provide initial suggestions on how to develop a use phase data strategy. In addition, the literature review pointed out that no support exists that just provides guidance for the development of a use phase data strategy. Existing support rather presents an overall picture of the data analytics process without discussing tasks and activities on a detailed level. Overall, the assessment of existing support shows that further research and support is needed in order to enable companies to exploit use phase data and derive a use phase data strategy because existing support is not enough to overcome the planning and managerial challenges.

Developing a use phase data strategy is a key success factor and therefore the objective is to close the research gap that current approaches do not address. A use phase data strategy connects the technical and the managerial perspective. Exploiting use phase data includes looking into technical aspects (e.g., required data quality, data transmission, or data storage) and managerial (e.g., required skills or cost-benefit analysis). Due to the complexity of the tasks, a structured approach is important to derive a use phase data strategy that considers all relevant topics in order to ensure that the use phase data strategy fits to the company context (BITKOM, 2013, p. 29). For data analytics projects as wells as strategy development, literature suggests using process models, which ensure a structured development process. In general process models help to plan and control processes (Lindemann, 2009, p. 36). Thus, the development of a process model seems suitable to provide support and guidance for companies to develop a use phase data strategy and exploit use phase data. At the same time, it is possible to include activities that address the planning and technical challenges during the development of a use phase data strategy. Existing process models for data analytics project and strategy development provide a suitable starting point to derive the fundamentals of the process model.

Overall, this chapter revealed a list of existing process models for data analytics projects. However, the assessment also uncovered the methodological gap that existing approaches leave. The intended solution approach should have the form of a process model because exploiting use phase data is a novel task for engineering companies, which entails that support on a detailed level is important. The overall process model should enable companies to derive a use phase data strategy and the related implementation concept in a structured and systematic way. Thus, the process model must support companies in understanding the context for strategy development, identify and select use cases, and formulate data needs. The next chapter derives the fundamentals for the solution approach to be developed.

5 Fundamentals of the solution approach

Existing process models for data analytic projects do not provide adequate support for companies to develop a use phase data strategy. Therefore, this chapter builds upon the requirements formulated in Chapter 4 in order to derive the fundamentals of the solution approach and to address the identified research gap. Section 5.1 starts with deriving the structural and functional design of the process model for the development of a use phase data strategy based on existing work on strategy development, data analytics projects and problem solving. Afterwards, Section 5.2 describes the findings of three orientating case studies in industry that build upon the concept for the solution approach. These three case studies provide valuable insights about the development process for a use phase data strategy in industry. Section 5.3 then makes use of the insights gained during the three orientating case studies in order to revise and advance the fundamentals of the solution approach.

5.1 Structural and functional design of the process model

Based on the findings in Section 4.3, the shortcomings of existing process models are clear and the need for additional research is visible. Therefore, the task is now to use these findings in order to come up with an initial concept for the process model that should enable companies to develop a use phase data strategy, which is important in order to exploit use phase data and extract value from it. Based on the work of Blessing and Chakrabarti (2014, pp. 144–145), the design of a solution approach consists in general of the following steps: task clarification, conceptual design, embodiment design, detailed design, and testing. Task clarification was the focus of Chapter 4 and, therefore, has already been considered. Overall, the previous chapters of this work present an important foundation for the development of the process model. The requirements highlight the importance of a structured approach that allows companies to formulate use cases and to derive an implementation concept in order to exploit use phase data in a systematic way. Thus, the objective of this section is to build upon this foundation and to derive a conceptual design of the process model that fulfils the defined requirements and addresses the research gap. Chapter 6 will then introduce the final process model for the development of a use phase data strategy.

Developing a use phase data strategy is a task that involves, among other topics, especially strategy development and data analytics. The process model is therefore rooted in the interface of these two research fields (Figure 5-1). As mentioned earlier, developing a use phase data strategy requires a link between the technical and managerial perspective. The objective is thus to derive the conceptual design in a structured way and to make use of existing research work in both fields as well as available empirical data. First, the objective is to derive the basic structure of the process model and the underlying problem-solving process. The structure should reflect the general process for strategy development. Afterwards, the next step is to identify the functions and tasks that the process model should comprise when developing a use phase data strategy. Deriving the functional design of the process model then transfers the basic structure of the process model into the desired use phase data strategy context by addressing the specific challenges.

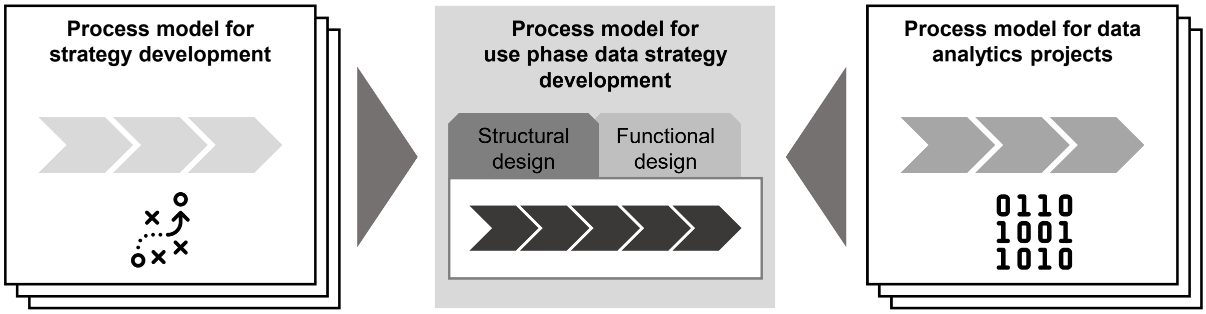

Figure 5-1: Placement of the intended process model within the two research fields

5.1.1 Structure of the process model

The first task for the conceptual design is to derive the basic structure of the process model. In order to build upon available work, the first step was to identify existing process models for strategy development. A first literature review on process models showed that a wide range of them exist due to the fact that the research field of strategic management already started to arise in academia in the 1950s and 1960s (Ghemawat, 2002, pp. 40–41). Because many scholars published process models as part of the strategy development stage, this work focuses only on more recent contributions, due to the belief that these most likely reflect the current understanding of strategy development. To further reduce the number of process models, the decision was made to pick contributions from books, journal papers, and other publications that address strategy development on a corporate or divisional level. In the end, nine process models were analysed in order to derive a conceptual design of the process model (Wilberg et al., 2018a, pp. 1444–1445). Appendix A3 provides a graphical representation for each process model.

The first objective was to compare the process models and extract the elementary steps for the development of a strategy. The second objective was to further detail the process model based on those findings. However, a first comparison highlighted that each of the process models has its own individual features and therefore no standard process model for strategy development exists. The comparison also highlighted the differences among the structure of the process models because the number of process steps varies as well as the order of the steps. Furthermore, the review shows that no consensus about the required steps for strategy development exists. However, it was possible to derive three main phases: preparation, strategy development, and strategy implementation. In order to identify similarities on a more detailed level, color-coding was used to make similar tasks visible. This process was carried out until each step of every process model was assigned to a new general process model for strategy development. The synthesis of the existing work helped to derive eight basic tasks for strategy development, which are listed in the left column of Table 5-1. The purpose of table is also to illustrate which process model from literature mentions which of the eight tasks. The findings show that all process models include the following three tasks: analysis of the actual state, analysis of the target state, and planning of initiatives for the implementation of a strategy. In contrast, only three process models mention learning as a task for strategy development. The analysis also shows that the process models of Mussnig and Granig (2013) and Kaplan and Norton (2009) contain all eight tasks and, therefore, present the most comprehensive process models. The comparison of the different process models also revealed that some suggested conducting an as-is analysis before defining the target state, whereas other process models propose the opposite order. Table 5-1 however, shows the most common order of tasks for strategy development based on the analysis. Overall, the analysis was very helpful to extract the main tasks for strategy development and to make the superior order of required tasks for strategy development visible.

Table 5-1: Comparison results of the process models for strategy development (Wilberg et al., 2018a)

Task for strategy development	**Kerth et al. (2011)**	**Mussnig and Granig (2013)**	**Hungenberg (2014)**	**Sternad (2015)**	**Probs and Wiedemann (2013)**	**Kaplan and Norton (2009)**	**Lombriser and Abplanalp (2012)**	**Tschandl et al. (2014)**	**Bradley et al. (2013)**
Analysis of actual state	●	●	●	●	●	●	●	●	●
Analysis of target state	●	●	●	●	●	●	●	●	●
Deployment of alternatives to close the gap between actual and target state	●	●	●	●	◑	●	●	◑	●
Evaluation of alternatives	●	●	●	●	◑	●	●	○	●
Deduction of strategic aims	●	●	●	●	●	●	◑	○	○
Planning of initiatives for the implementation strategy	●	●	●	●	●	●	●	●	●
Scrutiny	●	●	○	●	○	●	●	●	●
Learning	○	●	○	○	○	●	○	○	●

Legend: ○ : not existing ◑ : partially existing ● : existing

The solution approach should help engineering companies to derive a use phase data strategy. Therefore, it is also worthwhile to assess process models for problem solving used during product development. Within the engineering domain, a problem is a deviation between an initial state and a desired target state (Albers et al., 2005, p. 2). Thus, the development of a use phase data strategy also presents a problem-solving process because companies want to improve the current situation by exploiting use phase data in order to gain competitive advantages. In product development, different process models for problem solving exist: VDI-Fachbereich Produktentwicklung und Mechatronik (1993), Pahl et al. (2013), Lindemann (2009), or Albers et al. (2005). Comparing the different problem-solving process models reveals similar findings to the strategy development process, as a different number of steps for problem solving processes exist. The authors of the process models agree that an analysis is an important first step to understand the objectives and constraints for the problem solving process. Albers et al. (2005, p. 5) state that a problem solving process consists of three main phases: problem analysis, solutions search, and solution implementation. As mentioned earlier, the same phases can be found in strategy development (Kerth et al., 2015, p. 1; Sternad, 2015, p. 5). Overall, the structural comparison of process models for strategy development and problem solving helped to derive the basic structure for the solution approach.

5.1.2 Functions of the process model

After obtaining an understanding of the basic process structure for strategy development, the next step is to identify core functions of the process leading towards a use phase data strategy. A core challenge for the solution approach is to combine both the organisational and technical perspective. Developing a use phase data strategy requires, among other things, identifying and selecting use cases in order to form a suitable strategy. However, a use phase data strategy must fit to the organisational and competitive context in order to provide additional value for the company. The functional requirements highlight the importance of the identification and selection of use cases (see Section 4.2.2). Accordingly, the functional structure of the solution approach should combine functions for strategy development and data analytics.

The starting point was to derive functions for strategy development based on existing process models. The previous section briefly discussed nine process models for strategy development. The nine process models also served as a foundation to identify the core functions of strategy development. A detailed assessment of the textual description of the process models allowed for the derivation of the core activities for strategy development.

Table 5-2 summarizes and lists the identified activities. One finding was that all process models highlight the importance of an internal and external analysis when assessing the actual state. Successful strategy development requires a clear understanding about, for instance, the company's own competencies, market trends, market conditions, and strategies of competitors. Furthermore, the analysis revealed it is important to derive different strategic options in order to explore the range of possible alternatives. After deriving options, it is important to evaluate those using financial and non-financial measures. A common agreement of the process models was that the success of a strategy also depends on the implementation of it and, therefore, structured planning is crucial. Furthermore, some process models pointed out that it is important to implement mechanisms that check the success of a strategy and eventually trigger corrective actions. The analysis of the process models further revealed that a broad range of methods exist for strategy development.

Table 5-2: Overview of the core activities during strategy development and related methods

Strategy development task	Core activities of the task	Selection of supporting methods
Analysis of the actual state	Perform an Internal and external analysis, identify trends	SWOT analysis, stakeholder analysis, PESTEL analysis, BCG matrix, Porter's five forces
Analysis of the target state	Derive a mission, vision and objectives	SWOT analysis, Delta Model, Porter's Generic Competitive Strategies
Deployment of alternatives to close the gap between actual and target state	Generation of different strategy alternatives	Scenario technique, Ansoff matrix, morphological box, Gap analysis
Evaluation of the alternatives	Cost-benefit analysis, evaluation of economic efficiency, selection of a strategic alternative	Portfolio analysis, risk assessment, Economic Value Added, sensitivity analysis
Deduction of strategic aims	Detailing of the strategic objectives	Strategy document, strategy map
Planning of the strategy implementation	Communication of the strategy, develop a roadmap for the implementation	Balanced Scorecard, roadmapping
Controlling	Formulate indicators to monitor the effects of the strategy, ensure that the strategy is up-to-date	Balanced Scorecard, key performance indicators (KPIs)
Learning	Conduct review meetings for the strategy, update the strategy	After Action Review

Table 5-2 provides a list of methods in the right-hand column that support the different tasks for strategy development. Overall, the impression was that methods play an important role in strategy development. The collection of methods provides valuable input to further advance the process model for the development of a use phase data strategy later on in this work.

After analysing strategy development related activities, activities for data analytics projects were then focused on in order to identify specific functions for defining a use phase data strategy. Section 4.3 introduced thirteen different process models for data analytics projects. The analysis revealed that most of the existing models only provide limited support for the development of a use phase data strategy. However, the discussion also indicated that some parts might be useful for the development of the process model. Six of the process models seemed promising for a detailed analysis. The objective was to identify suitable activities that each process model suggests for the strategy development. Table 5-3 summarizes relevant activities that each of the process models mention and which seem relevant for strategy development. It is important to highlight that not every model uses the term "strategy" and, therefore, activities were selected that fit to the respective author's understanding of strategy development.

Table 5-3: Overview of suggested activities derived from process models for data analytics projects

Authors	Activities suggested for the development of a strategy for data analytics projects
BITKOM (2013)	• Identify opportunities and obstacles for the application of Big Data • Analyse the current infrastructure (IT infrastructure and Big Data competency) • Determine the Big Data maturity • Assess the importance of the opportunities for the company • Evaluate the feasibility and cost-benefit ratio of a possible solution • Develop a Big Data strategy and a roadmap
Chapman et al. (2000)	• Formulate project objectives and business requirements • Convert business problem into data mining problem • Analyse the current situation (risks, contingencies, costs, and benefits) • Develop a project plan • Collect initial data • Familiarise with the data (data quality problems and first insights)
Dutta and Bose (2015)	• Build up an understanding of the business process or problem • Collect input from different departments to frame the problem • Form a team with stakeholders from different disciplines • Analyse how similar problems have been solved in the past • Assess the current IT and analytics infrastructure • Develop a project roadmap
EMC Education Services (2015)	• Understand the domain problem for the project • Assess the available resources (technology, tools, systems, data, and people) • Describe the data that is needed for long-term goals • Transfer the business problem into a data analytics problem • Formulate the main objectives and key stakeholders • Define the analytics problem and the required data
Köhler and Meir-Hubert (2014)	• Identify opportunities and challenges for an application of Big Data • Outline available competencies and data sources • Assess the current data analytics infrastructure • Identify previous Big Data projects and determine maturity • Collect and analyse possible use cases • Conduct an industry sector internal and external market analysis
Vanauer et al. (2015)	• Derive business objectives and outline related challenges • Formulate use cases and define a possible value proposition • Analyse the current situation and available data • Perform a cost benefit analysis and ensure financial validity • Define business cases • Determine the required resources for an implementation and derive a roadmap

Overall, the analysis revealed that some activities occur in multiple process models. Three process models suggest defining the overall business objectives and problems that frame a data analytics project (Chapman et al., 2000; Dutta and Bose, 2015; Vanauer et al., 2015). It is important to know which benefits data should provide (e.g., cost reduction or improved product quality). Another important activity is to explore which tasks or departments data could provide value to. Due to a large number of possible use cases, it is crucial to obtain an overview of use cases and related obstacles first. In addition, the analysis revealed that data analytics projects often trigger a change process. Therefore, multiple process models suggest performing a comprehensive analysis of the current state (e.g., IT infrastructure and data analytics skills). A common suggestion is to create transparency regarding already available data because companies often have large data sets but do not have a complete overview of all available data. Before selecting a use case, it is recommended to carry out a structured assessment of use cases in order to reveal the connected benefits and costs. Lastly, three process models suggest deriving an implementation roadmap in order to make the required tasks more visible and to communicate the associated implications. Overall, the suggested activities outline the complexity of data exploitation processes and the importance of combining different perspectives in order to identify use cases and obstacles that a company needs to overcome.

Comparing the findings of both analyses highlights some overlaps, but also differences. It is clear that process models for strategy development focus on business related activities, whereas process models for data analytics projects especially address technical aspects. However, process models from both areas follow similar patterns: analysis of the current state, identification and elaboration of options, evaluation of options, and development of an implementation plan. Comparing the activities on a more granular level, however, highlights the differences. An analysis of the current state includes, among other tasks, performing a competitive analysis, identifying technological trends, and assessing one's own competitive edge. From a more technical perspective, such an analysis involves, for example, evaluating the current IT infrastructure, data analytics competencies, and available data. Overall, developing a use phase data strategy requires bringing both perspectives together. The process model to be developed should build upon the functions of both types of process models.

5.1.3 Merger of structural and functional design of the process model

Based on the discussion about structure and functions of process models, the objective is to derive a concept for the solution approach. Thus, the next step is to merge the insights from the previous two sections with findings from the empirical studies (see Chapter 3) and the requirements derived in Section 4.2. Combining those different sources should help to derive a concept for a process model that makes use of existing theory as well as the empirical data discussed in Chapter 3. Merging different perspectives intends to form an applicable approach that is also grounded in theory and that enables companies to develop a sound and suitable use phase data strategy.

The structural and functional analysis provide valuable input to define the structure of the process model and its related functions. In addition, the case study in collaboration with the company from the additive manufacturing sector further helped to highlight the tasks required for the development of a use phase data strategy (see Appendix A1.1). An important requirement for the process model is that it supports a top-down and bottom-up approach for the development of a use phase data strategy. Therefore, the decision was made to propose a process model which starts with an as-is analysis before defining the target state. Thus, companies can first understand, for instance, which use phase data is available. Two other important decisions concerning the design of the process model were that the two tasks, controlling and learning, do not occur as individual tasks. The suggestion is therefore to frequently perform checks during the application of the design support rather than just one at the end. The same idea applies to the learning step. Merging the different inputs from theory and empirical data leads to a six-step process model. Figure 5-2 illustrates the process model that aims to guide companies through the steps required for the development of a use phase data strategy. It is important to mention that this is only the first conceptual design of the process model and Chapter 6 will introduce the final process model in more detail.

Based on the structural analysis of existing process models for strategy development and process solving in engineering, the process model covers three main phases: problem analysis, solution search, and development of an implementation concept. The implementation itself is not part of the process model due to its strong dependency on the application context. The decision was to describe each process step with two main activities. The functional analysis of process models in the previous section helped to derive the six steps of the process model. As suggested by some data analytics process models, the process model starts with a definition of objectives in order to ensure a clear focus. The current state analysis combines input from a strategy and data analytics perspective because it is important to have a clear understanding of the competitive situation, but also to have a clear picture of available data and resources. The conceptual design of the process model further incorporates the idea of exploring the range of use cases before selecting certain ones. The main output of the process model is a use phase data strategy, but also an implementation concept in the form of a roadmap. Overall, the intention was to ensure that each process step has a clear objective and a defined scope.

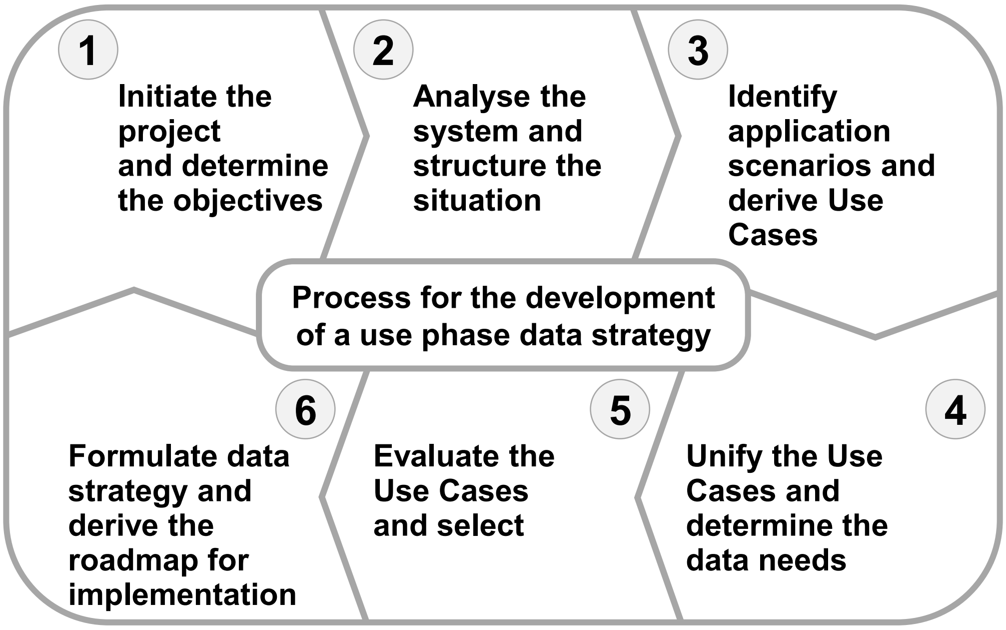

Figure 5-2: Conceptual design of the process model

The first step of the process model step is rather project management related because it defines team members and overall objectives for the development of a use phase data strategy (e.g., time frame or budget for use cases). Afterwards, step two focuses on the internal and external analysis of the current situation. Step three continues with the definition of the target state by defining promising use cases. The next step is then to further detail relevant use cases. The comparison with the general tasks for strategy development shows that these four steps cover the first three tasks that Table 5-2 outlines in the left column. This is then followed by an evaluation and selection of use cases in step five, which represents the fourth task of the basic strategy development process. The last step of the process model then derives the use phase data strategy and proposes an initial roadmap for the implementation. Therefore, the initial process model covers all basis tasks for strategy development and adapts them to the development of a use phase data strategy. Furthermore, the process model comes with a manual that describes the tasks and intended outcome of each process step. Additionally, the process manual of the process model suggests methods that might provide support based on common strategy development methods.

Overall, the conceptual design of the process model presents an initial support for companies that want to exploit use phase data. Due to the combination of existing research work on strategy development and data analytics projects, the process model builds a bridge between those two research fields. The combination of both should further allow companies to address the planning and managerial challenges described in Section 4.1.1 by also providing the adequate methodological support.

5.2 Orientating case studies applying the conceptual process model

The previous section introduced the conceptual design of the process model. The discussion showed how theory and empirical data contributed to the design of the process model. However, the description of the case studies in Section 3.1 was also especially helpful to identify the need for an additional solution approach and to derive the corresponding requirements. Nevertheless, the conducted case studies involved rather small companies with less experience in analysing data. Thus, empirical data from collaborations with more experienced companies would help to provide a more detailed understanding of the challenges that engineering companies face when planning to exploit use phase data in order to assess the derived research objectives.

The objective is therefore to advance the conceptual process model and to conduct an initial evaluation. The main research motive for all three case studies was to understand how the conceptual process model contributes to a systematic development of a use phase data strategy and which additional methods would support the strategy development process. Furthermore, the additional empirical data helps to provide an understanding of whether the conceptual design of the process model requires adjustments. Therefore, three additional orientating case studies with companies were conducted. Eisenhardt (1989, p. 545) suggests that researchers should analyse multiple case studies in order to deduct valid findings. Thus, the three case studies will help to assess the gap between the support that the process model is required to provide and the support that it actually provides.

It was possible to conduct three additional case studies with three different companies. Due to the selection of the case study partners, it was possible to collaborate with a small company (~200 employees) and two large companies (~5,000 employees and ~12,000 employees). In addition, the companies come from different industry sectors and have varying experience in exploiting use phase data. All three companies are OEMs and sell their products around the world. Compared with the case studies described in Section 3.1, the three additional case studies complement the available empirical data because they include companies with different characteristics. Table 5-4 provides an overview of the case studies and describes important characteristics of each case study.

Even though the motives and level of experience of each case study partner differ, the objective was to apply and evaluate the process model at each one because all companies wanted to develop a use phase data strategy. Thus, the research approach is an holistic multiple case study approach (Yin, 2012, pp. 7–9) because it involves different cases studies with the same research motive. Having different data sources during case studies helps to increase the quality of empirical data (Yin, 2012, p. 10). Therefore, data was captured during the case studies using questionnaires, workshops, interviews, and direct observations. The next sections provide a brief overview of the three case studies and the derived findings. Due to confidentiality reasons, no company details or exact numbers are given, and some results are abstracted.

Table 5-4: Overview of the orientating case studies

Characteristics	Orientating case study 1	Orientating case study 2	Orientating case study 3
Scope	Use cases for internal and external stakeholders	Use cases for product development	Use cases for customers and users
Industry sector	Construction equipment	Heating systems	Dosing systems
Company size	~ 5,000 employees	~ 12,000 employees	~ 1,000 employees
Department	Corporate digitalisation	Product development and data insights	R&D
Business relation	B2B	B2B	B2B
Availability of use phase data	Yes	Yes	No

5.2.1 Orientating case study 1 – Construction equipment sector

Description of the case study environment and research objective

The first case study was conducted in the form of two consecutive student projects (Fetscher, 2017; Kalla, 2017). Each student project lasted six months and the second one built upon the results of the first one. The findings of the case study are summarized in a paper by Wilberg et al. (2018b).

The company that participated in the case study offers concrete technology, compaction equipment, worksite technology and compact construction equipment. The development and production of the products is done by approximately 5,000 employees around the world. Due to the large range of products, the decision was made to conduct the case study at the construction equipment segment because this product segment already offers connected products. Furthermore, the products are within a price range where adding connectivity seemed economically reasonable for the case study partner.

The construction equipment sector is also impacted, like others, by the trend of digitalisation on technical products, services and business models. Thus, the case study partner wanted to apply the process model in order to derive a use phase data strategy that helps to exploit available use phase data and to derive future use cases. Therefore, the decision was to focus on use cases that provide value for internal and external stakeholders.

Execution and results of the case study

Over the course of the case study, different sources helped to capture the empirical data (e.g., interviews and workshops). The development of a use phase data strategy requires collaborations among different departments and disciplines. Therefore, different stakeholders from the product management, IT, project management, and technical service provided input during the case study and participated in the workshops.

The conceptual design of the process model provided the foundation for all tasks and activities during the case study. Nevertheless, the objective was to access the applicability and identify a need for improvement. Thus, the process model was not blindly followed and it was constantly assessed whether the tasks proposed by the process model fitted the current project needs and whether the order of the tasks seemed logical. The first student's project mainly focused on the first three steps of the process model. The second student's project therefore mostly addressed the last three steps of the process model and built upon the previous findings. In order to obtain detailed feedback concerning the process model, two evaluations with questionnaires were conducted. One evaluation took place after six months and the second one at the end of the case study.

During **Step 1** of the process model, important goals for the use phase data strategy were derived from the overall strategy of the company. The main objectives were to increase the service turnover, support the product development department, and to assess the value of available use phase data. Furthermore, a cross-disciplinary team of six people was appointed to develop the use phase data strategy at the case study partner. **Step 2** of the process model involves a comprehensive internal and external analysis in order to understand the company's own capabilities and the competitive situation. The analysis during the case study showed that only a small ratio of the construction equipment is sold with a telematics module for connectivity. Furthermore, the assessment of available use phase data revealed that the data has limited value due to lacking data quality. The analysis of the competitive situation showed that direct competitors already offer a broad range of IoT solutions and use cases. It became clear that use phase data could help to address customer needs more successfully and to gain competitive advantages. Afterwards, **Step 3** focused on the identification of use cases. Due to a broad range of possible use cases, the first task during the case study was to define possible application scenarios (e.g., department or functions that should benefit from use phase data). These insights allowed for the identification of stakeholders that could potentially help to derive use cases. Interviews with the different stakeholders then allowed for the collection of 60 possible use cases that provide value for internal and external stakeholders (e.g., customers, logistics, R&D, or sales). In order to pre-select use cases and reduce the number of them, expert interviews assessed the possible value of the use cases. **Step 4** of the process model then continued with the detailing of a limited set of possible use cases. The main point of interest was to understand what use phase data was required for each use case in order to derive the data derivation or data delta (difference between available and required use phase data). Joint workshops with different stakeholders helped to formulate the data needs. Finally, the analysis results led to the conclusion that the definition of a new CAN bus profile is important in order to collect relevant use phase data. The CAN bus (Controller Area Network) is a data communication protocol for vehicles, which connects the controllers of a vehicle. Afterwards, the next step was to identify clusters of use cases that provide similar benefits or build upon each other. The analysis resulted in the identification of eight use case clusters. Afterwards, the main task of **Step 5** was to evaluate the remaining use cases and select promising ones. The first task was an assessment of the use cases on a more detailed level using multiple criteria (i.e., timeline for the implementation or added value). The assessment further revealed that a strong dependency existed among the use cases because some use cases required that another use case had already been implemented. In the end, 34 use cases were selected for further consideration. During **Step 6,** the main findings of the previous steps were combined in order to formulate the use phase data strategy for the case study partner. Furthermore, an implementation roadmap for all use cases and detailed roadmaps for each use case was developed. The visualization of a possible implementation plan helped to describe required adjustments and to specify the timeline. The case study partner used the outcome of the application of the process model to trigger the adjustments needed to implement the use cases and use phase data strategy.

Learnings of the case study

This case study was the first application of the process model and therefore provides important empirical data to better support engineering companies in developing a suitable use phase data strategy in a systematic way. The experience gained during this case study highlighted the importance of a structured process for developing a use phase data strategy. The internal and external analysis during Step 2 helped to create transparency about available use phase data and competencies. This helped the case study partner to understand that comprehensive technological and organisational changes were required. During the search for use cases, it also became apparent that various stakeholders believed that use phase data could provide significant added value for internal and external stakeholders. Furthermore, many stakeholders already had ideas for use cases, but they only existed in their heads and were not documented, which made it difficult to work with these use cases. Detailing, structuring, and documenting the ideas for use cases made it possible to develop a use phase data strategy. The discussion of the use cases highlighted that the case study partner needs to provide clear value for their customers in order to convince them to share their use phase data. The legal department of the company also expressed their concerns in terms of data security because use phase data often contains sensitive data. Overall, the results of the case study encouraged the company to continue working on implementing the use phase data strategy and to add connectivity to their products.

The case study also included two evaluations of the results and the process model, which were both conducted using questionnaires. Both evaluations were conducted during a workshop with employees of the case study partner that were involved in the development of the use phase data strategy. The questionnaires used a six-point Likert scale (range: strongly disagree (-3) – strongly agree (+3).

The first evaluation after six months showed that the order of the steps of the process model is logical (ø = 2.6), but it also became clear that the objectives of each step were not always clear (ø = 0.6). Concerning the usefulness the evaluation, the evaluation indicated that the process model does not help to discover new use cases (ø = -0.8), but at the same time people who were interviewed confirmed that the process model fosters a systematic development of a use phase data strategy (ø = 1.6). The workshop finally also confirmed that the first part of the case study provided very good results and that the process model is applicable at the company.

The second evaluation at the end of the case study confirmed that the process model provides a logical structure for the development of a use phase data strategy (ø = 1.8). The participants also confirmed that the company previously lacked a structured approach to identify and select use cases (ø = 1.8). Furthermore, the evaluation results indicate that the application of the process model is clear (ø = 1.4) and that the process model supports the user in assessing and selecting use cases (ø = 2.2). The overall outcome of the second part was also evaluated as very positive and important for the competitiveness of the company.

5.2.2 Orientating case study 2 – Heating systems sector

Description of the case study environment and research objective

The second case study was conducted as part of student project that lasted six months (Nöthen, 2017). The case study partner is specialised in the development of heating, industrial, and refrigeration systems for private and industrial applications. The company develops, produces and sells their products around the world with more than 12,000 employees. The second case study partner also offers a broad range of different products and therefore it was important to define which products should be within the scope of the case study. The decision was to focus on gas heating systems because these products have the highest sales volume at the case study partner. In addition, the company already sells connected gas heating systems, which can be controlled using an app for mobile phones. Use phase data was thus already available at the company.

The case study partner already analyses and visualises use phase data to support customers, heating installers, and plumbers. Taking advantage of digitalisation is a major objective of the case study partner because new competitors are entering the market (e.g., nest labs). Therefore, the objective right from the beginning was to derive a use phase data strategy that addresses the needs of internal stakeholders (e.g., R&D or service department) because the previous motivation was to rather provide value for external stakeholders.

Execution and results of the case study

Prior to the case study, two workshops with the company were conducted in order to better understand their current situation and their needs. The workshops that were conducted along with four experienced employees highlighted that the engineers see high potential in use phase data, but also revealed that a clear vision about how to exploit use phase data was missing. In order to ensure that the case study merges the engineering and data analytics perspective, the case study was rooted in both departments of the company. During the case study, interviews and workshops helped to perform the steps of the process model. Due to time constraints, the last step of the process model was only partially completed.

During **Step 1** of the process model, the project team, consisting of a sponsor, project leader, and steering committee, was appointed. Furthermore, the following objectives were defined: the use phase data strategy should build upon services that already integrate use phase data, the use cases should mainly exploit available use phase data, and the assumed implementation time for use cases should be less than a year.

At the beginning of **Step 2**, a PESTEL analysis was conducted to understand the competitive and regulatory environment of the case study partner. The case study partner mainly follows a B2B business model because products are sold to craftsmen that then sell the products to the end user. The analysis revealed that limited contact with the end user makes it more challenging to convince them of the benefits that connectivity provides and therefore to ensure the access to use phase data. The analysis of the products' life cycles further highlighted that the average use phase of a product is 12 years long. Therefore, decisions about relevant use phase data could impact the available use phase data for many years and incorrect decisions can make certain use cases impossible due to missing data. The assessment of the digital maturity of the company confirmed that the case study partner already has a comprehensive collection of use phase data and previously hired employees with advanced data analytics skills. However, the internal analysis confirmed that very little value is exploited from use phase data for internal stakeholders (e.g., R&D or technical services).

During **Step 3,** the main objective was to identify application scenarios and derive use cases. Multiple workshops with experienced engineers were conducted during this step, which helped to formulate 36 different use cases. In order to ensure a broad range of use cases, engineers that were responsible for different product components were involved in the workshops. Use cases that were collected during the workshops aimed to provide engineers with insights about, for instance, the frequency that customers change the settings of their gas heating system. Another use case aimed at providing insights about the variation of the pressure within the heating circuit.

Afterwards, **Step 4** focused on reducing the number of use cases by clustering and detailing them. During the case study, the use cases were clustered based on the product module that they link to. Engineers that have in-depth knowledge about the different product modules helped to evaluate the use cases. Use cases with little added value or a presumed long implementation time were excluded. After reducing the number of use cases, the data needs for each use case were assessed.

Afterwards, **Step 5** continued with a comprehensive evaluation of the remaining use cases. Due to the fact that the use cases only address internal stakeholders, it became clear that the use cases could have the following benefits: cost reduction, quality improvement, or reduced downtime. In addition, the data analytics department got involved to further detail the use cases and assess the complexity of their implementation. In the end, the decision was to continue with six remaining use cases.

Step 6 was only conducted partially due to time constraints. Therefore, an implementation roadmap was developed only for one use case. Nevertheless, the company continued to detail the other use cases after the case study ended.

Learnings of the case study

The second case study provides valuable insights about the application of the process model in a different setting because the case study partner already offers use cases for their customers that build upon use phase data. However, little emphasis was previously put on how to assess use cases that support internal stakeholders. A key challenge at the beginning was to identify all relevant stakeholders for the development of a use phase data strategy. During the second step, it became clear that engineers had great interest in exploiting use phase data in order to improve product design, reduce over-engineering, or understand the operational conditions. However, it also became clear that the engineering department and the data insights team had limited touchpoints and did not work together on a regular basis. The structured process for the development of the use phase data strategy helped to connect the different stakeholders at the case study partner and therefore allowed them to understand the differing perspectives on use phase data and the products. The identified use cases raised awareness at the case study partner about how interdisciplinary work is needed to exploit use phase in order to provide additional value for the engineering department. During step 4, when the use cases were detailed and required data was identified, it became clear that the available use phase data did not fulfil the requirements of every use case, due to, for instance, missing data points or a low resolution. Furthermore, the structured strategy development revealed the importance of context data for many use cases because gas heating systems are operated under a broad range of possible settings (e.g., with or without underfloor heating). The case study showed the case study partner that additional use phase data must be collected in the future, which should occur on a use case driven basis, instead of just collecting data without having a strategy. Another important learning for the case study partner was that some of its existing use phase data could already address some of the engineer’s use cases, which was not clear before. Overall, the developed use phase data strategy led to transparency concerning the needs of the engineering department and helped to turn available use phase data into value. In addition, the strategy helped to define clear objectives regarding how use phase data should be exploited in the future.

The second case study also included a comprehensive evaluation of the process model and the case study. Based on the DRM (Blessing and Chakrabarti, 2014, p. 195), the objective was to evaluate the usability, usefulness, and applicability of the process model, using a questionnaire to make the answers comparable. The developed questionnaires consisted of closed and open questions. The closed questions used a six-point Likert scale (range: strongly disagree (-3) – strongly agree (+3)). The evaluation was conducted with two slightly different questionnaires during two workshops. The first workshop involved five engineers from the R&D department that developed use cases during the case study. The second workshop was done with four members of the project management team. Due to the high numbers of evaluation results, only the key questions are discussed in the following.

The engineers confirmed that it was possible for them to understand how use phase data could provide support for their daily work (ø= 1.75). In addition, the evaluation showed that the interdisciplinary composition of the strategy development project team helped to bring the different functions of a company together (ø= 2.6). At the same time, the engineers also confirmed that the strategy development improved the understanding of the needs and interests of the other internal stakeholder (ø= 2.5). The participants also mentioned that it was helpful to first identify use cases before looking into available use phase data (ø= 2.5). Concerning the learnings during the case study, the evaluation results also draw a positive picture. The participants from the engineering department stated that the strategy development improved their understanding of how data analysis works (ø= 2.6) and that a structured process is useful to identify suitable use cases (ø= 2.6). The participants also confirmed that the selected use cases have a positive cost-benefit ratio (ø= 2.4). Nevertheless, the participants also noted that the strategy development only revealed a limited number of new ideas for use cases (ø= 0.67).

During the second workshop with the project management team, the four participants were asked to evaluate the process model. The results show that the order of the steps is logical (ø= 1.5) and that the process model contains all required steps (ø= 2.0). The participants further confirmed that the process model fosters a structured development of a use phase data strategy (ø= 1.5). However, the evaluation also highlighted some potential for improvement. Based on the results, the process model and the manual describe the objectives of each step in a merely satisfactory way only (ø= 0.5). The list of supporting methods for each process step also provides limited support (ø= 0.33). However, the participants mentioned that they do not use many methods for strategy development during their work and therefore would be required to build up an understanding. Furthermore, the results indicate that the participants doubt that the process model helps to reveal new use cases. This finding is understandable because the main intention of the process model is the structured collection and selection of use cases function as a tool for fostering creativity. Overall, the project management team also confirmed that the interdisciplinary composition of the team was helpful for the development of the use case (ø= 3.0). In addition, the evaluation showed that a structured approach helps to collect use cases (ø= 1.0) and that the development of a use phase data strategy defines clear objectives for the future (ø= 1.75). Summing up, the second case study provides comprehensive insights into the process leading towards a use phase data strategy and the evaluation confirmed that the process model is complete and logical.

5.2.3 Orientating case study 3 – Dosing systems sector

Description of the case study environment and research objective

Similarly to the two previous case studies, the third case study was also conducted as part of a student thesis that lasted for six months (Rosenberger, 2017). The case study partner is a SME company with less than 1,000 employees that produces dosing systems for cement production and other industries that need to handle loose material. The machines that the company produces take great responsibility in ensuring that production processes run smoothly. In the production environment, the industry 4.0 trend aims to take advantage of connectivity to increase productivity and quality.

The case study company already develops mechatronic products with comprehensive control systems. Therefore, the products are already equipped with many sensors that generate data. However, until the case study started, none of the products was equipped with connectivity.

The objective of the case study partner was to develop a use phase data strategy that focuses on data-driven services for customers. The motivation for this was that use phase data can help to increase the availability of the dosing systems and therefore would lead to a competitive advantage.

Execution and results of the case study

Due to the fact that the main focus was to derive use phase data-driven services, the case study was conducted in collaboration with the R&D department, which is also responsible for service development. During the case study, interviews and workshops provided the main input for the strategy development. Due to time constraints, it was not possible to conduct step 6 of the process model during the case study.

During **Step 1** the strategy development team was assigned, which included the student and the head of R&D at the case study partner. The decision was further to develop a use phase data strategy for one of the company's specific dosing systems, because it was the bestseller and other products have a similar architecture. Concerning the objective, the decision was to focus on use phase data-driven services that could be realized in a shorter timeframe (less than five years). Another limitation was that the use cases should build upon the current machine design and should not trigger any large changes to the product itself.

The focus of **Step 2** was to gain a clear understanding of the competitive environment in terms of data-driven services and to increase internal transparency. A main task was a comprehensive online search to assess the maturity of data-driven services that direct and indirect competitors provided. The search indicated that many companies mentioned data-driven services, but the impression was that they presented a vision rather than a real service offering. The same was true of the direct competitor of the company. The next task during this step was to develop a customer profile that supports the use case generation by outlining how data-driven services can provide extra value for customers. The value proposition canvas was used as a basis for the customer profile (Osterwalder et al., 2014, pp. 8–9). The case study company only operates in a B2B context. Therefore, it became clear that the services need to create gains for and/or need to reduce the pains of the business customers. The analysis revealed five main categories of gains: high quality of cement, low production costs, high volume of production, decrease personnel resources and general enablers that make operations smoother. At the same time, five pain categories became clear: high downtime, demand too low, production costs too high, government shutdown and general problems. In order to match the current product and service offerings of the case study partner with these gains and pains, a new tool called fit-map was developed. Overall, the analysis revealed that there is potential to create extra value for customers by offering data-driven services. The next step was a thorough analysis of the use phase data that the machines already produced. For this purpose, a data map was derived that visualized available use phase data. The analysis revealed that three different data types existed: measured data points, calculated data points, and externally given data points. Furthermore, it was possible to assign all available data points to the four main components of the machines.

Afterwards, the main activity of **Step 3** was to derive use cases for services based on use phase data. The following sources served as input for use case ideas: expert knowledge (18 use cases), a review of literature and other companies (9 use cases), general knowledge (7 use cases) and available use case collections (11 use cases). Overall, it was possible to identify 45 use cases (e.g., vibration measuring and monitoring, Indicator-Cockpit, or assessment of the energy consumption of the motor). The customer profile and value proposition depiction were very helpful for developing ideas that directly address customer needs. Each use case was documented using a one-pager.

Due to the high number of use cases, **Step 4** focused on the consolidation of the use cases and assessment of the data needs. In order to evaluate the 45 use cases, each use case was evaluated using seven categories. Furthermore, the connections among the use cases were analysed. This step revealed that six clusters of use cases existed: augmented reality, intelligent manual, remote support, improved customer interaction, general business ideas, and remote service business cases. Afterwards, each use case was assessed in relation to its data needs. The detailed analysis of all use cases led to a list of 22 use cases.

The remaining use cases were further detailed and evaluated during **Step 5**. This task concluded in the formation of three business cases: remote service, predictive maintenance, and improved customer interaction. Each of the business cases was assessed regarding its value proposition and risk. At the end of this step, each of the three business cases was evaluated using seven criteria (e.g., value for customer, or complexity of realization).

Step 6 was not performed as part of the case study due to time constrains. Nevertheless, the case study partner decided to continue working on the use phase data strategy and to implement the relevant use cases.

Learnings of the case study

The third case study provides valuable empirical data concerning the development of use phase data-driven services. Due to the size of the company, it was possible to integrate stakeholders from different departments in order to drive suitable use cases and related business cases. The use and adaptation of methods from the field of business model development proved to be very helpful to understand the needs of the customers and their pain points.

The third case study also concluded with an evaluation of the process model and results of the case study. A workshop with seven participants from the case study company was used for the evaluation. In addition, an in-depth evaluation was conducted by an interview with the head of R&D. For the evaluation during the workshop, a questionnaire with a four-point Likert scale was used (range: strongly disagree (-2) – strongly agree (+2)).

Similar to the two previous case studies, the participants confirmed that the steps of the process model follow a logical order (ø= 1.3). The evaluation also highlighted that a structured approach helps to identify use cases (ø= 1.4). Afterwards, the participants were asked to rate the outcome of the case study and the process leading to the business cases. The evaluation results confirmed that the process leading to the business cases is logical (ø= 1.5) and that the formation of clusters helps to identify synergies among the use cases (ø= 1.8). Concerning the business cases, the participants stated that they believe that all three can provide value for customers. The questionnaire-based evaluation followed an open discussion that pointed out that the business cases require further detailing in order to assess their feasibility and to analyse customer acceptance.

The personal interview with the head of R&D showed that the data map did not provide any new insights but helped to increase transparency about the data that was generated. During the interview, the business cases were also discussed in detail. The feedback was that they were useful as they provided a common ground for discussion and highlighted three areas that could be implemented in a rather short time and could provide benefits for the case study company. Concerning the process model, the interview highlighted that it is applicable and usable. However, a challenge during the application was that the terms “use case” and “application scenario” were not clearly defined. Overall, the evaluation draws a positive picture of the design support (process model and developed methods) and case study results. Nevertheless, the case study partner now needs to work on further detailing business cases and preparing their implementation.

5.3 Conclusions drawn from the orientating case studies

The three orientating case studies provide valuable insights to further support the development of a use phase data strategy. Qualitative research should be iterative in order to increase the quality of the work, which means that design and implementation should alternate (Morse et al., 2002, p. 17). The cases studies allowed to closely follow the development process for a use phase data strategy at three different companies. Furthermore, the three orientating case studies allowed for the conceptual process model to be applied in three different settings because the case study partners, for instance, have different sizes, operate in different industry sectors, or have different business arrangements (B2B vs. B2C). Therefore, it was possible to observe strategy development in different settings and thus gain a detailed understanding of organisational needs, missing support when developing a use phase data strategy and obstacles that hinder the exploitation of use phase data. It is important to mention that each case study was part of an independent student project in order to avoid mutual interference and to obtain an overview about the differences during the development process.

Overall, the main contribution of the three case studies is twofold. First, the evaluation and experience gained during the case studies confirmed the motivation for the solution approach because it became clear that a use phase data strategy allows for the derivation of a sound vision that defines objectives concerning the use cases that a company wants to implement. In addition, the case studies showed that a structured process allows for the derivation of a use phase data strategy in a systematic and methodical manner, which helps not only to explore different use cases, but also to understand the company and competitive context. Secondly, the evaluation during the case studies confirmed that the developed process model provides valuable help for the development of a use phase data strategy. However, the next two sections discuss the underlying fundamentals for the solution approach and highlight potential for further enhancing the process model based on the experience gained during the case studies.

5.3.1 Discussion of the fundamentals for the solution approach

Insights gained during the literature review provided important theoretical input about the challenges that companies need to overcome when exploiting use phase data. These findings complement the empirical data stemming from the four initial case studies. Both sources provided the main input for the formulation of requirements in Section 4.2.These requirements served as an important foundation for the conceptual design of the process model. In addition, the structural and functional analysis of existing process models helped to derive the framework for the process model. The objective therefore is to compare the findings of the three orientating case studies with underlying fundamentals for the design support.

In order to assess the fundamentals, the research approach is to analyse the problems that hindered the exploitation of use phase data. The first case study highlighted the importance of considering organisational aspects when exploiting use phase data. The case study partner already collected use phase data, but nobody was responsible for its analysis. In addition, no detailed knowledge about the use phase data and the related quality was available. Due to this, no use phase data strategy existed and therefore use phase data did not provide any value to the company. It also became clear that it is important to have better coordination between the organisational structure, IT infrastructure, use phase data strategy, and product design in order to turn use phase data into value.

The second case study also highlighted that a use phase data strategy is important to foster collaboration between the different stakeholders (e.g., R&D and data insights) in order to realise use cases. Furthermore, the case study highlighted that just connecting products and storing large amounts of use phase data does not create benefits. The case study further showed that use phase data should not only be used to provide value for customers; use phase data can also support internal stakeholders and, therefore, available use phase data can be used more efficiently.

The third case study highlighted the importance of understanding the customer in order to derive use cases that provide additional value. Furthermore, the case study showed that it is important to analyse the dependencies between the use cases in order to generate synergies.

Besides the discrete problems that became visible, there were also similar problems among all three case studies. They all showed that a number of ideas for use cases already exist in the heads of the different stakeholders, but thus that use cases are only available in a fragmented and implicit manner. Furthermore, companies should not develop connected products without previously defining use cases that build upon use phase data in order to ensure that they collect data with a purpose in mind. It became clear that the collection of data without a purpose leads to incomplete and qualitatively insufficient use phase data. None of the three case study partners had a use phase data strategy that defined how they planned to exploit use phase data in the future. Therefore, central stakeholders (e.g., engineers, data analysts or service managers) did not collaborate on a regular basis. The lack of a strategy also caused a lack of coordination between product design, IT structure, and organisational setup. As highlighted earlier, the three case studies confirmed that managerial obstacles are a major source of problems when exploiting use phase data. Overall, the three case studies confirmed that the requirements describe a solution approach that addresses the needs of companies willing to exploit use phase data. Furthermore, the case studies also show that connecting the strategy development and data analytics perspective is useful in order to develop a use phase data strategy that fits the company and competitive context.

5.3.2 Learnings for the enhancement of the process model

The foundation for all three orientating case studies was the conceptual design of the process model, and therefore the research objective was not only to revise the fundamentals, but also to use the empirical data to further enhance and detail the process model. Each case study concluded with an evaluation of the process model. Conducting an application evaluation before the design support is finalised helps to ensure the applicability of the support (Blessing and Chakrabarti, 2014, p. 177). From looking at the steps of the process model, the results confirm that the order of the steps is logical. In addition, the first case study confirmed that the application process of the process model is clear. The second case study also confirmed that all of the important steps for the development of a use phase data strategy are included in the process model. Furthermore, the experience during the case studies showed that it is beneficial to also collect possible use cases before looking at the use phase data that is available (top-down approach) because as a result use cases that might be worthwhile to be implemented in the future are also considered. All three case study partners applied the process model for the first time, and therefore the discussions at the end of the case study revealed that experience with use phase data is beneficial when developing a use phase data strategy and applying the process model. The feedback from the case study partners also highlighted that an iterative application of the process model might be helpful, because the application fosters organisational learning, which helps to improve the use phase data strategy with each iteration. Overall, the findings indicate that the conceptual design provides a useful support for the development of a use phase data strategy.

The next step is to look at the design support on a more granular level. Therefore, a subsequent analysis compared, for each case study and for each step, the following aspects: tasks conducted, methods applied, and results. Afterwards, a comparison compared the findings of the case studies and the conceptual design of the process model. Figure 5-3 summarizes the approach to enhancing the process model. A general finding for all process steps was that the conceptual design of the process model mainly suggested general methods for the development of a strategy. Based on the experience gained during the case studies, it became clear that these methods are not sufficient for the development of a use phase data strategy. Therefore, additional methods were developed during the cases studies that helped to overcome the challenges that arose when developing a use phase data strategy. The next chapter provides a detailed description of the developed methods.

On a step-based level, the case studies provide the following insights. Concerning **Step 1**, the three case studies showed that it is very important to appoint a transdisciplinary team for the development of the use phase data strategy because a wide range of competencies, for instance, from engineering, data analytics, IT, or customer service, is needed in order to exploit use phase data. In addition, the case studies show that the process model should trigger an analysis of other strategies that influence or interfere with the use phase data strategy.

The three case studies highlighted that **Step 2** is very central for the development of a use phase data strategy because a main obstacle was that the case study partners had only limited internal transparency (e.g., regarding available use phase data). The experience also showed that the process model should trigger a comprehensive external analysis in order to derive a use phase data strategy that addresses the current and future competitive environment of a company.

An important learning for **Step 3** was that the term “application scenario” is misleading, and therefore caused confusion. Thus, the decision was to use the term “application area” instead. Furthermore, the use cases that come up during this step form the foundation for the following steps and the entire strategy. The evaluation results showed that the mere application of the process model does not lead to new use cases, which fits to the intended benefits of the process model. However, the experience showed that a collection of use cases for connected products could support the ideation during this step. This was a main motivation for the development of a use case catalogue (Wilberg et al., 2018c).

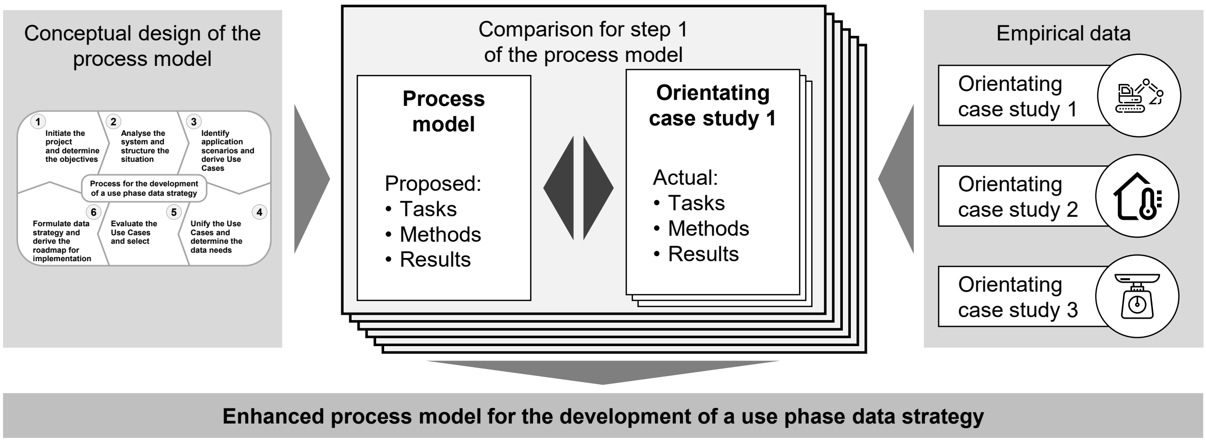

Figure 5-3: Approach for enhancing the conceptual design of the process model

A main challenge during **Step 4** was to reduce the number of use cases because it became clear that is not possible to detail 40 use cases. It is thus crucial to reduce the number of use cases, but also to identify synergies among these. For an analysis of synergies, a company needs to have knowledge about the required use phase data for each use case. Therefore, the order of the two main tasks (unify the use cases and determine the data needs) of this step was changed.

The evaluation of possible use cases during **Step 5** showed that a broad range of financial and non-financial evaluation criteria exist. Furthermore, the case studies showed that it could be beneficial to evaluate packages of use cases because they might be dependent on others or require consecutive implementation.

Unfortunately, only the first case study reached **Step 6** of the process model. However, the experience showed that it is important to derive a roadmap that integrates the use cases into the company’s context setting because a use phase data strategy often entails changes to products, organisational structures, or IT. Lastly, the first case study highlighted that it is important to conduct a review in order to assess the developed use phase data strategy at the end.

Overall, the empirical data contains important insights about the detailed process leading to a use phase data strategy. The experience also showed that it is important to consider both the technical and organisational perspective in order to gain an overview of planning and managerial challenges connected with the development of a use phase data strategy. These insights allowed for the derivation of the final process model, which the next chapter introduces and discusses.

6 Process model for the development of a use phase data strategy

The findings from applying the conceptual design of the process model confirmed the importance of methodological support and highlighted important tasks for the development of a use phase data strategy. Based on these learnings, this chapter introduces the process model that supports companies in developing a use phase data strategy in a structured way. At first, Section 6.1 introduces the six-step process model and describes its application. Afterwards, Sections 6.2 to 6.7 provide a detailed description of each step and introduce methods to support them. At the end, each section summarises the main outcome of the respective process step. Finally, Section 6.8 summarises the developed process model.

6.1 Introduction of the process model

The developed process model aims to support companies in deriving a sound use phase data strategy in a structured way. Therefore, the process model does not only provide guidance for the tasks that are required for developing a use phase data strategy. It also suggests additional methods that support its users in conducting the related tasks.

Use cases are the foundation of a use phase data strategy. Thus, the process model helps to collect, elaborate, and select use cases in order to integrate them into the strategy. An important feature is that the process model combines a technical or data analytics perspective with an organisational perspective, which is important to ensure that a use phase data strategy can be operationalised. The process model thus addresses the shortcomings of existing process models that address planning and managerial challenges on a rather abstract level. Altogether, the process model enables companies to derive a comprehensive use phase data strategy that describes how a company plans to exploit its use phase data in order to provide value for internal and external stakeholders.

Based on the insights gained through the three orientating case studies (see Section 5.2), the conceptual design was further improved and the process model was elaborated to better support companies in developing a use phase data strategy. The developed process model was first published by Wilberg et al. (2018a). The final version of the process model differs slightly from the first publication of the process model due to some additional insights derived from empirical data and discussions with researchers and practitioners. However, the changes were only minor.

Overview of the process model

Figure 6-1 illustrates the final process model for the development of a use phase data strategy that consists of six process steps. Based on the objective of this process model, to provide methodological support for the exploitation of use phase data, each of the steps contributes to the development of a use phase data strategy. **Step 1** initiates the development project for the use phase data strategy by appointing team members and defining the objectives for the project. **Step 2** triggers an internal analysis in order to assess the company's digital maturity and current situation (i.e., available use phase data, competitive situation, or IT infrastructure). The step also initiates an external analysis to assess the competitive environment. Insights from both analyses are merged to obtain a detailed understanding of the current situation. Afterwards, **Step 3** starts the search for application areas for use phase data and then collects possible use cases. **Step 4** further details the use cases by determining the data needs and then consolidates them. The main task of **Step 5** is to conduct a detailed evaluation of the remaining use cases, before selecting the use cases that should become part of the use phase data strategy. The remaining tasks of **Step 6** are to formulate the use phase data strategy and to derive an initial implementation roadmap. The process model concludes with a **Review** that assesses whether the defined objectives were reached or if the objectives changed over the course of the project, which allows for a readjustment of the use phase data strategy prior to implementation. After completing all six steps, the output should be a comprehensive use phase data strategy that describes which use cases are pursued and how a company plans to implement the strategy.

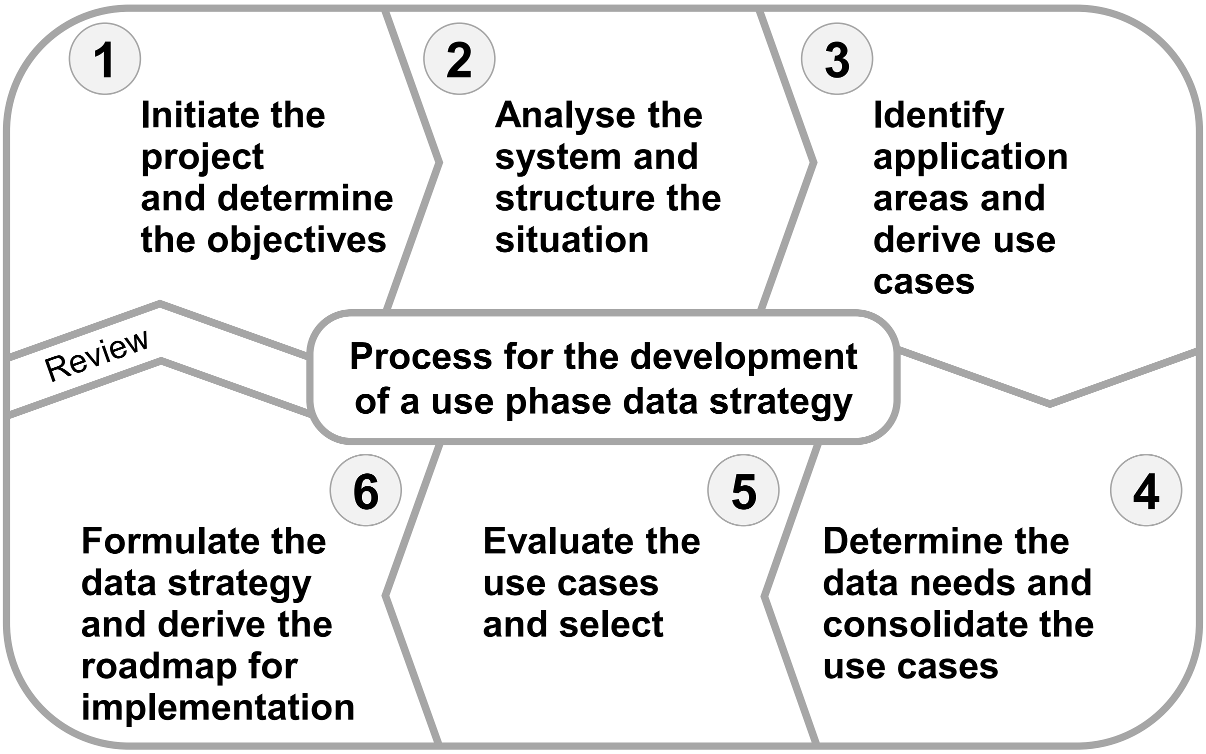

Figure 6-1: Process model for the development of a use phase data strategy

Suggestions for the application of the process model

Overall, the process model builds upon the **basic structure** of a problem-solving process and its three general steps are recognizable: problem analysis (Step 1 and Step 2), solution search (Step 3, Step 4, and Step 5), and solution implementation (Step 6). However, it is important to mention that the implementation involves many additional tasks, which are not covered by the process model. The model thus only provides initial input for these steps.

The design of the process model allows for **iterations** because companies often gain new insights and skills the longer, they work with data analytics. Furthermore, when starting to work with use phase data, the empirical data showed that it is beneficial to pick less complex use cases at the beginning and then increase the complexity with each iteration. Being able to iterate allows for the repetition of certain tasks or steps in the case that new circumstances arise or selected use cases prove to not be suitable, for instance, due to changes in the competitive environment, availability of new technologies, or occurrence of problems related to the implementation of use cases. Furthermore, it is also possible to review previously identified use cases during an iteration in order to assess them based on the current objectives and situation.

The process model should be used in a **flexible** way based on the application context. A common mistake of users of process models is that they forget to adjust the process model to the circumstances (Lindemann, 2009, p. 37). A process model can only provide help if the user applies it in a task- and problem-specific manner. The developed process model contains a long list of tasks for each step and also provides various methods, but users of the developed process model need to assess whether a task is needed or a method can provide additional support. However, the process model can only ensure an efficient and effective development of a use phase data strategy if users do not follow the process model blindly.

During the **search for possible solutions,** intermediate results on different concretization levels are generated in product development (Lindemann, 2016, p. 411). The search process for use cases therefore requires divergence and convergence in order to ensure that the search space for possible solutions is not too narrow but also not too wide. The SPALTEN[5] problem solving methodology of Albers et al. (2005) suggests to alternate between divergence and convergence. However, the process model for the development of a use phase data strategy suggests diverging until the end of Step 3 by identifying possible use cases. The bottom part of the process model then encourages convergence towards a reduced number of use cases that form a use phase data strategy. It is possible to reach divergence after Step 6 again by applying the model an additional time because it is then possible to identify new use cases or detail previously identified ones. The experiences during the orientating case studies showed that the search for possible use cases often results in a comprehensive list of options that needs to subsequently be narrowed down due to the fact that is quite resource consuming to detail use cases.

The applicability of the process model is an important requirement (see Section 4.2). Therefore, a **manual for the process model** was developed in German and English. The English version of the manual is shown in Appendix A5. The manual consists of eight pages and aims to support the application of the process model during the development of a use phase data strategy. For each process step, the process model lists the relevant tasks for the process steps including additional hints, suggests supporting methods, and describes the desired result of each process step.

The developed process model builds upon existing **methods** for strategy development. However, the orientating case studies showed that additional methods are required to support

[5] The name of the SPALTEN process derives from the German names of the seven process steps: **S**ituationsanalyse (Situation Analysis), **P**roblemeingrenzung (Problem Containment), **A**lternative Lösungssuche (Search for Alternative Solutions), **L**ösungsauswahl (Selection of Solutions), **T**ragweitenanalyse (Analysis of the Level of Fulfilment), **E**ntscheiden/Umsetzen (Make Decision/Implement), and **N**acharbeiten/Lernen (Recapitulate/Learn) (Albers et al., 2005, p. 4).

certain tasks during the development of a use phase data strategy. Therefore, Appendix A6 summarises the method box with its 15 methods.

In the following, each process step of the process model is described on a more detailed level and supporting methods for each step are introduced as well. Each process step consists of two main tasks, which are further broken down into sub-tasks. It is important to mention that the process model does not provide a use phase data strategy but **provides guidance** so that the users can develop a tailored strategy in a structured and methodological way. The process model also does not provide use cases but supports companies in searching for promising ones.

6.2 Step 1 – Initiate the project and determine the objectives

The objectives of the first step are to form the foundation for the project that develops the use phase data strategy and to define the scope of the use phase data strategy. In general terms, a project is a combination of different tasks with a desired outcome, which must be achieved within a certain amount of time and consumption of resources (Hobbs, 2015, p. 6). Based on this definition, the desired outcome of the project is a use phase data strategy. In order to ensure that projects provide the desired outcome, project management is needed to plan, monitor, and control projects (Lester, 2017, p. 7). The first step therefore ensures that the use phase data strategy development project can be managed.

The first task is to **initiate the use phase data development project**. Therefore, it is important to define responsibilities and to set up a project team right at the beginning (Sternad, 2015, p. 1). There are different reasons for developing a use phase data strategy because use phase data can provide a variety of benefits for internal and external stakeholders. Nevertheless, the development of a use phase data strategy means that, for instance, products, services, processes, or responsibilities will change. Therefore, it is important that the development project is backed by the management of a company (Fitzgerald et al., 2014, p. 4). A prerequisite for the project is that the management has decided that a use phase data strategy is needed. The management further needs to decide where the use phase data strategy should be implemented within the company. In general, a use phase data strategy can be developed, for example, for a business unit, product division, or the R&D department. This decision has a strong impact on the project definition because it determines if the project has the volume of a small exploratory project or rather turns out to be a large initiative that triggers comprehensive changes in different areas of the company. Main factors influencing this decision are the experience of working with use phase data, size of the company, and available resources. A last decision prior to defining the team members is to decide whether a company wants to rely only on internal stakeholders or wants to hire external stakeholders to support the project. In general, the strategy development can be done by hiring external consultants, setting up a staff position or defining an internal project team (Freidank and Mayer, 2003, p. 94).

Before selecting the different team members, it is important that all other roles are defined. The different roles within the project ensure clear decision-making competencies. However, project management changed in the last few decades due to new approaches, which originated from the computer science domain (Cervone, 2011, pp. 18–19). Agile project management, for examples originates from agile software development practices. Due to the novel perspectives on project management, “traditional” and “modern” approaches exist in parallel. In the following, roles within a project are described from both perspectives. However, the following Sections use the terms of the traditional roles within a project. The decision about which roles a project should compromise of must be made based on the common practices of the company.

Agile project management consists of many different approaches with Scrum being one very important method among these (Cervone, 2011, p. 19). Scrum is a general framework that aims to support companies in organising and managing work (Rubin, 2012, p. 13). In general, the Scrum framework consists of roles, processes, and artefacts (Cervone, 2011, p. 20). In the following the focus is only on the three roles within a Scrum team and the reader is asked to consult additional sources for details on agile project management or the Scrum framework (e.g., Highsmith (2010) or Schwaber (2009)). Figure 6-3 provides an overview of the competencies linked to the three roles within a Scrum team. The ScrumMaster is responsible for the underlying process and ensures that it fits to the organisation. Furthermore, the ScrumMaster needs to ensure that everyone follows the defined rules. The product owner represents the link between the Scrum team and the customer. Furthermore, the product owner maintains the product backlog, which is a list of requirements. The development team is responsible for designing a product that fulfils the product backlog. Within the context of this work, the product that a Scrum team needs to develop would be the use phase data strategy.

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Scrum role	Competency
ScrumMaster	Responsible for ensuring that the Scrum process and the rules are followed
Product owner	Representing the interests of the stakeholders and users
Development team	Development of the desired functionality

Figure 6-2: Overview of the roles within the Scrum framework (derived from Schwaber (2009, pp. 6–7))

Figure 6-3 illustrates the important roles within a project from a traditional perspective. Based on this perspective, every project should have a sponsor who initiates the project. The project sponsor approves the project and provides resources. In the end, the sponsor has the overall responsibility and needs to ensure that the project goals are reached. The project manager is responsible for ensuring that all goals are reached and appoints, together with the sponsor, the project team and project steering committee. Therefore, the project manager also has discretionary powers for the project team. The project manager also defines the schedule of the use phase data project and allocates resources. Due to the different stakeholders involved in the development of a use phase data strategy, the project manager needs to also maintain an overview of the project. Depending on the size of the use phase data project it might be advisable to set up a steering committee, which consists at least of the project sponsor. The committee should also have members of departments that are involved in the development of the use phase data strategy or departments that will implement the use phase data strategy later on. Therefore, the steering committee monitors the project, intervenes if necessary, and signs off the use phase data strategy. The last, and very important, element of a project is the project team itself, which has all the relevant domain knowledge and is responsible for the development of the use phase data strategy. The following paragraph focuses on the selection of the team.

Project role	Competency
Sponsor	Decision competence
Steering committee	Decision competence
Project manager	Process competence
Project team	Domain knowledge

Figure 6-3: Traditional roles within a project and their related competencies (based on Kuster et al. (2011, p. 101)).

After introducing the basis roles of a project, the next step is to set up the project team. The top management (C-level) is a main trigger for projects that aim to exploit use phase data (Kane et al., 2015, p. 20). Therefore, it is important that the top management not only triggers such projects, but also stays involved over the course of the project (Dutta and Bose, 2015, p. 304). Involving the management also ensures that the project has appropriate funding and access to resources (Sternad, 2015, p. 33). Besides having the management involved it is also important for data analytics projects to form an interdisciplinary project team (Dutta and Bose, 2015, p. 295; Palem, 2014, p. 28). Working with use phase data requires more than just data analytics skills because the analysis of data must have a link to an existing problem. For engineering companies, it is important to involve stakeholders with technical domain knowledge in the development of a use phase data strategy. For instance, only an engineer will be able to describe where sensors should monitor parts of products in order to detect failures. The development of a sound use phase data strategy is only possible when the different disciplines work closely together in order to ensure that a use phase data strategy can also be implemented later on. Therefore, the manager for the project must identify stakeholders based on the scope of the project from key functions like product development, IT, product management, service, sales, or data analytics. For example, the IT department is essential for evaluating the feasibility of use cases. The product management has a detailed overview of customer and market requirements, which is important in order to derive use cases. Use cases often provide a foundation for data-driven business models and therefore the sales or service department have an impact on the use phase data strategy as well.

The challenge is therefore to balance the different interests and perspectives of stakeholders in order to ensure that the project identifies use cases that are relevant, but also technically feasible. It is possible to define right at the beginning which functions should be part of the project, but it is advised to review the involvement based on the selected use cases because different skills or expertise might be required later on. Selecting the right stakeholders for the strategy development is important because involving people with relevant experience will also have a positive impact on the acceptance of the strategy. An ideal team has between four and eight team members (Lindemann, 2009, p. 24). However, this is only an indicator because the team size depends, for instance, on the task. Research findings indicate that a strategy development team should not exceed more than 11 people (Belbin, 2010, pp. 110–111). Before proceeding, the following criteria help to assess a strategy development team: diversity of perspectives, knowledge diversity, innovation power, central stakeholders, team dynamics, and availability of stakeholders. To ensure a successful development of the use phase data strategy, the project sponsor and project manager must ensure that the project team has adequate space to work. In the case that the project manager or sponsor expects conflicts or resistance to change triggered by the strategy, it can make sense to appoint a neutral moderator that resolves conflicts and helps to find a solution (Bohinc, 2006, p. 148). Especially when developing a use phase data strategy, many different stakeholders with diverse interests need to work closely together.

After the project is initiated and the team members are selected, the first task for the new team is to **determine the objectives** of the strategy development project. Research findings show that a poor definition of objectives is a main cause for project failure (Young, 2013, p. 10). The St. Gallen Management Model defines the following three management process layers: normative, strategic, and operational management (Bleicher, 2017, pp. 150–154). The normative layer is responsible for the overall vision and values of a company. Derived from the normative layer, the strategic layer is responsible for the organisational design and strategy of a company. The operational layer implements the strategy and ensures that the processes are followed. Based on this definition, a use phase data strategy development project happens on the strategy layer and therefore must fit to the overall vision of a company. Therefore, the first task is to analyse the company's vision and identify elements that influence the development process of the strategy in order to ensure that the use phase data strategy fits to the company's vision and values.

In addition, strategies exist in a company on a corporate, business, and functional level (Karami, 2016, p. 157). A use phase data strategy will be part of the business or functional level depending on the objectives. In the case that a use phase data strategy contains use cases to support product development, for instance to offer new product functionalities or provide additional services, the strategy will be on the business level. In such a case, the use phase data strategy complements the functional strategy of the R&D department. Nevertheless, it is important that the objectives of the use phase data strategy are not contradictory to the related business or functional strategy (Gao et al., 2015, p. 9). Based on the decision of the project sponsor about where the use phase data strategy should be implemented, the project team needs to analyse the relevant strategy that influences the development and selection of use cases later on. Understanding the context of the use phase data strategy reduces the risk of developing a strategy that does not fit to the product or service strategy. It is furthermore important, to analyse whether there are other ongoing or finished projects within a company that also focus on the exploitation of use phase data. If there are other projects, it is useful to define interfaces between the projects. Furthermore, it is also important to ensure a differentiation from other projects. In the case that a company already exploits use phase data or previously developed a use phase data strategy, it is also important to analyse these previous projects and its findings.

Table 6-1: Strategic options for companies working with connected products (based on Burkitt (2014, pp. 7–11))

Strategic option	Characteristics of the option
Enabler	• Building and maintaining IoT infrastructure • Enable engagers to develop connected products and services • Product examples: Platforms, cloud services, or hubs
Engagers	• Establishing the link between IoT technology and the market • Use technology to develop new products and services • Product examples: Smart thermostats, connected cars, or wearables
Enhancers	• Building upon products and services of engagers • Develop integrated services to extract additional value from data • Product examples: Health monitoring based on wearables or monitoring of a production line

After understanding the context, the next step is to define the framing objectives for the strategy development. Each step that leads towards the use phase data strategy decreases the uncertainty and therefore objectives might become clearer or become obsolete. Furthermore, objectives often form a system of objectives because interrelations exist among them (Albers et al., 2018a, pp. 2–3). At the same time, objectives mature over the course of a development process, which makes it important to handle them accordingly. Thus, the objectives should be adjusted and updated in a dynamic manner over the course of the project instead of treating them as being static. The definition of objectives can be supported by looking at the three different strategic options concerning the role that companies with connected products can adopt. Table 6-1 summarises the three different options that companies can follow within the environment of connected products. Companies often only choose one option to create value (Burkitt, 2014, p. 7). Enablers provide the technology and infrastructure for connected products. Engagers use the technology to develop new services and products for the market. In contrast, enhancers build upon the products and services of engagers to add additional value through services based on data analytics. Therefore, the project team can assess, based on the companies capabilities and competitive environment, which strategic option might be suitable (Burkitt, 2014, p. 11).

Figure 6-4 illustrates the domain and beneficiary matrix that also supports companies in defining the basic objectives of the use phase data strategy. The matrix provides an exemplary use case for each matrix cell. On a general level, a use case can link to the product or service. In the case that a company offers different products, it might be useful to assess whether the use phase data strategy should only be developed for certain products. Furthermore, a use case can provide value for internal or external stakeholders. Overall, the matrix enables the project team to define and visualise which cell or cells a use phase data strategy should address in order to narrow down the scope.

Besides these basic considerations, the objective should cover the following aspects: time, cost, and quality (Atkinson, 1999, pp. 337–338). Concerning the time, it is important to define the period for the strategy development and the timeline for the planned implementation of the use phase data strategy. When exploiting use phase data, it is advised to start with less complex use cases (e.g., use of available data or simple data analytics algorithms) and then increase the complexity over time (Gao et al., 2015, p. 13). In addition, the objectives should determine the monetary and personal resources that the project can use. Concerning the quality, the objectives should, for example, define how many use cases the strategy should consist of and how the results of the project should be documented. Furthermore, the team should clarify how comprehensive the initiated changes made to the product, service or organisation by the use phase data strategy can be. However, the project team should also identify objectives outside the three previously mentioned domains.

When documenting the objectives for the project, the SMART (specific, measurable, assignable, realistic, and time-related) criteria help to formulate them (Doran, 1981). Afterwards, the objectives for the project can be used to set a schedule for the project including important milestones. Overall, the objectives for the project should cover the following aspects:

- Time frame for the development of the use phase data strategy
- Time frame for the entire project including the implementation
- General purpose of the use phase data strategy
- Monetary and personal resources for the strategy development
- Main beneficiary of the use phase data strategy
- Product group for which the use phase data strategy should be developed
- Starting point for the search of use cases (use case driven or data-driven approach)

Due to the interrelation between the objectives and the company context, it might be required to repeat previous tasks, for instance, to adjust the team or define the interfaces with other objectives. The last task is to make the project known within the organisation to ensure that impacted and involved stakeholders are aware of the use phase data strategy development project. Making the project visible within the organisation will help to reduce the internal resistance to change triggered by the use phase data strategy (Kotter, 2012, p. 4).

Overall, the **main outcome** of Step 1 is a defined team for the development of the use phase data strategy. An interdisciplinary team is essential for the next steps in order to identify, elaborate, and select use cases that form a sound use phase data strategy. Furthermore, the definition of objectives is crucial to set the scope of the project and to ensure that the strategy fits to the company's context and meets expectations.

		Profiteer	
		Internal	**External**
Domain	**Product**	Requirements definition	New functionalities
	Service	Improvement of service processes	Predictive maintenance

Figure 6-4: Domain and beneficiary matrix for the development of a use phase data strategy

6.3 Step 2 – Analyse the system and structure the situation

After framing the development project for the use phase data strategy, the next step is to conduct an internal and external analysis in order to understand the framing conditions for the strategy. Conducting an external and internal analysis is important to reach a clear understanding of the current situation in order to develop a use phase data strategy that builds upon it. Both the internal and external context have a strong influence on the development of connected products (Valencia et al., 2015, p. 25). Thus, the quality of a strategy is strongly impacted by the quality of the system analysis (Schwaninger, 1987, p. 77). An external analysis should reveal the opportunities that the environment offers but should also highlight risks that arise from outside the company. An internal analysis is important for the development of a use phase data strategy as it allows for transparency about the company's capabilities and weaknesses, for example, in terms of data analytics skills or available data. The structured description of the situation merges the analysis results and is an important foundation for deriving use cases in the next step. Figure 6-5 illustrates the main tasks of the external and internal analysis leading towards a comprehensive understanding of the situation framing the strategy development.

A comprehensive **system analysis** is therefore the first task, which consists of an external and internal analysis. The starting point is the ***external analysis***, which assesses the environment of a company. Understanding the environment is very important for companies because without knowledge of the market and customer needs, it is difficult to develop novel solutions (Petrick and Martinelli, 2012, p. 56). Especially for companies with less experience, a use phase data strategy will lead to new products or services. The environment of a company in general is complex, dynamic and uncertain (Hungenberg, 2014, pp. 87–89). Therefore, the project team needs to determine the scope of the external analysis in order to find a balance between the effort needed for the analysis and the level of detail. Due to the complexity of the environment, it can be separated into a macro environment and a competitive environment (Kaplan and Norton, 2009, p. 23; Lombriser and Abplanalp, 2012, p. 136).

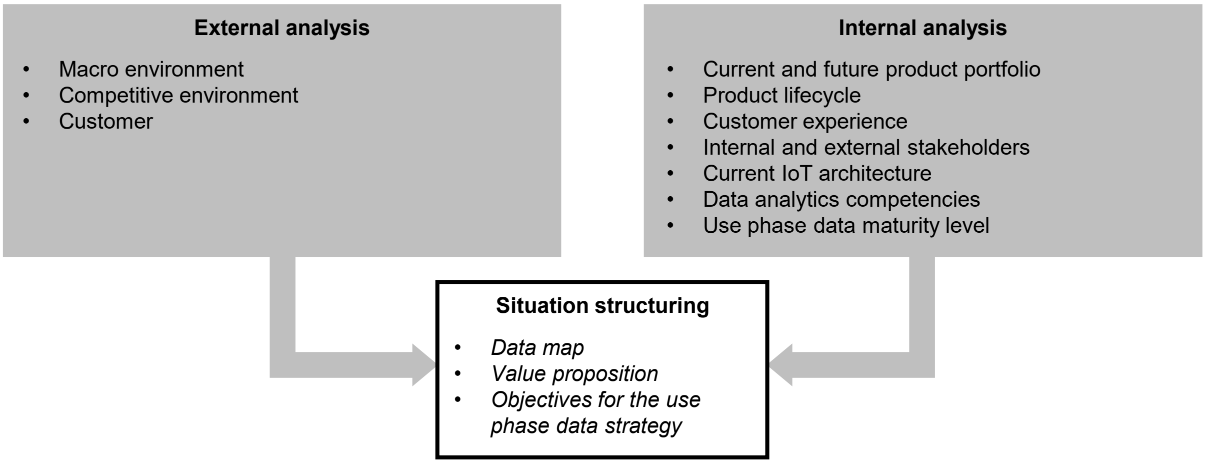


Figure 6-5: Main tasks of Step 2 of the developed process model

The *macro environment* covers all influencing factors that all companies are exposed to, no matter which industry sector they work in (Johnson et al., 2011, p. 78). There are different ways to split the macro environment into factors, for instance into political and economic, or social and technical factors (White, 2004, pp. 162–163). The challenge with analysing the macro environment is that the factors overlap, which requires a structured approach for the analysis. A common tool to conduct this analysis is the PESTEL analysis (Johnson et al., 2011, p. 78). The PESTEL analysis looks at the following factors (Yeates and Wakefield, 2004, pp. 265–266):

- **P**olitical, e.g., political decisions or trade policies
- **E**conomic, e.g., economic growth or inflation
- **S**ocial, e.g., demographic changes, or working conditions
- **T**echnological, e.g., production technology or data analytics
- **E**nvironmental, e.g., pollution or sustainability
- **L**egal, e.g., data privacy or safety standards

It is not possible to point out what the most influential factors are for a use phase data strategy. However, findings from empirical data indicate that especially the social, technological, and legal factors play an important role. The forecasts state that the numbers of connected product will strongly increase and therefore connected products will play an ever more important role in daily life. At the same time, the technological environment is changing at a fast pace, for instance, offering new opportunities to track and monitor connected products (Yeo et al., 2015, p. 571). The exploitation of use phase data builds strongly on technology and therefore technological factors should be analysed carefully. The legal environment also has a strong influence on connected products and adds additional complexity because the legislation strongly depends on the country (Kalmar et al., 2016, p. 15). Due to the dynamic nature of the company’s environment, it is important to also identify possibilities for change. A helpful approach for this is scenario planning, which leads to a limited number of possible scenarios for the future (Schoemaker, 1995, p. 26). Combing a PESTEL analysis with scenario planning can help to obtain a detailed understanding of the future macro environment of a company (Walsh, 2005, p. 120). The derived factors will be important for evaluating possible use cases later on.

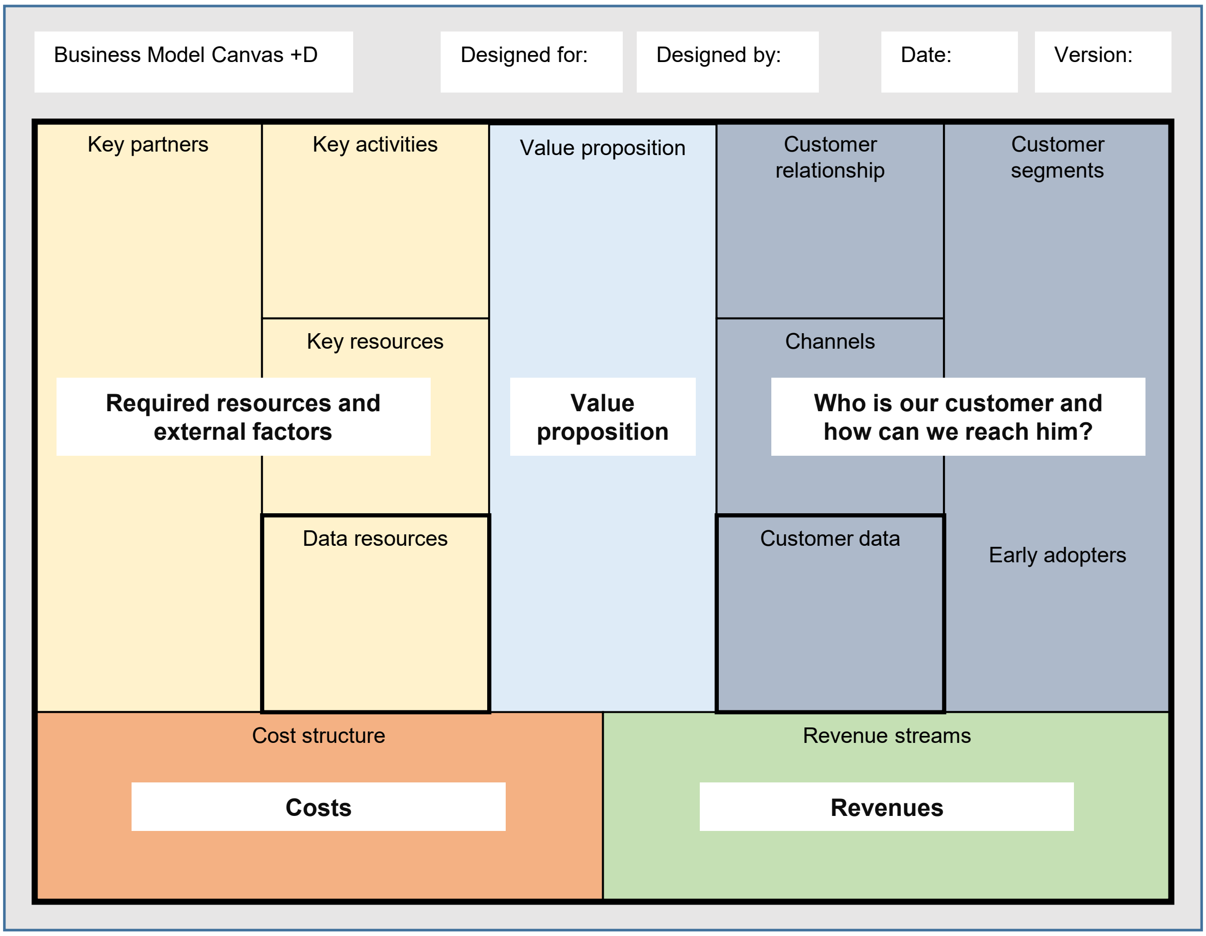


Figure 6-6: Data enhanced business model canvas (based on Benta et al. (2017, p. 352))

The *competitive environment* covers the surrounding environment of organisations and companies which offer similar products or services (Johnson et al., 2011, p. 79). A detailed understanding of the competitive situation is essential to derive a strategy that provides competitive advantages (Porter and Heppelmann, 2015, pp. 61–62). A main challenge with this analysis is therefore that it should be done on a more detailed level. Porter's Five Forces analysis can help to gain an initial understanding of the current competitive situation (Porter, 1979, p. 141). The model proposes the following five factors to assess the competitive situation: threat of new entrants, threat of substitutes, bargaining power of customers, bargaining power of suppliers, and industry rivalry. These factors in general help to identify current and future risks for a company. For the development of a use phase data strategy, all five forces are important to consider. Advances in technology (e.g., data analytics) allow companies to develop products with novel functionalities or innovative services (Porter and Heppelmann, 2014, pp. 4–5). Therefore, new companies can enter the market and change the competitive situation. Connected products often rely on technologies like cloud services or data analytics tools, which are provided by suppliers that companies have not worked with before. Therefore, the project team needs to assess the bargaining power of these new suppliers of key technologies for connected products. Companies with no or little experience in exploiting use phase data, will most likely require a partner for the implementation of a use phase data strategy (Porter and Heppelmann, 2014, pp. 12–13). It is therefore important to evaluate how the critical dependence on suppliers should be treated. However, it is not only new entrants that pose a risk for a company, but also direct competitors (Porter and Heppelmann, 2014, pp. 10–11). Offering connected products and exploiting use phase data enables competitors to develop new products and services, which can have a strong impact on their competitive situation.

In order to gain a more detailed understanding of the competitive situation, a *detailed competitive analysis* is needed (Hungenberg, 2014, p. 124). It is important to identify and assess current and future competitors. A key aspect to consider is which products and services competitors already offer. In addition, the analysis should describe how competitors already exploit use phase data and which use cases they already offer. This analysis also provides valuable insights about the competitor's capabilities and maturity in terms of exploiting data (Michaeli, 2006, p. 294). Using the data enhanced business model canvas, which is depicted in Figure 6-6, helps to provide a structured depiction of the competitor's business model. The data enhanced business model canvas includes two additional fields to describe the data resources that a business model uses and the insights derived from data (Benta et al., 2017, p. 352). Of special interest is also an understanding of the sales concept that competitors use for their connected products and services. The results of this competitor analysis should result in a detailed description of the competitors' use phase data strategies. Figure 6-7 illustrates how exemplary results of a competitive analysis for the construction equipment sector could look like. The results of the analysis show the availability of connected products, the sales concept, and the functionalities of the products for each competitor.

A comprehensive understanding of competitors' use phase data strategies is of great importance because it allows for positioning oneself with one's own strategy (Michaeli, 2006, p. 292). The last task of the competitive analysis should be strategic segmentation of the competitors (Michaeli, 2006, p. 300). Such a segmentation based on use phase data is important in order to identify direct threats or technology pioneers. It is then possible to show how the developed use phase data strategy aims to improve the company's own competitive situation. It can also be useful to conduct a competitive analysis in other industries, but with companies addressing similar customer needs on an abstract level. To support the identification of use cases during Step 3, it is helpful to collect and document the use cases of other companies. Such use cases from other companies can serve as a reference system for novel use cases later on. Identifying a reference system or product allows for the development of the company's own solution based on existing work, which can help reduce development time and complexity (Albers et al., 2015, pp. 4–5).

Name	Connected product	Sales concept	Range of functionalities
Bobcat	✗	-	No provider solution – only local vendor solutions
Caterpillar	✓	Machines > 16t: for free Machines < 16t: for a surcharge	Fleet management, productivity, security, and sustainability
Hitachi	✓	Machines > 13t: for free Machines < 13t: for a surcharge	Operating hours, fuel consumption, monthly reports of machine data, and alarm function
JCB	✓	Machines > 6t: for free Machines < 6t: for a surcharge	Improved security, improved maintenance and services, higher productivity, and lower operating costs
Komatsu	✓	No information	Fleet management, service management, filling level, DEF Level, dashboard, motor blockage, machine hours of attachment parts, and diesel particulate filter
Kubota	✗	-	No provider solution – only local vendor solutions
VOLVO	✓	Machines > 10t: for free Machines < 10t: for a surcharge	Fleet management, anti-theft protection, service management, and productivity
Takeuchi	✗	-	No provider solution – only local vendor solutions

Figure 6-7: Exemplary summary of results of the competitive analysis for the construction equipment sector

The next task is to perform a detailed *customer analysis*. For strategy development it is important to understand which stakeholders a company wants to address and what the needs of the stakeholders are (Wicharz, 2015, p. 23). In order to avoid that too much time is spent on a customer analysis, the project team should assess whether the objectives defined during Step 1 of the process model narrow down the scope of the customer analysis. For example, in the case that the use phase data strategy should only be developed for certain products, not all customers might be of interest. When conducting the customer analysis, it is useful to look at current and potential future customers (Cole, 2003, p. 29). Offering connected products can expand the range of customers that a company serves with their products and services (Porter and Heppelmann, 2014, pp. 13–14). Therefore, the strategy development team should anticipate whether the strategy might lead to new customers that the company will need to address in the future. However, the list of current and future customers is only preliminary as the search for use cases during Step 3 will influence which customers a company addresses.

To proceed with the customer analysis the project team should clarify, whether the company wants to address a business-to-customer (B2C) or business-to-business (B2B) segment. It is further important to understand whether the customer is also the user of the product because users might have differing needs from customers. A use case therefore might provide a different value to customers than it does to users. Often a company serves different groups of stakeholders that have different needs (Hungenberg, 2014, pp. 124–125). Therefore, it helps to segment customers using a set of criteria to make differences and similarities visible (Hax, 2010, pp. 33–34).

Companies that work in the B2C segment can use, for example, the following criteria to segment their customers: geographic, demographic, psychological, or behaviour (Kotler et al., 2011, pp. 463–464). For the development of the use phase data strategy, it is important to assess, for instance, the openness towards connected products, acceptance of sharing use phase data, or level of digital affinity. A segmentation of customers in a B2B context can be done based on the size of the company, requested technology, or the sales volume (Hungenberg, 2014, pp. 126–127).

In order to gain insights about customers, information from marketing or product management might be helpful. Eventually, available use phase data can be useful for gaining insights about customers' preferences. A helpful tool for documenting the findings is a customer profile for each segment (Osterwalder et al., 2014, p. 10). The customer profile outlines gains, pains, and customer jobs. The gains of a customer cover all the aspects that a customer wants to achieve (e.g., smooth operation of the equipment). The pains include all negative outcomes, risks, and problems that hinder customer jobs (e.g., unforeseen breakdown of equipment). The customer jobs describe what customers want to achieve during their work or life (e.g., produce a steady amount of components). Osterwalder et al. (2014, p. 16) suggest to further differentiate between required gains, expected gains, desired gains, and unexpected gains. For pains, the following classification is suggested: undesired outcomes, obstacles, and risks. After filling out the customer profiles for each segment, it is useful to rank the three criteria: customer job (important to insignificant), pain (extreme to moderate), and gain (essential to nice to have) (Osterwalder et al., 2014, pp. 20–21). Overall, understanding the customer is an important foundation to developing use phase data strategy that creates additional value by increasing the gains and reducing the pains of customers.

Following the insights gained during the external analysis, the next task is to perform an ***internal analysis*** to assess the company's capabilities and weaknesses. An internal analysis is important to understand whether a company is able to take the chances offered by the environment and to see if a company is able to cope with the external risks (Hungenberg, 2014, p. 144). The internal analysis compromises of an analysis of the product portfolio, processes, IT infrastructure, data analytics competencies, (use phase data) strategy, and data map.

The starting point is the analysis of the *current and future product portfolio*. The focus should be to understand which products are already connected and which will be connected in the future. However, depending on the scope of the use phase data strategy, it is not necessary to consider the entire product portfolio. Understanding the differences between the products is, however, important because the implementation effort for the use phase data strategy and use cases might strongly depend on the product. Decomposing products into their main components helps to obtain an understanding of the product's structure. To further advance the understanding, the analysis must identify sensors that a product already has and the bus system that connects the sensors. In the case that the product is already connected then the analysis should also examine how data is currently transmitted (e.g., wireless LAN or mobile telephone network) and what the related specifications are. Afterwards, the analysis should focus on the services offered in combination with the product. It is helpful to have an overview of the services that a company already provides for customers. It is also important to highlight services that already build upon use phase data and connectivity. The outcome should be a clear description of the company's offerings in terms of products and services.

Afterwards, the objective is to look at products from a process perspective. The starting point should be a clear understanding of the *product lifecycle*. The product lifecycle covers all phases starting with the identification of requirements and ending with the recycling of the product (Eigner and Stelzer, 2013, p. 9). Gaining an understanding of the entire lifecycle helps to identify use cases later on that provide additional value not just during the use phase or product development phase, because taking a lifecycle perspective looks at the product in a more holistic way. Based on the understanding of the lifecycle and scope of the use phase data strategy, the next step is a detailed analysis of the product development process and related activities. Use phase data can provide valuable insights for product development because insights can help, for instance, to reduce over-engineering or adjust product design. Having a clear understanding of product development activities supports the identification of links between use phase data and development activities in Step 3. Companies often have defined development processes, which provide valuable input for this task. However, it is also important to have a closer look at the actual use phase of a product. The analysis should reveal the main activities and their frequency during the use phase (e.g., maintenance or overhaul). Assessing the lifecycle therefore also involves understanding at which phase services are offered. The average duration of each lifecycle phase should be noted.

Using customer journeys can help to gain a differentiated understanding of the customer experience and touch points during the interaction with the product, service or company (Lemon and Verhoef, 2016, pp. 74–78). A user experience journey is an enhanced tool for this analysis, which provides detailed information about the interaction between product and user (Kremer et al., 2017, pp. 485–486). This tool might be helpful because the connectivity of products allows manufacturers to improve the user experience of their product (Barton and Court, 2012, p. 80; Porter and Heppelmann, 2014, p. 81). However, connectivity requires that companies design user experience differently (Valencia et al., 2015, p. 22). Customer journeys are a suitable tool to analyse and design the user experience of connected products (Valencia et al., 2015, p. 25). At the same time, connectivity leads to new touchpoints, new possible features, and an increased complexity, which needs to be handled by designers. Existing approaches for analysing and designing the user experience of connected products only address these challenges on an abstract level. Therefore, a specific data journey template was developed based on the user experience journeys of Kremer et al. (2017).

Figure 6-8 illustrates the data journey template for a washing machine and Appendix A6.5 provides additional details for this method. The template consists of different parts that help to analyse and design the user experience for connected products. However, a user journey and thus a data journey should always be tailored to the application context (Kremer et al., 2017, p. 487). Afterwards, the first task is to define the starting point and endpoint for analysing the interaction between customer and product. The main enhancements of the developed data journey template are that it helps to describe which sensors already provide use phase data during which interaction step. The template further helps to show where remote control is already possible (e.g., using a mobile app) and at which points users receive recommendations based on their usage of the product. The suggested template also includes an emotional user experience curve. Overall, the data journey allows for a description of the current interaction between the user and the product or service.

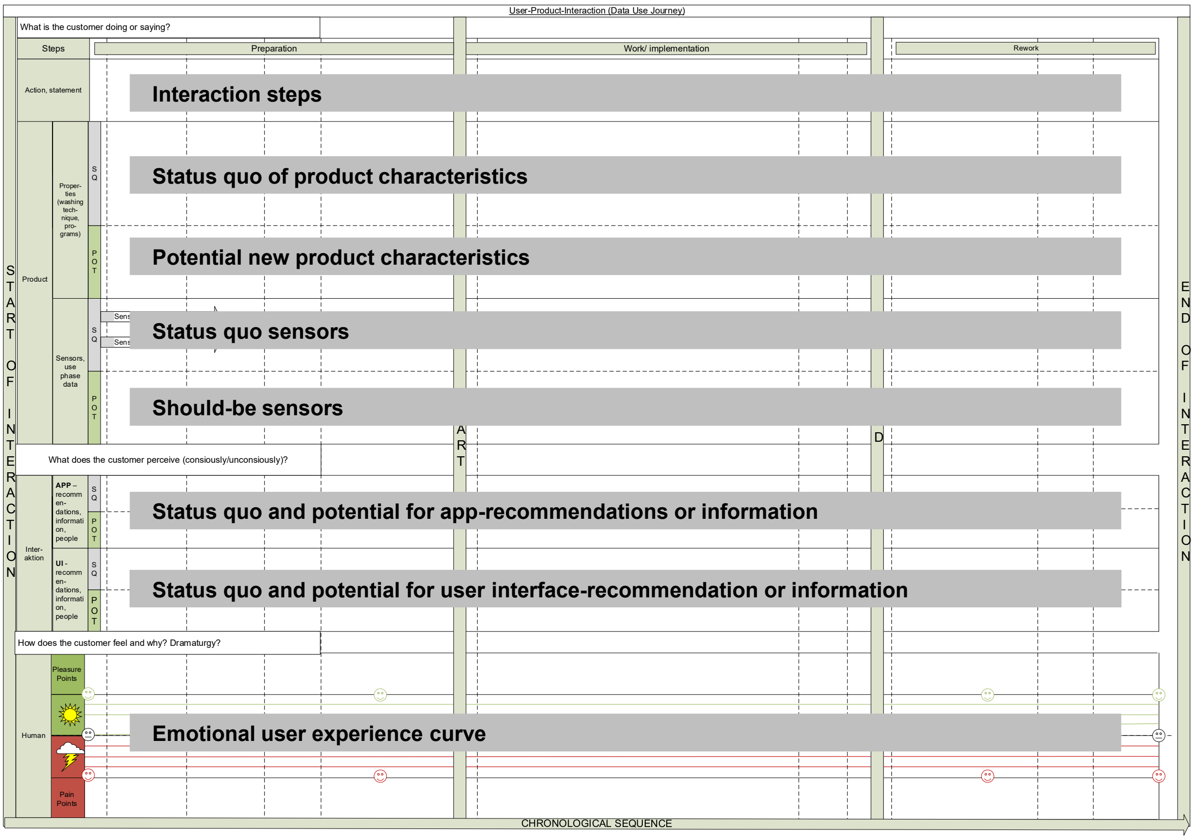


Figure 6-8: General template for a data journey (based on Dorynek (2018))

After building up an understanding of the product lifecycle, the next task is to obtain a detailed understanding of the *internal and external stakeholders*. Companies operate in a complex environment of different stakeholders (Wicharz, 2015, pp. 27–28). A main challenge is that stakeholders have different objectives, which often also conflict. Conducting a systematic stakeholder analysis is a suitable approach to obtain an overview of the relevant stakeholders (Varvasovszky, 2000, pp. 338–339). The results of the previous customer analysis provide additional input for this analysis. It is a main characteristic of strategy to provide objectives for the future. Therefore, the stakeholder analysis should identify current and future stakeholders that are relevant for the development of the use phase data strategy.

In order to conduct a meaningful stakeholder analysis, it is important to be clear about the analysis's objective (Varvasovszky, 2000, p. 338). For the development of a use phase data strategy all stakeholders that either can benefit from use phase data or have skills required for the exploitation of use phase data are relevant. In the case that a company offers connected products already, the analysis should also reveal current roles and stakeholders. Conducting a stakeholder analysis in a team helps to ensure results that are more objective. There is no fixed set of methods to identify relevant stakeholders, but interviews and questionnaires are helpful (Varvasovszky, 2000, p. 341). In addition, analysing internal and external documents (e.g., press statements, meeting minutes, or organisational charts) can further support the identification of stakeholders. Based on the insights gained, it is possible to derive an initial overview of the stakeholders. Depending on the application context, external stakeholders do not only consist of customers and users, but also external companies that install the product or repair the product. However, the visualization of stakeholders can have different formats and therefore depends on the specific needs. The stakeholder analysis should also include the identification of stakeholder related competencies and experience in terms of data exploitation.

The strategy development team should check the completeness of the stakeholder overview before proceeding to the next step. There are different ways to summarise the findings of a stakeholder analysis (Varvasovszky, 2000, pp. 342–343). To complete the stakeholder analysis, it is helpful to combine that stakeholder overview with the depiction of the product lifecycle. The outcome should be a processual stakeholder map that illustrates, which stakeholders will get involved during which activity over the course of the product lifecycle. Another possibility is a stakeholder map, which is a graphical representation of the stakeholder analysis that makes dependencies visible (Andersen et al., 2008, pp. 29–30).

The successful exploitation of use phase data requires that suitable architecture for connected products is available. Therefore, the next task is to conduct a detailed *analysis of the current IoT architecture* at the company. Section 2.3.2 introduces the five general layers of an IoT architecture that should be considered during the analysis: perception, network, middleware, application, and business layer (Khan et al., 2012, pp. 258–259). The fifth layer is the one where the use phase data strategy would link to.

The starting point for the analysis is the perception layer. The objective is to obtain a clear understanding of the current product or products based on the scope of the use phase data development project. Previously, the product was decomposed into its main components. Now, the task is to identify sensors and other sources of use phase data. Thus, it is also to understand which data is generated by the related services during the use phase (e.g., mobile applications or maintenance services). During this analysis, it is also important to include decisions about future products and services. This task should provide a detailed understanding of the current and future sources of use phase data. It is important to highlight that this overview contains all data points regardless of whether they are transmitted or not.

Afterwards, the next task is to examine the network layer. In the case that the company already sells connected products, the objective is to obtain a detailed understanding of the gateways (e.g., wireless LAN module or mobile internet module) that transmit use phase data. During this task, the analysis should create clarity about which of the data points created on the perception layer are currently transmitted. Available use phase data can be clustered based on the following four types: location, condition, availability, or usage (Ellen MacArthur Foundation, 2016, pp. 49–50). Based on this it is possible to describe currently available use phase data, which is important if the use phase data strategy should focus on a bottom-up approach. The current resolution of use phase data is useful to assess the data quality at first glance.

Afterwards, the middleware layer is analysed because this layer analyses and pre-processes data. The layer is also responsible for providing the use phase data for the different applications. The objective is therefore to understand the current data analytics capabilities. A clear understanding is important to assess the feasibility of, and implementation effort required for, use cases later on.

To obtain a clear picture of the application layer, it is necessary to gather current use cases that build upon the available use phase data. Therefore, the strategy development team gets a clear understanding of realized use cases and the experience gained in this context. The analysis should also reveal which stakeholders are currently addressed by the use cases.

Lastly, the objective is to have a look at the business layer, which provides direct input for the development of the use phase data strategy. The analysis should assess the current business model and use phase data strategy of the company or product segment in the case that they are already developed or formulated. It is important to understand what the current objectives are and what the intended value proposition is. The data enhanced business model canvas is helpful to describe the current business model (see Figure 6-6). Because use phase data can also support internal stakeholders, it should also be highlighted how internal stakeholders currently benefit from use phase data. Afterwards, it is useful to have a look at the current sales concept and the sales volume of the company's connected products and services. Based on this, the current customer structure should be detailed (e.g., countries that connected products are sold to, connected products per industry sector, or number of connected products per customer). Lastly, internal support and structure of the management for connected products need assessment. After completing this task, the project team should have a detailed description of the current IoT architecture, which provides a crucial foundation for the development of the use phase data strategy as the current situation determines which use cases will be possible.

Analysing the IoT infrastructure rather provides a technical perspective on connected products. The next task is to look at *data analytics competencies* from an organisational perspective. The use phase data strategy should provide a clear vision for its implementation. Therefore, it is important to understand what data analytics competencies and skilled employees a company already has. The stakeholder map provides valuable input for this task. In addition, the analysis should assess the current process for data analytics projects and tasks in order to understand stakeholder involvement and responsibility distribution.

The last task of the internal analysis is the assessment of the company's own *use phase data maturity level*. A structured analysis of the maturity level is very important for the development of a use phase data strategy (Coleman et al., 2016, p. 2158). In literature, different models exist to evaluate the data analytics maturity level (Morabito, 2015, pp. 91–96). The maturity models consist of a different number of maturity levels, but the key message is that maturity increases with standardised analytics processes, data sharing across the organisation, and the level of data analytics. Many of the maturity models also highlight that more mature companies have a clear strategy for exploiting data. LaValle et al. (2010, pp. 5–6) suggest dividing companies into the following three levels: aspiration (analytics to justify actions), experienced (analytics guides actions), and transformed (analytics prescribes actions).

Figure 6-9 shows a portfolio that helps to determine maturity level based on the data analytics skills and availability of use phase data. The assessment is important to identify the limiting factors and identify key activities for the implementation of the use phase data strategy. The maturity level also influences the range of possible use cases, because it will be very challenging for a company to exploit use phase data in the near future, if their products do not even currently transmit use phase data and the data analytics skills are aspirational.

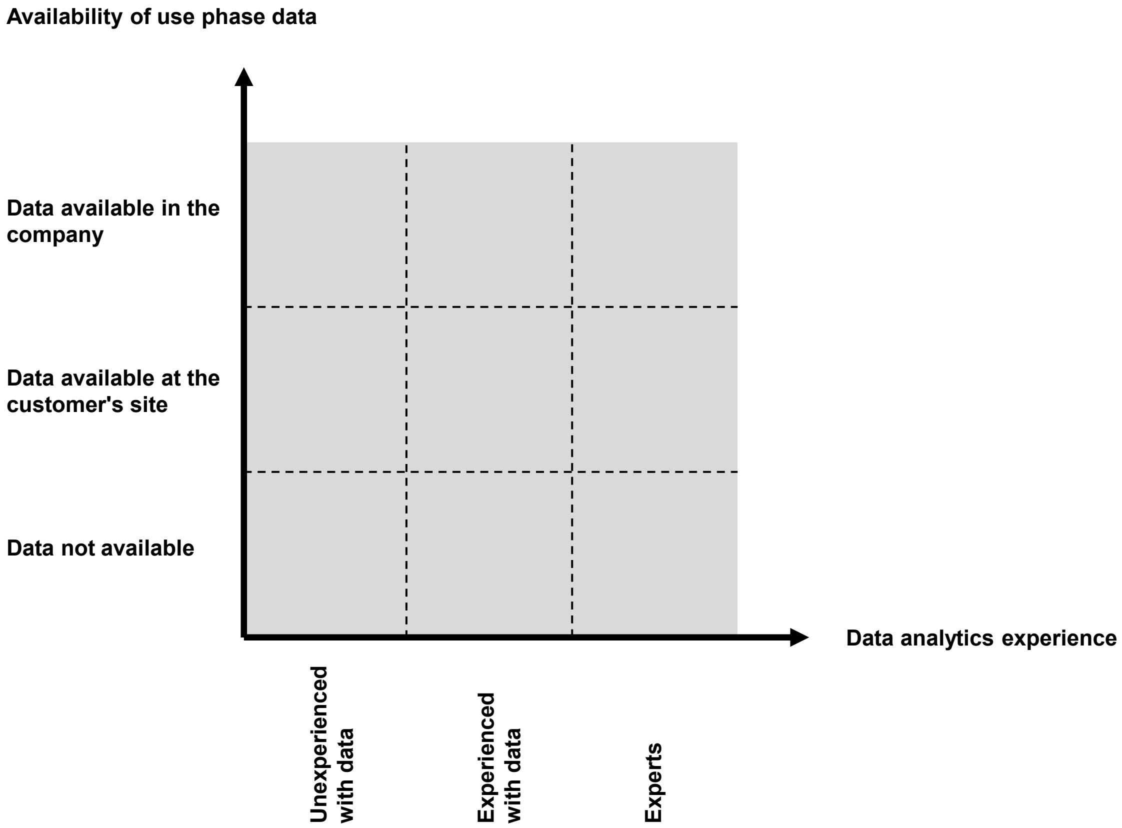


Figure 6-9: Portfolio to assess the use phase data maturity

The last part of this process step is to **structure the situation**, which involves linking the results of the external and internal analyses. The main objective is to derive detailed conclusions in order to frame the development of the use phase data strategy. Matching external chances and risks with internal strengths and weaknesses helps to ensure a strategic fit (Hungenberg, 2014, p. 149).

At first, it is useful to derive a *data map* for the current situation. The map should depict all relevant data sources, data streams, data storage, and data targets. Use phase data and important context data at least should be included in the data map, but depending on the company objectives, additional data (e.g., development documents) should also be included in the overview. The objective is to have a clear understanding about the use phase data that is already accessible for exploitation. Based on the complexity of this map, it might be necessary to set narrower system boundaries and only look at the data sources inside a product. In the case that the product (e.g., car) consists of many data sources, grouping them together reduces the complexity. A second process visualisation should further describe the data analytics process. The visualization should highlight the flow of data between the different systems, data owners, and analytics tools. The visualization is important for identifying missing data points in a later step of the process model.

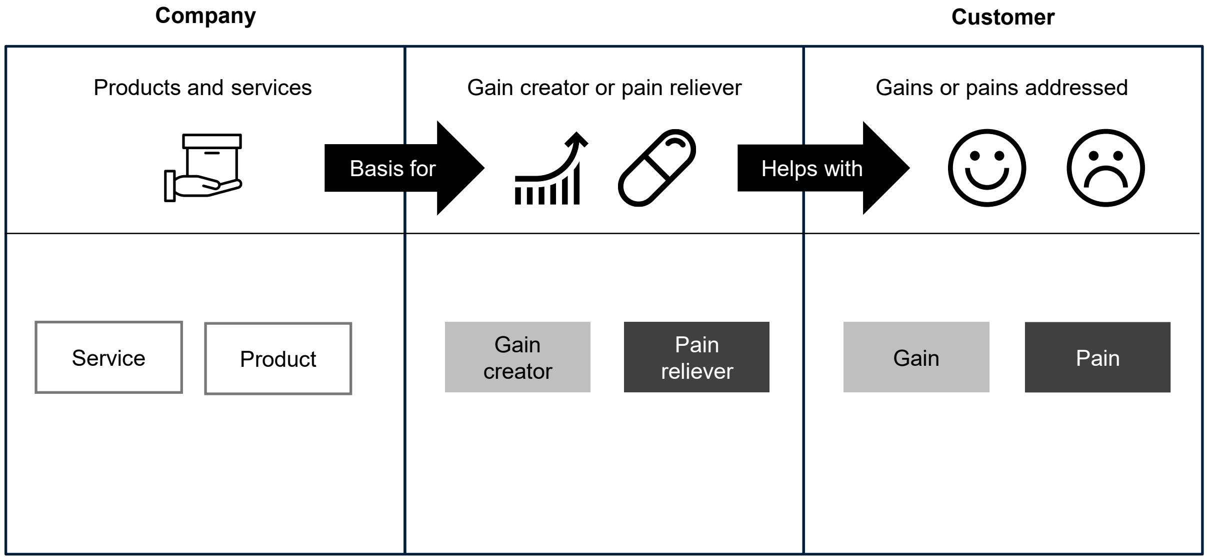


Figure 6-10: Depiction of the developed template for a fit-map (based on Rosenberger (2017))

A central task during the external analysis was to define customer profiles. Now the main interest is to *evaluate the company's value proposition*, which reveals whether the company addresses the needs of customers in an adequate way. Deriving a value map helps to describe the value proposition of a company's products and services (Osterwalder et al., 2014, pp. 8–9). The value map describes products and services that a company offers and names the related gain creators and pain relievers. However, the challenge is to achieve a fit between the needs of the customer and the value proposition (Osterwalder et al., 2014, p. 3). In order to make the fit or the lack of a fit between both sides visible, a new method called fit map was developed. The method helps to visualize how existing product and service features address gains and pains of customers. However, the method also helps to highlight gains and pains which are currently not addressed, which could potentially be done by exploiting use phase data. Figure 6-10 shows the template for a fit-map. A detailed description of the method can be found in Appendix A6.1. Workshops with internal stakeholders can help the project team to fill the fit-map.

The next task aims at understanding the current situation better is to compare external market opportunities with the current product offerings of the company. It is important to assess the company's own product portfolio in order to reveal where additional use cases can provide value (Burkitt, 2014, p. 12). Figure 6-11 depicts a product-market matrix, which provides assistance for this analysis. The matrix consists of a product portfolio dimension and market dimension. Therefore, the method first helps to show which products are provided for which markets. Furthermore, the matrix also describes the data generation, data transition, and data usage level for each product. In addition, the matrix helps to identify market segment that could benefit from a data-driven value proposition. The main benefit of the matrix is twofold. On one hand, the results show which product the company does not have use phase data or does not exploit available use phase data for. On the other hand, the matrix highlights the markets with higher relevance for additional use phase data exploitation. Current weaknesses and strengths on the company side therefore become visible. Appendix A6.3 provides further details about the application of the method.

		Market 1		Market 2		Market 3		...
		Data usage	X %	Data usage	X %	Data usage	X %	
Product 1								...
Data generation	X %							
Data transmission	X %							
Data usage	X %							
Product 2								
Data generation	X %							
Data transmission	X %							
Data usage	X %							
Product 3								
Data generation	X %							
Data transmission	X %							
Data usage	X %							
...		...						

Figure 6-11: Product market matrix for connected products (based on Wilberg et al. (2018b, 5.f))

Besides understanding the current value proposition, the next step is to compare the company's own capabilities in terms of use phase data exploitation with those of a direct competitor. For the analysis, a competitor should be selected that operates in similar markets and already offers connected products with the corresponding use cases. A strength-weakness analysis is a suitable method for this task because important resources and capabilities are evaluated in comparison with a competitor (Kollmann, 2009, pp. 371–372). The analysis helps to reveal company's own strengths, which can lead to competitive advantages, but also points out weaknesses that have a negative effect on its competitiveness. With a general application the method assesses, for instance, functionalities of products, prices, sales changes, or human capital (Günes et al., 2010, p. 30). Figure 6-12 depicts an exemplary result of such a strength-weakness analysis. The assessment factors focus especially on the assessment of capabilities important for the exploitation of use phase data. The method should always be adjusted to the application context. An interdisciplinary team should apply this method to ensure that all factors can be assessed correctly. The strength-weakness analysis is further elaborated on in Appendix A6.4.

Merging the findings of the internal and external analysis is important in order to derive implications for the strategy development. The SWOT (strengths, weaknesses, opportunities, and threats) analysis is a suitable method for deriving conclusions from the previous analysis (Hungenberg, 2014, pp. 86–87). The analysis assesses the current situation from an internal (strengths and weaknesses) and external (opportunities and threats) perspective. For the development of a use phase data strategy, the analysis should point out which strengths of the company (e.g., data analytics skills or range of connected products) help to take advantage of market opportunities (e.g., willingness of customers to pay for services of connected products). The analysis also reveals opportunities that the company cannot take advantage of because data analytics skills are missing or products are not connected yet. The environment might also include some threats (e.g., new digital business models or new competitors). Therefore, the analysis helps to highlight how the company's own strengths help to address threats and at the same time which of their own weaknesses expose them to certain risks. Overall, the analysis should focus on the important aspects related to exploitation of use phase data.

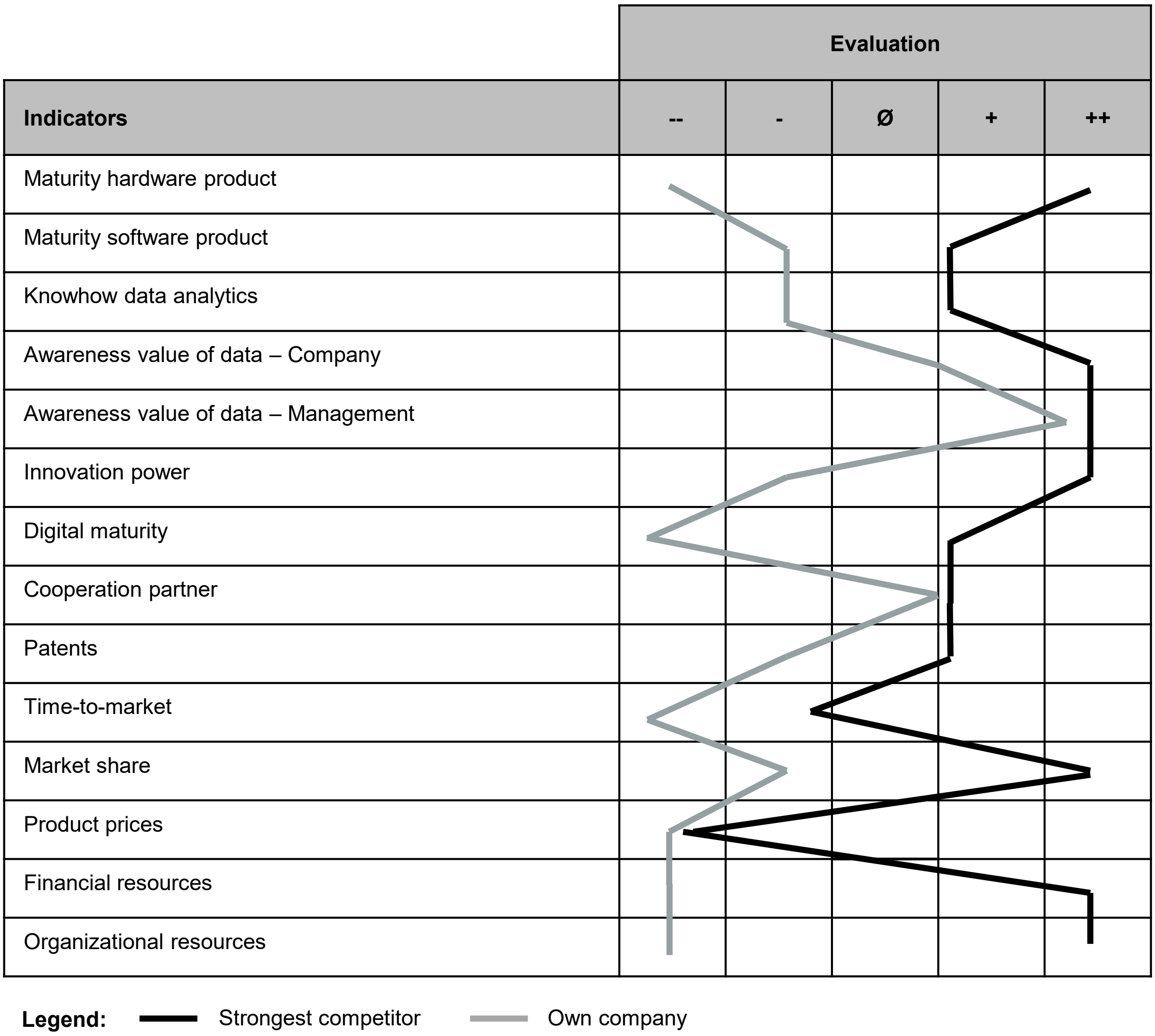


Figure 6-12: Strength-weakness analysis (Wilberg et al., 2018b, p. 5)

The final task of this step is to *revise the objectives* defined during Step 1 of the process model. Based on the analysis results of this step, it might be necessary to focus only on use cases for certain product segments. The stakeholder analysis can also reveal that the project team for the development of the use phase data strategy requires adjustment. In general, the findings of the internal and external analysis provide important input for the development context of the use phase data strategy.

Overall, the **main outcome** of Step 2 is a comprehensive understanding of the environment in which a company operates combined with a detailed internal analysis. The findings provide important insights about the complete environment within which the use phase data strategy development takes places. Furthermore, the analysis points out internal and external stakeholders that can benefit from use phase data. Based on the internal analysis, the results create transparency about the company's own maturity and capabilities. This knowledge is important for the use phase data strategy because the strategy builds upon this foundation. Furthermore, understanding which use phase data is already available is crucial for deriving use cases that take advantage of available data but also for identifying a gap between required and available use phase data.

6.4 Step 3 – Identify application areas and derive use cases

The third step is crucial for the overall success of the use phase data strategy development because this step provides the use cases that form the foundation of the strategy. The main challenge is that a wide range of possible use cases exist that have potential to provide value for internal and external stakeholders (Schüritz et al., 2017, p. 3). However, the key obstacle for companies is to identify the most suitable use cases (Gao et al., 2015, p. 9; Mazzei and Noble, 2017, p. 406). Therefore, Step 3 firstly identifies application areas and then derives use cases for these selected areas. A use case can be anything that matches the definition presented in Section 2.3.6. In general, it is important to involve an interdisciplinary group of stakeholders for the ideation during this step. Depending on the members of the project team, it might be useful to get additional stakeholders involved over the course of this step who have special domain knowledge (e.g., service, customer needs, or product development). Before starting the first task, the objectives for the strategy development should be reviewed to avoid that use cases are identified for products or stakeholders that are not being focussed on.

The **identification of application areas** is important preparation for searching for use cases. An application area can be, for example, a department of a company, benefit cluster, or a phase of the product lifecycle. Obtaining an overview first helps to avoid that potential application areas are overlooked. Without an overview, there is a risk that the ideation focuses on a certain area right from the beginning. Therefore, the objective of the first task is to create transparency about the range of possibilities before going into detail when searching for use cases. It is important to mention that an application area is not a use case, but a high-level cluster that groups use cases under a certain category. Furthermore, it is likely that stakeholders will already mention use cases during the discussion about possible application areas. It is important to document these use cases for the second part of this step, but they should not be discussed before the application areas are defined. It is possible to subdivide the search into a product and corporate, stakeholder (internal and external), and competitor driven approach.

Initiating the search for application areas with a *product and corporate driven approach* includes four different starting points. First, the description of the product lifecycle provides a comprehensive overview because the lifecycle contains both an internal and external perspective. A workshop with different stakeholders is useful to review the lifecycle and to identify application areas for use phase data. For this task, it is also necessary to understand which application areas are already addressed by use cases at a company. Such an analysis can reveal, for example, that current services do not use any use phase data, which could be an indicator that a detailed search for use cases should be conducted in this domain later on.

A second starting point for the search for application areas could be the SWOT analysis from the end of the previous step. The findings can highlight application areas that are worthwhile to consider in order to take advantages of external opportunities. For example, assuming that the analysis revealed that customers are willing to pay more for products that make the usage of products easier (opportunity), then it might be logical to search for new product functionalities later on.

The third possibility is to use the product-market matrix derived during Step 2 to identify possible application areas (Figure 6-11). The matrix can help to point out application areas in two ways. First, it provides information about the maturity of the different product segments. Therefore, the matrix might indicate which segments already offer connected products that transmit use phase data. A company that wants to implement use cases might prefer to focus only on connected products that do not require any comprehensive adjustments (e.g., development of a model for connectivity or integration of a new bus system for the product). Secondly, the matrix indicates which markets offer potential for a data-driven value proposition. Combined with the information about whether the company already offers a product for this market, the finding might be to focus on certain markets.

	Benefit cluster				
Application areas	Stabilisation/ Retention	Individuali-sation	Performance improvement	Monitoring and analysis	Communi-cation
Service and product deployment					
Operations					
Marketing and customer loyalty					
Supply-chain-management					
Research and development					
Project management					

Figure 6-13: Functional perspective on possible application areas (derived from Wilberg et al. (2018c))

The fourth starting point is to identify application areas based on the functions within a company and its value provision. In general, a company consists of different business functions (e.g., marketing, service, and R&D) (Kurbel, 2013, p. 95). There are different ways to decompose a company into business functions, but no matter which structure is used, all functions of a company need to work together in order to be successful. Figure 6-13 provides an overview of a possible decomposition of an engineering company. Furthermore, the figure suggests five benefit clusters linked to use cases: performance improvement, individualization, stabilization & retention, monitoring and analysis, and communication (Wilberg et al., 2018c, p. 1459). Therefore, it is possible to outline the organisational function and the corresponding benefit cluster to come up with application areas. There are however, different ways to cluster the benefits of connected products and data analytics. Table 6-2 provides an overview of alternative ways to cluster benefits of connected products and data analytics. The table provides examples for benefits that have been derived from literature. Using the overview of benefits during a workshop can help to stimulate creativity and to identify additional application areas.

Table 6-2: Overview of possible benefits of connected products and data analytics derived from literature

Source	**Potential benefits**
Benefits of smart PSS (Valencia et al., 2015)	• Consumer empowerment • Individualisation of services • Community feeling • Service involvement • Product ownership • Individual/shared experience.
Rewards of IoT (Bartolomeo, 2014)	• Enhanced customer service • Increased revenue from services and/or products • Improved use of assets in the field • More information to feed big data/analytics efforts
Application areas for IoT (Chui et al., 2010)	• Tracking behaviour • Enhanced situational awareness • Sensor-driven decision analytics • Process optimisation • Optimised resource consumption • Complex autonomous systems

The next step is to apply a *stakeholder driven approach* to identify possible application areas. Therefore, it is helpful to look at internal and external stakeholders. The findings of the stakeholder analysis and stakeholder map derived during Step 2 provide useful insights for the search. Based on this overview, it is possible to further analyse the characteristics and interests of different internal stakeholders (Varvasovszky, 2000, p. 342). For the development of a use phase data strategy it is important to understand the activities that stakeholders conduct, which is similar to the customer jobs derived for the customer profile. In addition, it is important to analyse which basic interests each stakeholder has in exploiting use phase data. Interviews with the different stakeholders help to collect relevant information for a detailed description of stakeholders' interests and motives. These insights help to derive application areas within the company. Furthermore, the interviews are also helpful for getting in contact with stakeholders who might provide use cases later on. Understanding the needs of stakeholders is crucial to making similarities visible and deriving use case that fit their problems. Table 6-3 depicts an exemplary table, which summarizes the results of a stakeholder analysis that highlights their main interests in use phase data and their relevant competencies.

Table 6-3: Exemplary table that summarises the findings of a stakeholder analysis

Phase in lifecycle	Stakeholder	Activities and interests	Interest in use phase data
Market and customer analysis	Marketing and communication	• Product evaluation • Customer analysis • Support in product planning	• What product is bought most often by which customer group? • How often is a certain service used?
	Sales	• Commercial product specification - Market analysis • Customer analysis	• What specifications does a product need to be relevant for the customer segment?
Product planning	Product management	• Technical product specification • Specification sheet	• How successful were appliance sales in the field? • Did the performance classes fit to the actual performance needs?
	Requirements engineering	• Identify, specify and validate product requirements	• Could legal limits be kept? • Is the cycle number as assumed in the field?
	Quality management	• Quality planning • FMEA • Risk analysis • Process control	• What part led to problems in the field?
Product development	Research and development	• Component and appliance specification • Error diagnosis • Design of test plans • New product innovations	• What are the real operation costs in the specification field?

After searching for application areas internally, the next option is to have a closer look at customers and users to search for application areas. During Step 2 customer profiles, a user journey, and a data journey were derived. These documents offer different perspectives on the needs of customers and users. Therefore, these documents can help to identify the needs of customers and users that can be addressed through the exploitation of use phase data. The analysis should point out if, for example, customers would rather prefer additional product functionalities or services. However, application areas on the customer side should not only arise from an internal perspective because this might lead to wrong assumptions. Therefore, it is also important to involve external sources in this search and ideation phase (Ili and Albers, 2010, pp. 45–46). The integration of external sources can be done by using Open Innovation, which is a known approach that brings together internal and external ideas during the innovation process (Chesbrough, 2006, p. 43). A main benefit of following an Open Innovation approach is that external sources provide additional ideas. In general, a variety of different tools and methods exist to understand the needs of customers (Coppenhaver, 2018, p. 68). The following examples are additional methods that can support the ideation: focus groups, customer interviews, or lead-user analysis. A very effective way to gather information about customer needs is to conduct interviews (Coppenhaver, 2018, p. 69).

The last option is to follow a *competitor driven approach* to identify application areas. Insights gained during the competitive analysis in Step 3 provide an overview of how competitors extract value from use phase data. Depending on the availability of information, it might not be possible to assess fully how competitors exploit use phase data internally, but it is possible to assess the products, services, or business models of competitors. Besides looking at direct competitors, it can also be useful to look at companies in other industry sectors that address similar customer needs (e.g., high availability of a product).

After collecting areas for which use phase data could provide additional value, the next task is to *consolidate the ideas for application areas*. Therefore, it is helpful to cluster the ideas. Clustering all identified application areas allows for the identification of hotspots that are a good starting point for beginning the detailed search for use cases. Starting the search for detailed use cases requires, most likely, that the number of application areas is reduced. Selecting application areas can be done by extracting assessment criteria from the objectives defined at the beginning of the use phase data strategy development project. Before proceeding with a reduced number of application areas, it is important to name the stakeholders required to derive use cases.

Based on the selected application areas, the next task is to **derive use cases**. This should result in a comprehensive list of possible use cases. During the collection of use cases, it is important to avoid making any premature judgements in order to ensure that interesting use cases are not overlooked or excluded based on stakeholders' preferences. This includes not assessing technical feasibility at first. Obtaining a broad selection of possible use cases for the application areas requires a combination of different methods. Therefore, it is not possible to propose one ideation method for all use cases. Experience from empirical data shows that combining different sources for use cases leads to better and more diverse results.

Design Thinking can provide some useful input for the ideation phase because it aims to support product development or service development where novel ideas are required (Luchs et al., 2016, p. 2). Three principles of Design Thinking that are valuable for the search for use cases are: user-centricity, divergent and convergent idea search, and interdisciplinarity (Brenner et al., 2016, pp. 8–10; Luchs et al., 2016, pp. 9–10). Translated into the context of use phase data strategy development, the first principle entails that use cases should address the needs of internal or external stakeholders. Use cases must have a clear value. Secondly, the ideation should also focus on unconventional and out-of-the-box use cases that do not only fit the common mind-set. However, it is important to converge in order to reduce the number of ideas. The third principle means that different stakeholders from various disciplines get involved in the ideation phase. Exploiting use phase data requires that different disciplines work together to derive novel use cases. The general ideation process can be subdivided into the following four steps: Planning, idea generation, selection, and documentation (Stickdorn et al., 2018, pp. 163–169).

The *planning stage* of the identification of use cases includes different tasks (Stickdorn et al., 2018, p. 164). Defining the scope is very important to ensure that suitable ideas are generated later on in the process. The previous selection of application areas helps to narrow down the scope for the ideation. However, the project team should review the scope in order to avoid that it is too wide. Examples for defining the scope could be to only look at services for customers or to only follow a use phase data-driven approach (bottom-up). Setting the scope should also include the definition of a time frame for idea generation and number of use cases desired because an ideation process can otherwise take very long. Previous steps of the process model create important input for the ideation (e.g., customer profiles). Assessing the quality of these documents ensures that the use cases are derived from a solid foundation. Furthermore, use cases identified in previous projects and their status should be revised in order to benefit from previous experience. The same goes for use cases that were mentioned during the identification of application areas.

After preparing the material, the next task is to decide about the actual design of the ideation process. The range of possible use cases can be quite wide. The overall objective should therefore be further subdivided, which helps to reduce the task-related complexity and can be done based on the application areas. After this, it is possible to identify relevant stakeholders and suitable methods to derive use cases. The overview about internal and external stakeholders should help to decide which ones to involve. Based on the background and the diversity of the stakeholders, the search for use cases requires different environments or methods. Therefore, it is important to understand the prerequisites of stakeholders in terms of experience or technical knowledge. Based on this, it is possible to group stakeholders and select ideation methods that fit. In general, methods supporting idea generation either follow an intuitive or a systematic approach (Boyd and Goldenberg, 2018, p. 17; Gausemeier et al., 2001, pp. 123–124). Intuitive methods like brainstorming aim to generate ideas through intuitive, unplanned and creative processes. In contrast, systematic methods like morphological boxes lead to ideas by triggering distinct thinking processes. A detailed overview of methods supporting ideation can be found in numerous publications (e.g., Lindemann (2009), Goldenberg and Mazursky (2002), Münzberg (2018), or VanGundy (2005)). The Munich Model of Methods helps to select and adapt methods based on the application context (Lindemann, 2003, pp. 5–8).

The next task is the *idea generation,* which is the main challenge of this process step because it provides the main input for a use phase data strategy. The main objective is to think about use cases that provide value for internal or external stakeholders. Therefore, the needs of the stakeholders should be at the forefront during the idea generation in order to identify use cases that make a difference and have a positive impact. The empirical data shows that multiple steps help stakeholders to provide use cases and experience shows that stakeholders struggle to instantly name use cases, especially if they have not encountered use cases based on use phase data before. For the identification of use cases, the following four sources exist: internal stakeholders, external stakeholders, competition and other companies, and a use case catalogue.

Internal stakeholders are a very important source for use cases because they have domain knowledge (e.g., product functions, markets, or customer profile). They are also accessible and approaching them is often easy. At the same time, internal stakeholders are biased because they have worked at the company for some time and can therefore struggle to think outside the box when searching for use cases. Nevertheless, internal stakeholders can provide valuable use cases that address the needs of both internal and external stakeholders. For internal ones, workshops in combination with ideation methods and documents from previous steps, helps to derive use cases. First option is to take a processual perspective by having a closer look at the product development process. During the product development process, many decisions about the product design are made (e.g., functions, requirements, or durability). A main advantage of use phase data is that it provides valuable insights about the actual product usage. An option for finding use cases is to ask engineers at which steps of the development process they make assumptions about the product's usage that would be more accurate if actual data was available. One possibility is to conduct a workshop that asks participants to highlight process-related activities (e.g., product development process) for which additional insights about the product's usage would be helpful.

Another possible approach is to identify use cases by decomposing the product or service. Using a depiction of the process, which shows the important modules, then enables the identification of components that can be improved with use phase data. A third option for identifying possible use cases is to trigger the ideation with available use phase data and use a data-driven approach. Therefore, stakeholders should obtain an overview of the use phase data that the company already has (e.g., using the data map). Afterwards, the task is to derive use cases that are possible with the available data. This option can also lead to use cases for customers and users by thinking about the value that such data points can provide for them.

Besides searching for use cases that address the needs of internal stakeholders, the objective must also be to address customer needs. During the previous step, the suggestion was to derive a data journey, customer profile, and fit-map. These documents provide valuable insights about the customer needs. Analysing the customer profile is useful for deriving use cases that lead to gains or reduce pains. Figure 6-8 illustrates a possible structure of a data journey for connected products. The developed data journey aims to support the analysis of the current state, but also to design the user experience of connected products (Appendix A6.4 provides more details about the data journey). Having a clear understanding of the needs of users helps to design connected products that provide additional value and increase the user experience (Troilo et al., 2017, p. 620; Valencia et al., 2015, p. 25). During this step, the data journey can help to identify pain points during the use phase. Thus, the data journey can be discussed in workshops in order to identify interaction steps between the user and product that can be improved through use phase data. Such a workshop can also help to identify use cases that have a possible impact on the emotional user experience curve. Depending on the design of the data journey, it is also possible to identify use cases that provide recommendations for the user. Overall, applying the data journey can help to identify use cases that improve user experience based on the connectivity of products and services.

Besides using internal knowledge, it is very important to also involve external stakeholders like customers and users. Asking users directly which use cases would provide additional value for them can reduce the risk of implementing use cases that do not fit the users' needs. A main challenge for this task is to identify suitable users or customers. It is important to check that the selected stakeholders are a suitable representation of the customers that a company wants to address with their products and services. Common methods for this task are interviews or surveys with customers and users (Coppenhaver, 2018, pp. 66–67). Another possibility is to visit customers and observe how they use products and services in order to solve their problems (Geirl and Helm, 2007, pp. 320–321; Herrmann and Huber, 2013, p. 153). Observing how customers are using the product is helpful to reveal problems that were unknown before. These problems can then be the starting point for deriving use cases. Following this approach helps to ensure that use cases better fit to the actual usage. Another option to understand customer needs is to analyse complaints from a complaint management system (Herrmann and Huber, 2013, pp. 152–153). The analysis of complaints especially helps to improve existing products, which means that complaints might help to improve use cases that are already implemented.

Another important source for ideas is to analyse direct competitors and companies in other industry sectors (Herrmann and Huber, 2013, p. 155). Ideas from other companies serve as a reference system for the company's own ideas, which are then adjusted and tailored to the company's context (Albers et al., 2015, p. 6). A key benefit of this approach is that it helps to reduce development efforts and costs because parts of the solution can be transferred into the company's own context. A main task of Step 2 was to conduct a competitive analysis and these results provide a good starting point for identifying use cases that other competitors already offer. However, it might be challenging to find out how other companies exploit use phase data to support internal stakeholders. Nevertheless, this analysis should not only look at direct competitors, but also companies from other sectors. Companies from other sectors strive to extract value from connectivity and use phase data as well. Thus, other sectors might have started exploiting data earlier, which provides the opportunity to learn from them. A starting point for identifying relevant sectors can be to search for those that address similar customer problems or needs (e.g., nonstop operation of the product).

An additional source for use cases of other companies is the use case catalogue developed as part of this research. Appendix A6.6 describes the use case catalogue. The use case catalogue provides a comprehensive overview of more than 200 use cases realized by other companies across different industries. Appendix A7 provides a list with all use cases of the catalogue. The use cases stem from a literature review, interviews, and online search (Wilberg et al., 2018c, p. 1457). The developed software prototype for the catalogue makes the handling of the use case catalogue more user-friendly and intuitive. Figure 6-14 illustrates the software prototype. The left screenshot shows the list of use cases and the right one shows the detailed description of one exemplary use case. The underlying idea of the use case catalogue is to apply analogy building to support the search for use cases during Step 3. The basic idea behind analogies is to use existing ideas as inspiration to trigger own ideas (Boyd and Goldenberg, 2018, p. 18; Stickdorn et al., 2018, p. 181). The underlying assumption for the catalogue is that reading about use cases implemented by other companies or industries helps to overcome one's own thinking barriers and triggers novel ideas for use cases (Wilberg et al., 2018c, p. 1458).

Using analogy building in general requires that the person applying this approach matches their own problem (target problem) with an external problem (source problem) (Gavetti and Rivkin, 2005, 56-57). Accordingly, the application of general application process for the use case catalogue consists of three steps (Wilberg et al., 2018c, pp. 1458–1459). First of all, the user of the catalogue must abstract, based on the selected application areas for the use phase data strategy, which core problems or benefits the use cases should address (e.g., better guidance for the user during product usage). Secondly, the user can then explore the use case catalogue and identify concrete use cases meaning the source problem (e.g., behaviour-based payment for insurance or enhanced product functionalities via remote updates) that match the abstracted target problem or benefit description. The user then selects relevant use cases that seem suitable for their own business. The third step is to tailor the selected use cases to the individual context. This way, the use case catalogue helps to create novel ideas that serve as an input for the subsequent steps of the strategy development.

To ensure an easy comparison of use cases, each use case is described using the same template, which provides a textual description of the use case and its intended benefits as well as technical information about the type of use phase data and data analytics approach needed (for further details please consult Appendix A6.4). The software implementation of the use case catalogue allows the user to search for use cases in four different ways (Wilberg et al., 2018c, p. 1459). Users can search for a use case based on the functional perspective of application areas (see Figure 6-13), keywords (e.g., predictive maintenance), data features (e.g., type of use phase data or data analytics approach), and benefits of a use case (e.g., downtime reduction or simplified design). Overall, it is possible that one person explores the use case catalogue individually, but it is also possible to integrate the catalogue into an ideation workshop.

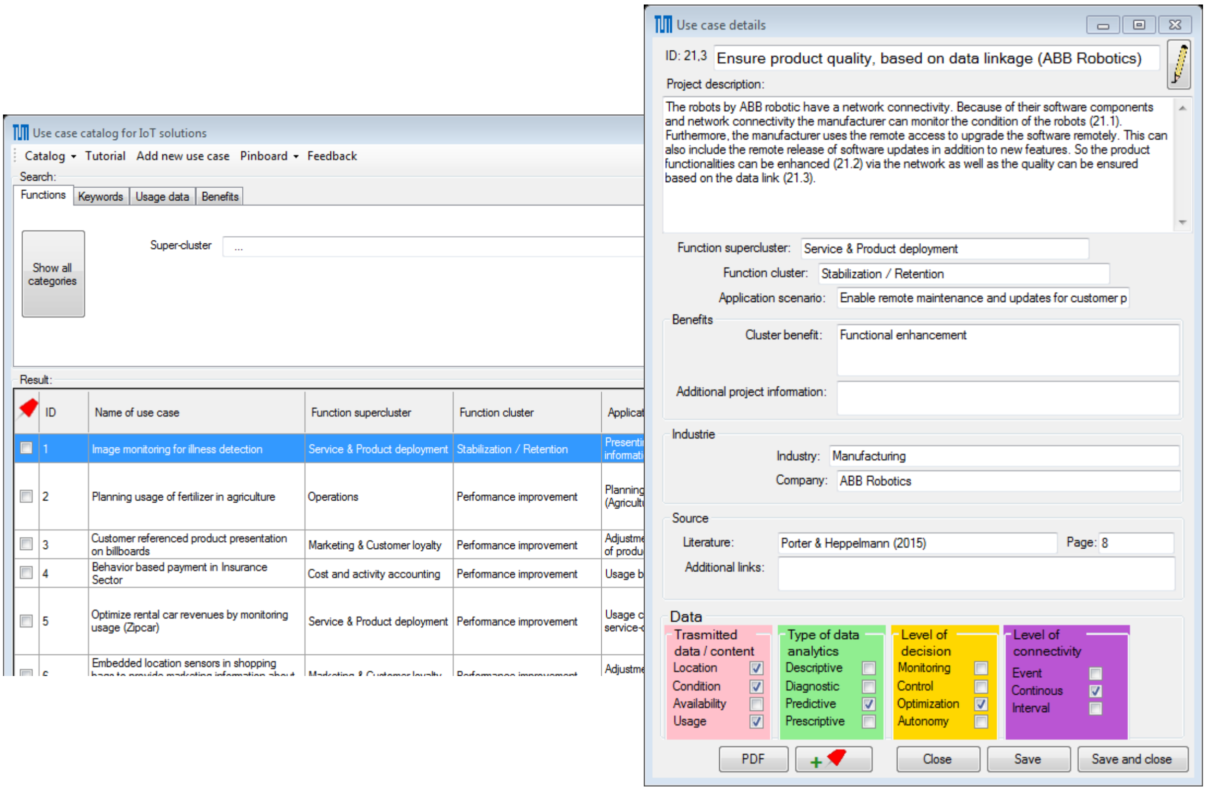


Figure 6-14: Screenshots of the software prototype for the use case catalogue

The next task after the ideation is the *selection* of use cases that are suitable to proceed with. After divergence during the idea generation, the objective is to then converge. Selecting suitable ideas from a large set often requires several selection steps (Gaubinger et al., 2014, p. 106). At this stage, the selection can only be done roughly because the main selection of the use cases will happen in Step 5 once more details for each use case are available. Nevertheless, it is not useful to continue with all use cases that arise during the idea generation because it would be too time consuming to follow up on all possible use cases. As a first step, duplicates should be removed. Afterwards, the abstraction level of the use cases must be compared. Some ideas might be just vague descriptions and others might entail multiple use cases. It is important that all use cases have a similar abstraction level in order to compare and assess them later on. Clustering the use cases or selecting model use cases helps to make expectations more clear. Use cases that are too high-level should be reworked together with the stakeholders that provided the input for them. Afterwards, each use case must be checked against the objectives and scope of the use phase data development project. Another possibility to reduce the number of use cases at this stage is to formulate knockout criteria (e.g., data security concerns, violation of data privacy rules, or technical complexity). Certainly, there are different ways to derive a reduced selection of use cases, but what is important is that the number of remaining use cases matches the available time for detailing them in the next steps.

The last task is the *documentation* of the remaining use cases to prepare for detailing them during the next step. Even though not all use cases will become part of the strategy, it is important to document them in a systematic way to make the ideas accessible for other projects or stakeholders. At this stage, a one-pager is suitable to describe each use case on an adequate level. The one-pager should contain the following information: use case number, use case title, short description, addressed stakeholder need, and stakeholder that provided the use case. The selection of use cases is the input for the next steps, subsequently helping to derive a use phase data strategy from them.

Overall, the **main outcome** of Step 3 is a comprehensive overview of possible application areas within and outside the company. The search for application areas helps to provide an understanding of which areas and stakeholders could benefit from exploiting use phase data. Based on these findings, it is possible to derive a comprehensive list of use cases. The idea generation requires planning to ensure that relevant stakeholders get involved and suitable methods are applied. The selection and documentation of use cases in a consistent way ensures that it is possible to further detail and asses the use cases during the following steps.

6.5 Step 4 – Determine the data needs and consolidate the use cases

After obtaining a list of possible use cases, the objective of this step is to examine the use case. At the current state, the list provides only vague descriptions of the use case. Therefore, it is important to understand which data and architecture is required for these use cases. Moreover, to proceed it is important to reduce the number of use cases. Grouping and comparing the use cases further helps to identify clusters of use cases and relationships among them.

Turning use phase data into value is the main objective of the use phase data strategy. Therefore, the first task is to **determine the data needs**, which involves looking at both use phase and context data. As mentioned before, context data (e.g., age of the user, country of usage, or size of a household) is not dynamic, but often very important to interpret and analyse use phase data. Understanding the data needs of use cases is accordingly a critical aspect (Wirth and Wirth, 2017, p. 33). Besides looking only at the analysis results for the perception level derived during the analysis of IoT architecture in Step 2, it is also important later on to assess the needs of the network, middleware, and application layer. The following tasks will thus increase knowledge about the use cases significantly. Determining the data needs therefore involves defining a documentation format, detailing the use cases, determining data needs, evaluating the data delta, assessing the data quality, and identifying suitable analytics approaches.

At the beginning, the *definition of a structured documentation* format is very important to make the selection of use cases traceable and generated knowledge accessible to other stakeholders. Using a one-pager for documenting all aspects is not sufficient due to the required level of detail. Therefore, using a comprehensive template will allow for an adequate documentation. It is important to highlight that a template is not only useful for documenting ideas, but also supports the creative process because templates help to decompose problems or solutions into more manageable chunks (Boyd and Goldenberg, 2018, pp. 19–20). Appendix A6.8 provides a detailed description of a developed use case template. The suggested template consists of eight sections:

1. General information about the use case (e.g., title, contact person, and use case number)
2. Detailed description of the use case (e.g., stakeholders and related interests, data needs, or requirements of the IoT architecture)
3. Processual description of the use case (e.g., trigger, process of the use case, or ending condition)
4. General assessment (e.g., level of innovation or costs)
5. Effort for IoT systems (e.g., additional middleware or servers)
6. Additional information (e.g., connection with other use cases)
7. Effort-value matrix
8. Open points (e.g., tasks to prepare the implementation)

The template combines different perspectives on use cases resulting from the various stakeholders involved in the use phase data strategy development process. It is important to highlight that the template should be constantly filled with new information gained during the use phase data strategy development process. Furthermore, the proposed template only presents a starting point for the documentation of use cases and the template should be adjusted to the specific needs of the company, for instance by using additional categories to evaluate a use case.

After preparing the documentation, the task is now to *detail the remaining use cases* in order to determine the data needs. In order to do that, a detailed understanding of the underlying process of the use case is required. Each use case should therefore be translated into a process description that covers its entire sequence. Workshops done together with the stakeholders that provided the idea for the use case help to ensure that the initial idea is not misinterpreted. However, it is important to distinguish between use cases that are performed ones (e.g., analyse the loads that a product experiences during usage) and those that are repeated automatically or multiple times after the implementation (e.g., automated theft control based on the position of product). Use cases that are repeated frequently most likely require use phase data during the set up phase as well as during the operation phase. Therefore, differentiation between these two types of use cases is important to obtain a clear understanding of the data needs. A service blueprint is a common method for modelling services during PSS development (Geum and Park, 2011, p. 1603), which was proposed by Shostack (1982). The main advantage of a blueprint is that it allows for the visualisation and structuring of a service on different levels (Kleinaltenkamp, 2000, p. 10). However, the tool is not completely suitable to model data-driven services because the data domain is not covered (Wilberg et al., 2018b, pp. 8–9). Therefore, a data blueprint was developed that aims to better support the modelling of use phase data-driven services. Figure 6-15 depicts the general structure of the data blueprint. A main adjustment was that an automation (middleware) layer was added to better respect its important role for data-driven services. A detailed description of the data blueprint can be found in Appendix A6.12.

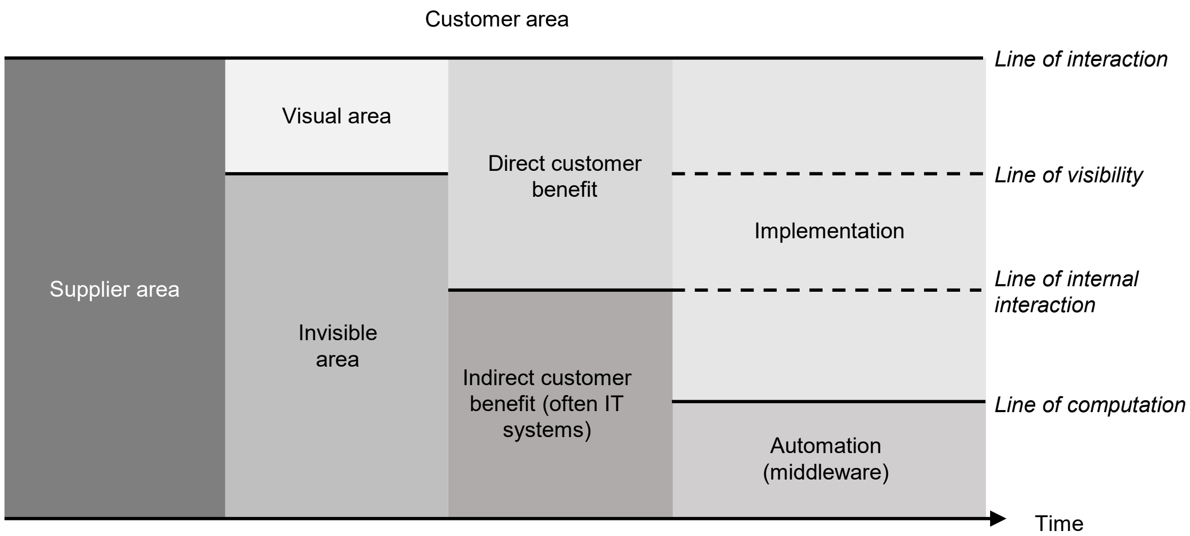


Figure 6-15: General structure of the developed data blueprint (based on Wilberg et al. (2018b, p. 9))

The structured description of the use cases prepares the *determination of the data needs* for each use case. In order to achieve this, workshops should be conducted that involve, for instance, the person that proposed the use case, the beneficiary of the use case, and stakeholders that have knowledge about the available use phase data. If a bottom-up approach was followed during Step 3 to derive use cases or a data map was used during the ideation. The data needs might have already been formulated during the search for suitable use cases. Nevertheless, the information should be checked at this stage to ensure completeness. For each use case, it should be also determined what context data is required.

After having an overview of the required use phase and context data points, the next task is to *reveal the data delta*. The data delta is the difference between required and available data, which is an important indicator for feasibility and implementation effort. The previously developed data map is essential for this task because it highlights data sources (e.g., sensors or actuators of a product) and available use phase data. The overview of the data needs for each use case is then extended by defining which data source (product or service) provides the relevant data point. It is also possible to calculate or derive a data point based on data coming from other data sources. After matching required data points and available data sources, the data delta is clear. Figure 6-16 depicts the information for each use case that should be available at this point. For each use case it should be clear, which data points are currently not available. To ensure that the required data sources are accessible, it is crucial to determine the owner of the data in order to avoid complications later on.

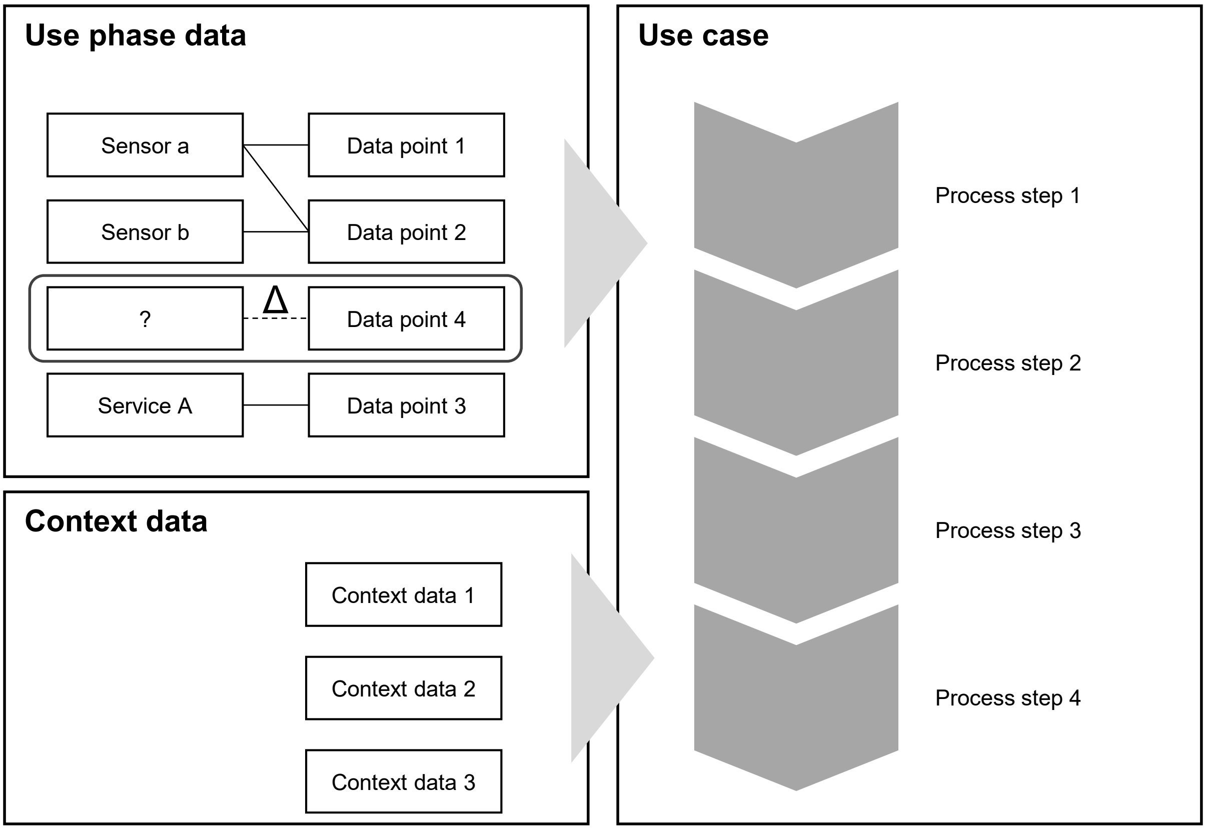


Figure 6-16: Description of use cases to determine the data needs and data delta

However, it is not only important to assess whether data is available or not, but also to *analyse the data quality* (Wirth and Wirth, 2017, p. 35). Some use cases (e.g., optimization of product settings during usage) lead to high demands in data quality due to the dynamic nature of process that is of interest. Therefore, a main success factor for analytics projects is to ensure that the data fulfils the quality requirements (Saltz, 2015, pp. 2069–2070). The quality of data can be assessed using different dimensions (Müller and Lenz, 2013, pp. 38–42; Strong et al., 1997, p. 104). A systematic literature review showed that the following three criteria were among the most mentioned dimensions to evaluate data quality:

- Consistency
- Accuracy
- Currency

The currency describes how up-to-date the data is. More data is generated nowadays, but at the same time data analytics tasks are becoming more complex, which leads to higher demands in terms of data quality (Cai and Zhu, 2015, pp. 2–3; Merino et al., 2016, pp. 125–126). The developed data quality template helps to compare required and available data quality in order to identify data quality problems. The template was derived from a literature review and is shown in Appendix A6.9. The template compromises of 26 criteria of which 15 are suggested as mandatory for every quality assessment. However, at this state it might only be possible to perform a qualitative assessment of the data quality. Assessing the data quality also involves looking at the network layer of the IoT architecture because this layer also has an impact. The sensors of a product might produce data with a high resolution, but due to bandwidth restrictions or available space for storage, use phase data might be transmitted to the company with a much lower resolution. The same goes for the currency of the data transmission, which might be limited for products that are operated in remote areas that have no mobile networks.

The last task is to *identify the data analytics approach* that will be required for a use case. The main methods in data analytics are: visualization, correlation, regression, forecasting, classification, and clustering (Runkler, 2016, pp. 2–3). Gaining an initial understanding of the required data analytics methods allows the company to determine whether the current middleware and application layer is suitable for the use cases.

Based on the understanding of the data needs and the previous analysis of the use cases, it is important to **consolidate the use cases** in order to reduce the number of possible ones. Understanding the links and similarities between the use cases also helps to create synergies. Clustering and grouping use cases makes dependencies visible and therefore also allows for the definition of packages.

As a first step, the remaining use cases should be clustered using a *stakeholder driven approach* in order to describe which stakeholder they address. Figure 6-17 shows how a stakeholder-based clustering of the use cases could be done. On a first level, use cases can be split into those that either address internal or external stakeholders. Afterwards, it is possible to further subdivide both categories. Using a functional decomposition based on the functions of a company works for internal use cases. For use cases that address external stakeholders, it is advisable to assign them to subcategories. Customers and users are not always the same and therefore more differentiation might be helpful. If a company has defined groups of customers, then this would be another suitable way to cluster use cases. The stakeholder map can serve as a foundation for this task. Having an overview about the stakeholders that the use cases address helps later on to better assess the value that use cases aim to provide.

The second approach to cluster use cases is to *analyse the dependencies among use cases*. Often use cases have interconnections, which means that one use case contributes to another use case. In an exemplary situation with 20 use cases, the project team would be required to assess 380 connections ($20^2 - 20 = 380$). Applying structural complexity management is suitable at this situation because it allows for the modelling, analysis, and optimisation of complex systems (Lindemann et al., 2009, pp. 61–62). Structural complexity management is a matrix-based approach that uses matrices to describe dependencies among system elements of the same domain (DSM – Dependency Structure Matrix) or elements of two different domains (DMM – Domain Mapping Matrix) (Lindemann et al., 2009, pp. 50–55). To model the different connections within one domain and across different domains, a Multiple-Domain Matrix (MDM) is used, which consists of DSMs and DMMs (Lindemann et al., 2009, pp. 69–73). Structural complexity is thus helpful to model and analyse the dependencies among use cases, but also to analyse connections of use cases with other domains. Figure 6-18 depicts a DSM that describes the dependencies among eight use cases. The numbers in the cells indicate how helpful one use case is for another one (3 – extremely helpful, 2 – helpful, and 1 – little helpful). Deriving this rating can be done in workshops or interviews. Applying clustering algorithms helps to find clusters of strongly connected use cases (Lindemann et al., 2009, pp. 53–54). Identifying such clusters then helps to form use case packages or groups for a later implementation.

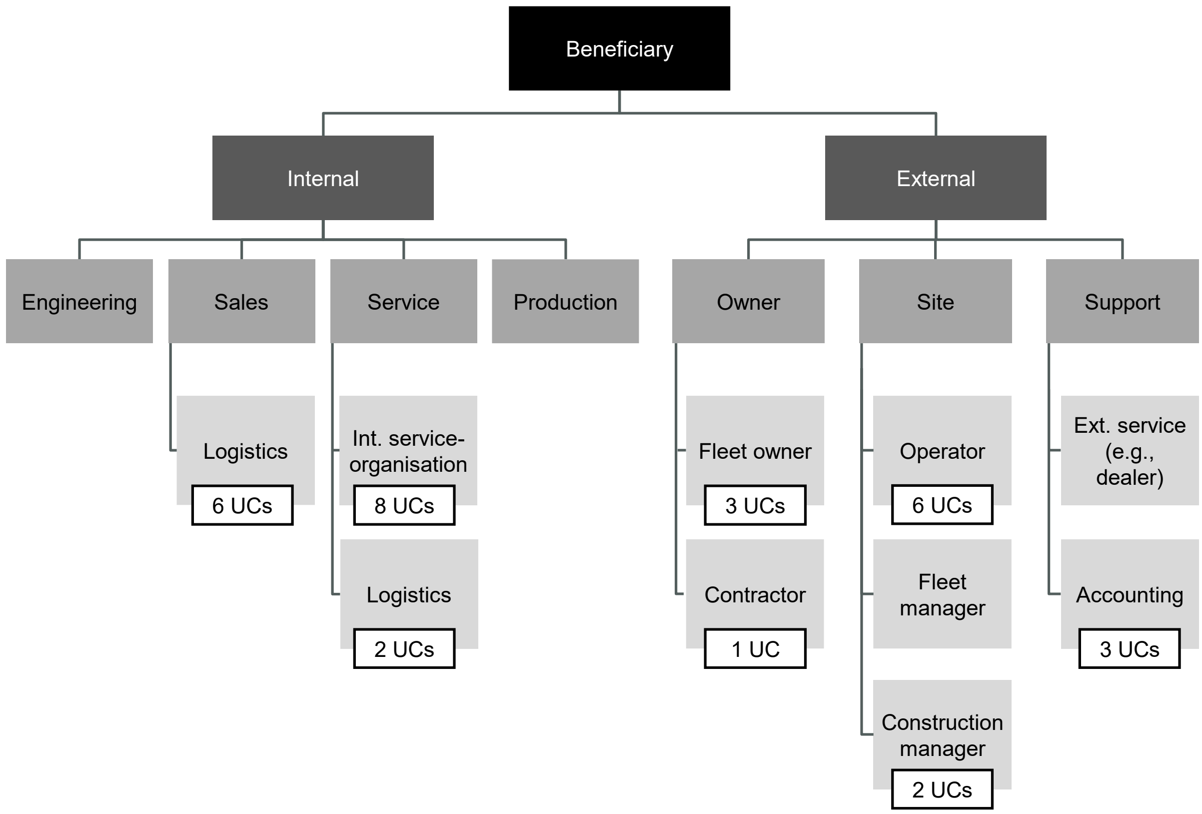


Figure 6-17: Exemplary stakeholder-based clustering of use cases for a construction equipment manufacturer

Besides looking at dependencies among use cases, it is also important to *assess the links between use cases and their required data points* (use phase data and context data). The previous analysis highlights the data needs for each use case. Comparing the data needs of use cases helps to also identify clusters of use cases that depend for instance on the same sensor. Figure 6-19 illustrates how a matrix can help to describe dependencies between use cases and data points. A main benefit of this comparison is that it outlines clusters of use cases that depend on similar sensors. This transparency is important for an assessment of the use cases because embedding a new sensor in a product might require a significant investment, but at the same time enables three new use cases. For this analysis, DMMs can be used because they allow for modelling the dependency between use cases and data points. Figure 6-19 shows an exemplary DMM that describes the connection between use cases and their required data. The figure also highlights clusters of use cases that become visible due to this analysis.

However, it is not only useful to look at the data needs, but also to analyse the links between use cases and intended benefits in order to *derive benefit clusters*. Based on the selection of use cases, it is possible to derive benefit categories (e.g., improve product's usability or reduce over-engineering). Therefore, it is worth it to analyse which benefits the use cases intend to provide. It is thus possible to derive benefit clusters. Identifying such clusters allows the company to derive a use phase data strategy that aims to provide distinct benefits by combining use cases. Another possibility for utilising DMMs is to analyse the dependencies between use cases and strategy goals in order to depict how different use cases contribute to the company's strategic goals.

Name of the Use Case	38	12	4	32	22	2	11	30	…	**Active sum**	**Overall sum**
UC #38 User profiles		3	3	2	3	2	3	2		78	118
UC #12 Intelligent manual	3		2	2			2	2		34	54
UC #4 Data support for sales	1	1		2			2	2		24	40
UC #32 Remote support	2					2		3		29	69
UC #22 Power by the hour	2					2	3		…	48	90
UC #2 Wear indicator				1	3		3	1		48	94
UC #11 Integrated service contracts	1		2	3	3	2		3		52	103
UC #30 Remote support package	2	2		3		2	2			47	92
…					…					…	
Passive sum	40	20	16	40	42	46	51	45	…	…	

Figure 6-18: Matrix-based approach to evaluate the interdependencies among the use cases

The activity involved in this step is to merge the insights to *reduce the number of use cases* and to derive groups of use cases. The first task of this step in particular provides valuable insights about data needs and the underlying process of use cases. In combination with the use case-data DMM it is possible to obtain an understanding concerning the implementation effort. Depending on the objectives of the use phase data strategy development project, it is possible to group the use cases based on the estimated time required for the implementation (short-, middle-, and long-term), value (low, middle, and high), or complexity of an implementation (low, middle, and high). However, the project team must define the underlying values for each criterion. Subsequent cross-disciplinary workshops help to assess the use cases. Based on the objectives defined during Step 1, it is possible to remove use cases, for instance, that require a longer implementation time than desired. It is advised to continue with at least some use cases that can be implemented in the short-term because having success stories helps to increase acceptance among the stakeholders (Kotter, 2012, p. 7).

	Data point 1	**Data point 2**	**Data point 3**	**…**	**…**	**Data point *m***
Use case 1	x	x			x	
Use case 2	x	x	x		x	
Use case 3	x	x			x	x
Use case 4	x	x			x	
Use case 5			x	x	x	
Use case 6	x		x	x	x	
…		x	x	x	x	
…	x				x	
…		x			x	x
Use case *n*	x		x	x	x	x

Legend: Functional cluster

Figure 6-19: Matrix-based approach for the identification of use case clusters

Besides this approach, it is also possible to define *business clusters and consecutive use cases.* Business clusters provide similar benefits or address similar pain points of customers or users. This helps to derive thematic clusters that could be implemented during a consistent initiative. Understanding how use cases depend on each other helps in identifying consecutive use cases that require implementation one after another. Furthermore, it is possible to describe the relationship between stakeholders that benefit from use cases and those who need to work on the implementation. Figure 6-20 depicts an exemplary portfolio that shows which stakeholders benefit from a use case and which ones need to put effort in for an implementation. The portfolio for each use case highlights which stakeholders should be involved to select the use cases in the next steps. These insights about the data needs of the use cases further enable the identification of use cases that require data points or sensors, which will not be accessible or likely to be implemented. After conducting all tasks, it is possible to derive a set of use cases that will then be assessed in more detail in the next step. It is crucial to document the reasons for the exclusion of a use case in the template in order to make these decisions transparent.

The **main output** of Step 4 is increased transparency concerning the data and infrastructure needs. Furthermore, this step provides a clearer picture of the underlying processes of the use cases, which helps to gain first insights into the implementation effort needed. Furthermore, the consolidation allows for dependencies among use cases to be made clear. This allows for the identification of use case clusters and consecutive use cases. Applying the developed template ensures consistent documentation of the results.

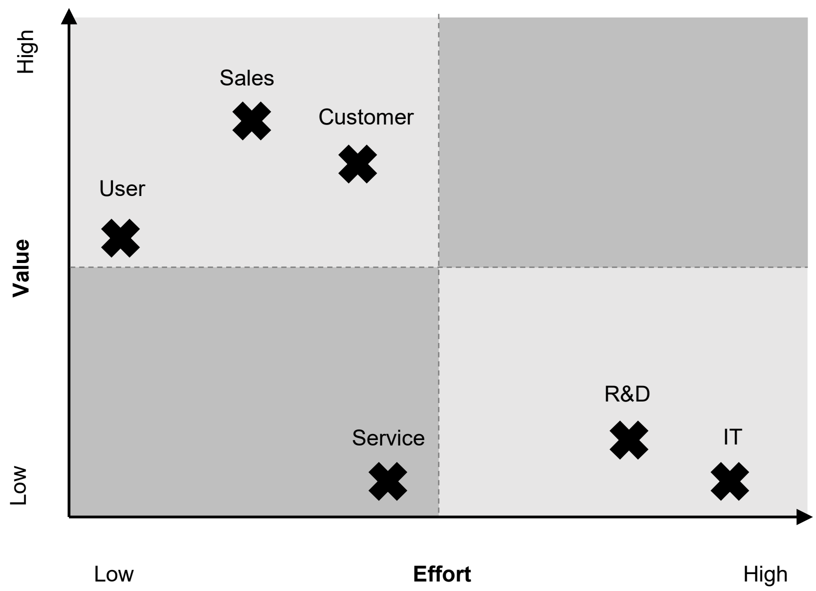


Figure 6-20: Stakeholder-centred effort-value portfolio (based on Wilberg et al. (2018b, p. 7))

6.6 Step 5 – Evaluate the use cases and select

The previous step provides a detailed understanding of use case related data needs and dependencies. This step subsequently uses this information to conduct a detailed evaluation of the use cases and select suitable ones in order to form a use phase data strategy. The structured evaluation aims to ensure that only use cases that provide a sufficient financial (e.g., additional turnover or cost savings) or non-financial benefits (e.g., higher customer satisfaction or improved customer understanding) are selected. Thus, the aim of this step is to ensure a conscious decision based on evaluation insights.

The first task of this step is to conduct the **evaluation of the use cases**. Based on the decisions made during Step 4, the task can be to evaluate individual use cases as well as clusters of use cases. In previous steps, use cases were already examined, but on a lower level of detail. Therefore, the objective is to evaluate the use cases on a more detailed level, but this entails that all use cases are available on a similar level of detail. In general, the evaluation can be qualitative (e.g., scoring system using different criteria) or quantitative (e.g., monetary cost-benefit analysis). The selection of an evaluation approach should be made based on the time available for the evaluation and the maturity of the use cases. An important requirement for the evaluation and selection process is that the process will be transparent and comprehensive for stakeholders in the future (Lindemann, 2009, p. 187). A clear documentation of this process is therefore crucial. In addition, it must be ensured that the number of remaining use cases is not too high in order to make a detailed evaluation possible within a feasible time. Conducting the evaluation of the use cases includes making decisions about evaluation criteria, preparing the assessment, performing the evaluation, and checking as well as documenting the results.

To prepare the evaluation of use cases or clusters of them, it is important to *decide about evaluation criteria*. The decision regarding the criteria and approach determine the level of detail of the use cases. It is not possible to suggest one approach to evaluate the use cases because this should always be adjusted to the context of the use phase data strategy development (Eversheim, 2009, p. 87). In the case that the objective of the use phase data strategy is to support internal stakeholders (e.g., R&D or customer service) then it might be more desirable to save money or speed up processes. In the case that the use cases rather address the needs of external stakeholders, the main criterion will most likely be to generate additional turnover. To evaluate ideas, Disselkamp (2012, pp. 163–164) suggests using the following two main evaluation categories: feasibility and attractiveness. Using both categories for an evaluation helps to compare the advantages and disadvantages of a use case. However, these two categories contain more detailed criteria. The assessment of the feasibility of a use case involves, among other criteria, assessing the following aspects:

- Technical feasibility
- Changes to the current product
- Data privacy
- User acceptance
- Implementation time
- Required data analytics skills of employees
- IT infrastructure
- Personnel resources
- Data security
- Data storage and transmission

The selection of criteria highlights that not only purely technical aspects should be considered because a use phase data strategy also impacts organisational topics. Offering a use phase data-driven service, for instance, can require that customer service is available 24/7 in order to respond to customer requests. Another aspect that should be considered is the amount of data that is produced by a use case. Depending on the number of products that will be connected, a large amount of data might need to be stored. Depending on the use case, it might also be necessary to store use phase data for a long time to enable a use case over the entire lifetime of a product.

The next step is to define the criteria for evaluating the attractiveness of the use cases. It is important to mention that attractiveness must be evaluated from a company’s and beneficiary’s perspective (Disselkamp, 2012, pp. 167–168). The stakeholder that benefits from a use case can be internal or external. Therefore, it is important to be clear about whom the use case is providing the main benefit for. It is not enough to provide benefits just for customers or users; it also needs to be ensured that the company has a benefit from implementing a use case.

The following list provides exemplary criteria for an assessment of the attractiveness of a use case:

- Innovativeness
- Market attractiveness
- Competitive advantage
- Cost saving potential
- Process improvement
- Quality improvement
- Benefits for users or customers
- Impact on customer satisfaction
- Business potential

This list of criteria highlights the broad spectrum of benefits related to use cases. The definition of the objectives for the use phase data strategy during Step 2 showed that connected products could lead to a variety of benefits. In general, use cases can provide financial and non-financial benefits (Uckelmann et al., 2011, p. 8; Vanauer et al., 2015, p. 913). Therefore, the criteria should cover both aspects in order to have a balanced perspective of the attractiveness of use cases. Insights and documents that arose from previous process steps help to identify suitable criteria (e.g., fit-map, data journey, or customer profile). If the use case strategy should consist of use cases for internal and external stakeholders, it might be required to derive two sets of criteria depending on how different the value proposition is. Depending on the number of criteria, it can be helpful to weight these based on the main objective of the use phase data strategy development project. A pairwise comparison matrix can help to derive a ranking of the criteria and therefore define weights (Gavalec et al., 2014, p. 28).

After selecting the evaluation criteria, the *preparation of the assessment* comes next. First, the assessment process should be outlined, which includes defining who will evaluate the use cases. To evaluate the complexity and costs of a use case both data analysts and IT experts should be involved. Furthermore, the strategy development team needs to decide about the format of the evaluation (e.g., questionnaires, workshops, or interviews). It is also important to decide whether the evaluation is done for each use case individually or for clusters of use cases. Afterwards, the use cases need to be prepared for the evaluation. Based on the evaluation criteria, the use cases must be detailed together with the relevant stakeholders. The use case template supports the identification and documentation of all relevant details for a use case. Overall, it is important to ensure that all use cases are on the same level of detail in order to enable an equivalent comparison of the use cases.

The results of Step 4 and the use of modelling techniques like the data or service blueprint help to detail the use cases. In addition, consecutive use cases should be identified because some use cases might require the previous implementation of other use cases. Therefore, it would not be suitable to evaluate the feasibility and attractiveness of the "final" use case without looking at enabler use cases. If dependencies exist, then each group of consecutive use cases should be outlined. For each expansion stage, it must be clear which use case is needed to reach the final use case. For use cases that aim to provide benefits for external stakeholders (e.g., monitoring of the product's performance or theft protection), an idea of the business model should be available. Different approaches exist that help to derive business models for connected products and IoT (e.g., Dijkman et al. (2015) or Bucherer and Uckelmann (2011)). For documenting the underlying business model, the business model canvas (Osterwalder and Pigneur, 2013) or the data-enhanced business model canvas can be used (Benta et al., 2017).

After the preparation is completed, the next task is to *conduct the evaluation* of the use cases. As mentioned earlier, it is possible to evaluate use cases in a qualitative or quantitative way. Depending on the availability of use phase data, it is important to test use cases that are shortlisted (Wirth and Wirth, 2017, p. 34). The prototypical implementation of use cases allows for first insights concerning the feasibility and required effort. Therefore, the development of use case prototypes can reduce the risk of selecting use cases that cannot be implemented later on. Another important aspect to consider during the evaluation is the amount of use phase data that would be generated for a certain use case. It is important to understand how long use phase data needs to be stored in order to provide use cases in the future. An indicator for this can be the average lifetime of a product. One option is to use a scoring method to evaluate the criteria for feasibility and attractiveness. Due to the variety of aspects to consider, one stakeholder might not be able to assess all criteria for a use case. However, using a scoring method and the evaluation criteria allows having a comprehensive assessment of use cases or use case clusters. Figure 6-21 illustrates exemplary results of a use case evaluation using a scoring approach.

	Value for the customer	Innovation	Complexity of realisation	Costs of realisation	Business potential	Relations to other use cases	Time horizon for implementation	Sum
UC #30 Remote support package "Data analyst"	4	3	3	4	4	4	4	26
UC #29 Remote support package "Emergency basic"	3	1	4	5	3	4	4	24
UC #11 Integrated service contracts	5	3	2	2	4	4	3	23
UC #21 Pay for performance	5	5	1	1	5	5	1	23
UC #26 Prognoses for spare parts	3	2	3	4	4	3	3	22
UC #27 Reduce over-engineering	1	1	3	3	2	2	3	15
UC #37 Surveillance of product quality	1	2	2	3	1	4	2	15
...	...							...

Legend: Very bad, Bad, Neutral, Good, Very good

Figure 6-21: Exemplary assessment of use cases using a scoring approach

A second approach for the evaluation is a cost-benefit analysis. Depending on the remaining use cases and objectives of the use phase data strategy, a detailed cost-benefit analysis for the remaining use cases on a quantitative level might be relevant. The general objective should be that the benefits (financial and non-financial) exceed the costs required for development, implementation, and operation of a use case or a cluster of use cases (consecutive use cases that require an implementation together). Depending on the use phase data maturity of the company, the implementation of use cases might require significant investment. Therefore, a structured cost-benefit analysis is important in order to ensure an informed selection of suitable use cases. A collaboration with an industry partner and student project (Straub, 2018) helped to derive a comprehensive approach for a cost-benefit analysis of use cases. Investing in a use phase data strategy generally should entail that the benefits exceed the costs. Therefore, the main objective of the approach is to enable a uniform and transparent evaluation of individual use cases, but also the evaluation of clusters of use cases. The approach should also allow for the rough testing of possible business models. Figure 6-22 depicts the general process for conducting a cost-benefit analysis of use cases. The approach for the cost-benefit analysis consists of four process steps: benefit evaluation, cost estimation, cost allocation, and cost-benefit assessment. Appendix A6.14 provides further information on the approach. The following paragraphs briefly describe the individual steps of the cost-benefit analysis.

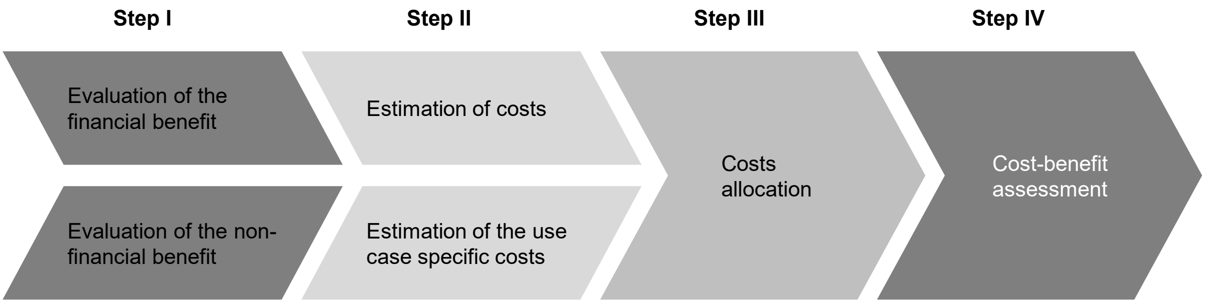


Figure 6-22: General process for a cost-benefit analysis of use cases (based on Straub (2018))

Step I of the analysis is an assessment of the financial and non-financial benefits of each use case. Understanding the non-financial benefits is challenging because they are intangible, but at the same time important for the overall success of a company (Kaplan and Norton, 1996, p. 75). Exemplary categories for a non-financial assessment are provision of customer support, innovation, process improvement, or support for employees. Financial benefits can be an increased turnover (e.g., additional earning through services or increased product sales) or reduced costs (e.g., reduction of over-engineering which allows for using cheaper parts). However, time is also important when analysing the financial benefits because accelerating a process can also lead to a reduction of costs. Overall, the assessment of the financial and non-financial benefits should be done in workshops or interviews involving relevant stakeholders.

Afterwards, Step II is to estimate the associated costs of implementing a use case or a cluster of use cases. Figure 6-23 provides an overview of possible cost categories for use cases. The categories highlight that costs can occur at many different points during the development and operation phase of use cases. In addition, the figure highlights that not only should the costs that occur throughout the process from data collection until data exploitation be looked at, but also the costs for support and organisation (e.g., training of employees or development of a new sales strategy). The company needs to decide whether it requires external support (e.g., development of a connectivity module). Even though the company plans to use external input, it is still important to understand the related costs (Wierse and Riedel, 2017, p. 378). The focus should be on obtaining rough cost estimations for all use cases. However, at this stage it is not possible to have a detailed estimation of the costs because the use cases require further detailing. Therefore, the focus should be to identify cost drivers that significantly influence the costs during the development and operation phases. Afterwards, the costs for all use cases should be estimated. The next task of Step II of the cost-benefit analysis is to derive ratios that allocate the overall costs to clusters of use cases and, later, to individual use cases based on their contribution to the overall costs. However, allocating the costs for IT infrastructure, and service and organisation to use cases individually might be difficult because all use cases require an IT infrastructure. A solution might be an equal allocation of these costs among all use cases.

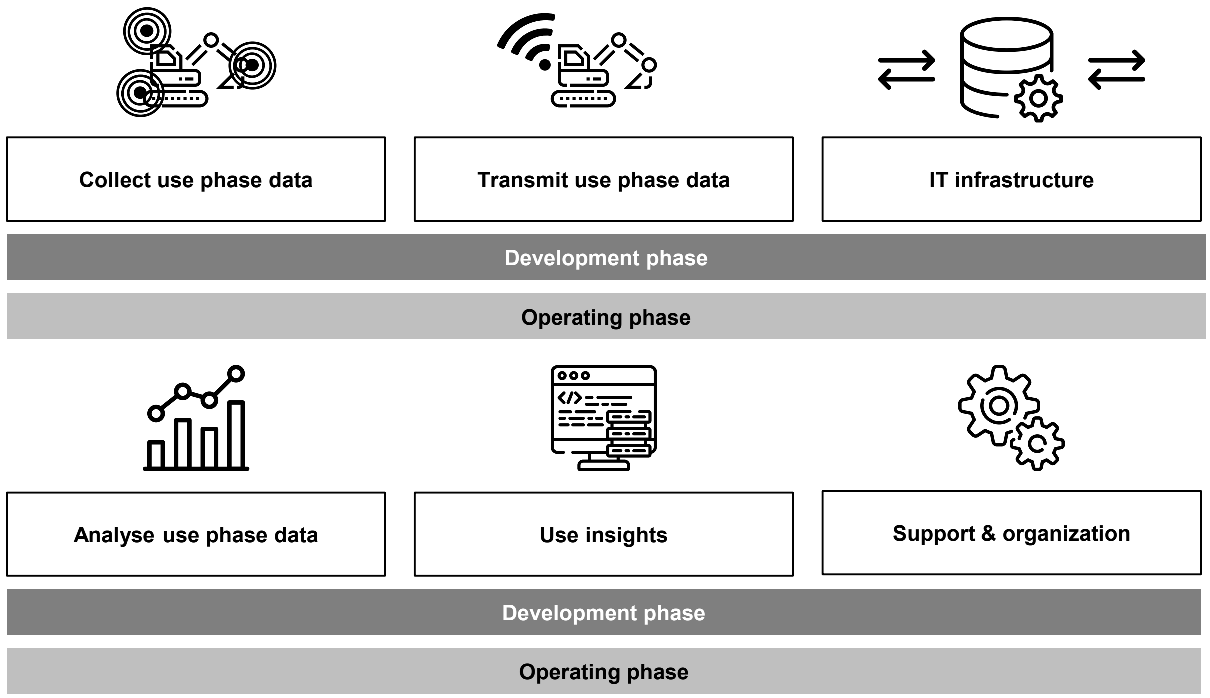


Figure 6-23: Categories for an analysis of the use case-related costs

After obtaining an overview of the overall costs and the ratios that allocate the costs to the different use cases, Step III of the cost-benefit analysis is to calculate the costs caused by a use case and a cluster of use cases.

The final task is the cost-benefit analysis during Step IV. The analysis consists of a financial and a non-financial part. It is only possible to compare financial benefits and costs on a quantitative level. For non-financial benefits, a qualitative evaluation is only possible because it is challenging, for instance, to express an increase in customer satisfaction with a numerical value. Overall, it is important to conduct a qualitative cost-benefit analysis for the non-financial aspects. In the case that ideas for an underlying business model for the use cases exists, the cost-benefit analysis should also evaluate how long it takes until the profits exceed the costs linked to a use case. Successful strategy development also involves thinking ahead and considering different scenarios for the future (Gausemeier et al., 2016, p. 17). Therefore, the cost-benefit analysis should also involve an assessment of different future scenarios in order to use different options that drive the cost savings and benefits (e.g., lower costs for data storage, cheaper data transmission, or willingness of customers to pay for certain services). Overall, the cost-benefit analysis provides a comprehensive foundation for the selection of suitable use cases that add significant value.

Then, the next task is to perform a risk assessment. Understanding the risk is an important task during the detailed assessment of ideas (Herrmann and Huber, 2013, p. 176). The development of new products and ideas always happens under uncertainty, which leads to risk (Sommer et al., 2008, p. 439). Understanding the uncertainty helps to make better informed decisions (Vose, 2008, p. 3). However, risks do not exclusively have a negative impact on projects because talking risks also leads to new chances for companies to be successful (Oehmen, 2016, p. 59). Looking at the risk does not only involve evaluating technical aspects, but also stakeholders. The risk should be assessed from sociotechnical perspective that takes the following elements, amongst others, into account: environment, management and organisation, humans, software and hardware (Rausand, 2013, pp. 12–13). Risk management aims to support companies in dealing with risk, which includes performing a risk analysis, risk evaluation, as well as risk control (Rausand, 2013, pp. 7–10; Sommer et al., 2008, pp. 446–448).

The first task is to identify the possible risk related to each use case, but also to look at the risks connected with the development and implementation of a use phase data strategy overall. To identify potential risks of innovation projects, the following three risk categories should be considered: business and market risks, technology and product risks, and project risks (Rafinejad, 2007, pp. 328–329). The first category contains risks like the decreasing acceptance of use cases by users or increased competition. Especially in innovative environments, it is important to assess the risk of competitors entering the market with similar products (Adner, 2006, p. 100). Due to the fact that connectivity of products and data analytics are trends for research and industry, the likelihood of this risk should be considered. In addition, innovation can also lead to new dependencies with suppliers (Adner, 2006, p. 100). Companies unexperienced with exploiting use phase data, for instance, might be in need of an external partner that performs the data analytics tasks.

The second risk category includes aspects like technological maturity, safety, or product performance. For use cases that build upon connectivity, it is also important to assess risks related with information technology (Macaulay, 2016, p. 1). Cyberattacks or data theft are only two examples of risks that can occur due to the connectivity of products and services. Macaulay (2016) provides a detailed approach to evaluating and managing the risk related to the IoT. The third risk category includes schedule overruns or resource shortage. Exploiting use phase data might require a set of data analytics skills that is not available within the company. At this point, the risk can only be assessed for a singular use case, but later on this should also be done for the developed use phase data strategy. In general, a wide range of approaches exist to identify potential risks (Vose, 2008, p. 5). It is therefore important to apply suitable approaches in order to identify the risks related to the different use cases.

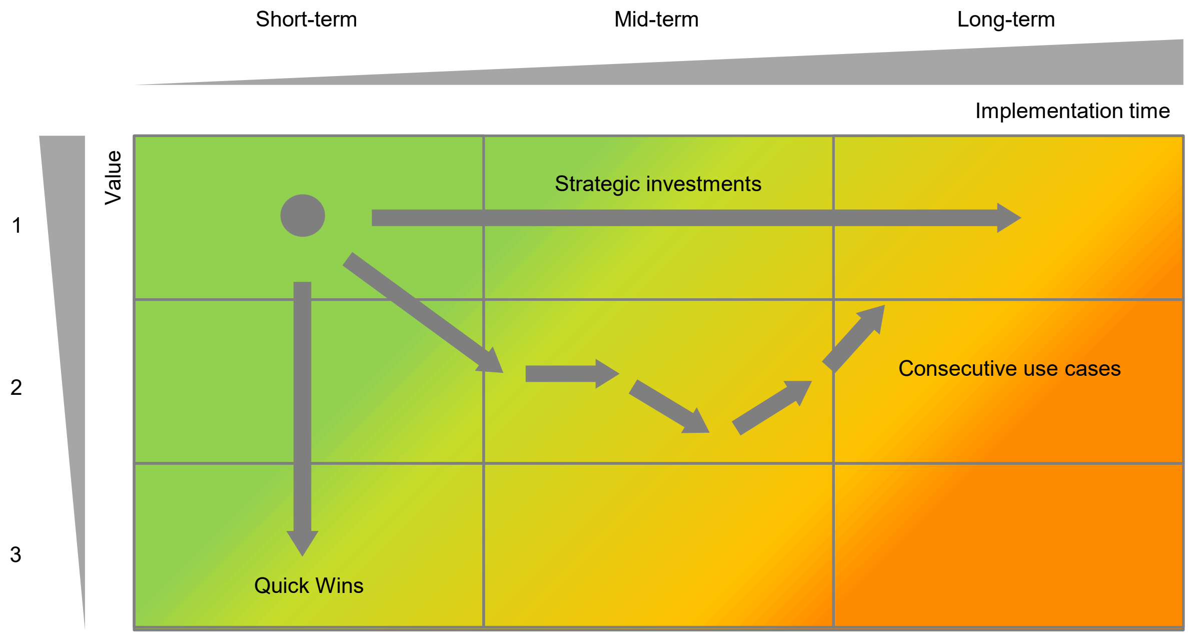
After all of the potential risks are identified, the next step is to evaluate them. In innovation projects, risks should be evaluated based on the following three criteria: impact on the company's performance indicators (e.g., customer reputation or use case costs), difficulty to resolve an occurring risk, and likelihood of occurrence (Rafinejad, 2007, p. 329). Each criterion should be assessed using a scoring system. By multiplying the different scores for each risk, it is possible to compare the different risks.

Afterwards, the next step is to decide how the risks should be controlled. However, risk can be divided into controllable and uncontrollable ones (Sommer et al., 2008, p. 448). In the case that a risk can be controlled, three options to deal with a risk exist: risk avoidance, risk mitigation, or risk transfer. For each relevant risk, a decision should be made about how the company wants to deal with it. The analysis might reveal that some risks occur across use cases (e.g., data theft) and others might be use case specific. The final task is to document the findings for the risk management.

Before proceeding with the selection of use cases, it is important to *check the results of the assessment* and to *ensure a comprehensive documentation*. The use case template is suitable for documenting the evaluation results for each use case. Nevertheless, the assessment of ideas happens under uncertainty and novel ideas especially bear the risk that the intended outcomes are not reached. Conducting a sensitivity and plausibility analysis can help to ensure a correct and sound evaluation (Lindemann, 2009, pp. 188–189).

The last task of Step 5 is the **selection of use cases**. The previous steps revealed a range of possible use cases, but it is important to select a set of use cases now that provide worthwhile value for internal and external stakeholders. It is also important to select a set of use cases that can be implemented in a defined timeframe because continuing with a very large set of use cases will cause the implementation to be highly complex. The first task of this process step provides a detailed evaluation of the use cases concerning their feasibility and attractiveness. Furthermore, a cost-benefit analysis is available. In addition, the related risks are known for the use cases. The selection of suitable use case now builds upon these results. Based on the objectives defined for the use phase data strategy, using weighing factors for the different criteria can help to define focal points for the selection of use cases.

To prepare for the selection of use cases, it helps to *visualize and summarize the evaluation results*. A portfolio analysis using portfolio matrices is a suitable approach to contrast different alternatives in a visual way and therefore support the selection of alternatives (Mikkola, 2001, p. 423). A main challenge when using portfolio matrices is to select suitable variables for the axis of the matrix that ensure orthogonality. When dealing with innovative ideas, different perspectives exist for assessing them. The same goes for the selection of use cases because the strategy development team needs to decide about relevant variables based on the main objectives of the company. An exemplary situation can be to select the use cases based on the value that they provide and time horizon required for an implementation. Figure 6-24 shows a portfolio matrix that can be used to contrast the use cases based on these two variables. The matrix can help to highlight three different types of use cases: quick wins, strategic investments, or consecutive use cases. Use cases that serve as quick wins provide a high value for internal or external stakeholders and at the same time require little time for an implementation. In contrast, strategic investments also provide a high value, but involve a longer implementation time. In addition, the portfolio matrix allows for the visualisation of consecutive use cases by showing which use cases must be implemented in order to enable other use cases. Thus, it is possible to take intermediate steps, which ensures that the initial benefits do not only occur far into the future. It is important to select use cases that provide value fast (Gao et al., 2015, p. 9). However, there are also other options for visualising use cases in a portfolio matrix. Another possibility is to contrast the effort required and value of the remaining use cases. The approach for the cost-benefit analysis provides suitable input for this matrix.



Legend:
Value: 1 = direct customer demand, 2 = improvement of customer experience, 3 = supporting
Implementation time: short-term = up to 6 months, mid-term = up to 2 years, long-term = 2 years and more

Figure 6-24: Portfolio matrix to visualize the results of the use case evaluation (based on Kalla (2017, p.89))

Hsuan and Vepsäläinen (1999, pp. 60–61) suggest another portfolio matrix for R&D projects, which is depicted in Figure 6-25. The first dimension is the competitive advantage, which indicates the competitive benefits that a company can gain through a technology or product design. Benefits to the customer is the second axis and indicates how suitable an alternative is to achieve customer satisfaction. The portfolio matrix allows for alternatives to be divided into four different categories: stars (desired due to a high value for the company and customers), flops (limited customer value and competitive advantage), snobs (high competitive advantage but only limited value for customers), and fads (high value for customers but low impact on the competitive edge of a company) (Hsuan and Vepsäläinen, 1999, pp. 62–63). In general, using visualizations is helpful to summarize the evaluation results.

Before selecting the use cases, it is helpful to *review the underlying motivation and objectives* for the use phase data strategy. To ensure that a consistent set of use cases is selected, different strategic alternatives exists that a company can take. Porter (2013, pp. 73–74) suggests that a company should either aim for overall cost leadership, differentiation, or focus. These three strategic positions should help companies to outperform competitors. The selection of the use cases thus needs to lead towards a use phase data strategy that generates competitive advantages. Concerning the related risks and opportunities of use cases, three different strategic options exists: no-regret moves, options, and big bets (Courtney et al., 1997, p. 76). The three options allow for the selection of use cases based on the risk a company wants to take and the uncertainty that future scenarios entail. Hax (2010, p. 15) suggests the delta model that consists of three strategic options: best product, total customer solutions, and system lock-in. The underlying assumption of the model is that customer bonding is the key for the future success of a company. The total customer solution option means that the company aims to satisfy almost all customer needs by offering relevant products and services (Hax, 2010, pp. 18–19). Nevertheless, the three possibilities help to define a strategic foundation for the selection of the use cases. Another important aspect to consider is that users and customers often expect benefits for them in order to motivate them to share their use phase data. Thus, combining use cases for internal stakeholders with ones for external stakeholders can help to increase acceptance. Afterwards, a team consisting of stakeholders that represent the different perspectives on use cases (e.g., engineering, IT, marketing, or business) should conduct the *final selection* of use cases. The last task is to *document* the selected set of use cases and the underlying reasons for the selection of the final use cases.

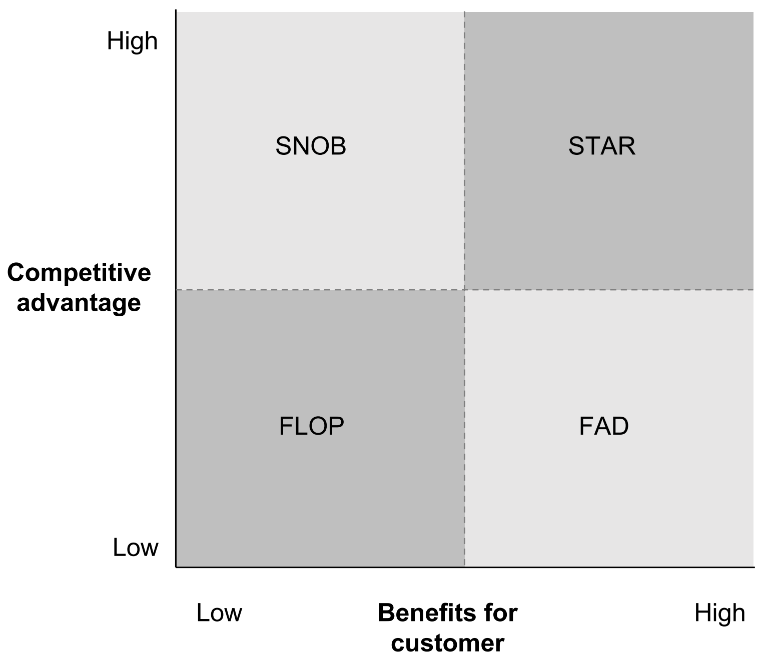


Figure 6-25: Portfolio matrix for R&D projects (derived from Mikkola (2001, p. 426))

The **main outcome** of this process step is a detailed evaluation of the use cases concerning their attractiveness and feasibility. Furthermore, the assessment of the profitability (cost-benefit ratio) of use cases also provides an initial indication for possible financial and non-financial benefits in comparison with the required efforts. The detailed assessment of the use cases is a prerequisite for an informed selection of use cases. Most importantly, the selection during this step provides the company with the final set of use cases that will be used to derive a use phase data strategy in the next step.

6.7 Step 6 – Formulate the data strategy and derive the roadmap for implementation

After selecting suitable use cases, this step merges the results of the previous steps in order to formulate the use phase data strategy and the implementation concept. The development of a roadmap helps to visualise the implementation concept, including the underlying time planning and related tasks for an implementation of the use phase data strategy. Step 6 is critical for the overall success of the use phase data strategy because the implementation significantly determines the value of a developed strategy (Peppard and Ward, 2016, p. 122).

The first task is now to **formulate a use phase data strategy** that is sound and fits to the company context. Deriving a use phase data strategy is essential in order to prepare the organisational implementation of the use cases. Having individual use cases with no defined strategy is not sufficient because without an overall framework the use cases have little impact. A use phase data strategy provides such a framework because it connects the selected use cases and adds an organisational perspective. The formulation of a strategy fulfils two tasks (Sternad, 2015, p. 3). On one hand, a strategy defines the objectives that a company plans to follow. On the other hand, a strategy also proposes how to proceed in order to reach these objectives. Four main tasks are required for the formulation of the strategy: drafting the strategy, checking the strategy, documenting the strategy, and implementing monitoring system.

The *drafting of the strategy* requires that all remaining use cases are linked together in order to derive the objectives of the overall use phase data strategy. Depending on the selected use cases, the use phase data strategy provides value for internal and external stakeholders. Therefore, it is important to formulate the objectives that the use phase data strategy wants to fulfil. The objectives should not only cover financial ones, but also non-financial ones (e.g., increased customer satisfaction). It is required that each use case therefore contributes towards at least one objective, which entails that it is important to outline the connection between the use cases and objectives of the strategy. In general, it is crucial that the objectives are complementary and do not conflict with each other (Grant, 2016, pp. 10–11). An important goal of the use phase data strategy is to ensure competitiveness in the future (Kaplan and Norton, 2009, pp. 80–81). Thus, it is important to outline the competitive advantage that the use phase data strategy aims to achieve. At the same time, the strategy must have a link to a product, market, or customer segment. The results of the SWOT analysis during Step 2 provide valuable input for outlining the intended competitive advantages of the strategy. The draft of the use phase data strategy ends with the textual description of the strategy, which should only consist of one or a few sentences that address important aspects and objectives (Kaplan and Norton, 2009, p. 81).

Volkswagen's strategy is an example of such a formulation "We are a globally leading provider of sustainable mobility" (Volkswagen AG, 2018).

A *check of the strategy draft* then follows in order to ensure that the strategy can be implemented. The check should look at the strategy from different perspectives and should include relevant stakeholders that did not participate in the development in order to ensure an independent assessment. Hungenberg (2014, pp. 276–278) suggests to check a strategy in terms of plausibility, fit, and feasibility. Evaluating the plausibility involves having a look at the underlying assumptions of a strategy. A developed strategy always builds upon assumptions about future circumstances. Therefore, it is important to assess the influencing factors for the strategy and the desired effects. An exemplary use phase data strategy might assume that customers are willing to share large amounts of their use phase data in order to benefit from certain services or product features. However, it might happen that the added value is not sufficient enough to convince customers to share their data. In addition, it is also advisable to review whether the strategy can lead to the intended financial benefits (e.g., increase in turnover). Strategies always face uncertainty, which is an opportunity and a challenge at the same time (Courtney et al., 1997, p. 79). Therefore, it is important that the underlying assumptions for the strategy undergo a critical review.

Evaluating the fit of the strategy aims to ensure consistency (Hungenberg, 2014, p. 277). First, the use phase data strategy should fit to the whole environment and consider external developments. In addition, the use phase data strategy must be consistent with the company context. The strategy must furthermore comply with the objectives that the team defined at the beginning of the project. A use phase data strategy also complements other strategies within a company. Therefore, it is critical to ensure that the use phase data strategy fits to the surrounding strategies (e.g., strategy or R&D strategy) and that no contradictions occur. Lastly, the use phase data strategy should help to address the overall vision of the company. Due to the fact that data analytics can provide value for different departments, the check should also ensure that the use phase data strategy does not conflict with other data analytics or IT strategies within the company (Köhler and Meir-Huber, 2014, p. 124). In order to assess the fit, the strategy development team should gather all relevant elements (e.g., R&D strategy), which should not be in contradiction to the use phase data strategy. The findings gathered during the definition of objectives during Step 1 can be helpful for this. For the assessment of the fit, the stakeholders who are responsible for the element, should participate in order to resolve contradictions.

The last criterion is the feasibility of the strategy (Hungenberg, 2014, pp. 277–278). The main task is to evaluate whether the company will be able to implement the use phase data strategy because an implementation requires a certain set of resources and skills. The analysis should therefore reveal if the company already has the required resources and skills, or at least will be able to procure them in the future. Based on the evaluation using the three criteria, the last aspect of the check is to carry out a risk assessment of the use phase data strategy. The risk assessment complements the assessment of the individual use cases that was part of Step 5. Therefore, it is possible to also apply the same risk criteria for the strategy: business and market risks, technology and product risks, and project risks (Rafinejad, 2007, pp. 328–329). The findings of the check help to adjust the use phase data strategy accordingly before proceeding.

After the use phase data strategy check is completed, the *documentation of the strategy* follows. It is important to document the strategy in a written way (Lombriser and Abplanalp, 2012, p. 34). A written document helps to increase the transparency concerning the use phase data strategy and supports stakeholders in aligning their activities with the activities required for its implementation (Lombriser and Abplanalp, 2012, p. 38). One possibility for documenting a strategy is to use a strategy map (Kaplan and Norton, 2004, pp. 9–10; Morabito et al., 2018, p. 365). The strategy map comprises the four perspectives of the Balanced Scorecard, which are: financial, internal business, innovation and learning, and customer (Kaplan and Norton, 1995, pp. 67–68; Kaplan and Norton, 2004, p. 9). The strategy map also considers the time-based dynamics of a strategy and therefore helps to link strategy development and implementation (Kaplan and Norton, 2004, p. 10). A main advantage is that the strategy map not only covers financial aspects, but also includes three non-financial ones, which ensures a more holistic description of the use phase data strategy. Figure 6-26 depicts an exemplary strategy map for the documentation of a use phase data strategy. The figure shows how the sub objectives for the finance, customer, process, and learning and growth perspective contribute to the overall objectives of the use phase data strategy.

However, for companies with technical products and related services, it is also important to understand how the use phase data strategy influences their technical products because use cases might, for example, add functionalities to the product. Thus, a use phase data strategy can also trigger the development of a new product generation. Therefore, it is important to highlight how the selected use cases complement existing or future products. Product profiles are a tool that help to describe product ideas in an early stage of the development process (Albers et al., 2018b, p. 256). Figure 6-28 illustrates the template for a product profile. Using a product profile allows for the description future products after the implementation of use cases. In general, the profile provides a description of, among other aspects, the product itself, benefits for users and customers, product attributes, and boundary conditions. The template also allows for documenting the link to other reference systems that offer similar use phase data-driven use cases. Therefore, it is possible to learn from existing solutions. Overall, using product profiles helps to establish a connection between the use phase data strategy, including its use cases, and the technical product and services. Therefore, a possible solution becomes more tangible and conflicts are more visible. It is thus possible to outline the additional value that certain use cases intend to add to the technical product. Depending on the number of use cases, it can be helpful to derive a set of product profiles with different combinations of use cases in order to discuss a variety of concepts.

Nonetheless, it is also important to document the impact of the use phase data strategy outside the technical domain because a use phase data strategy also has an impact on the organisation and its operation system. The operation system consists of activities, methods, processes, and resources required for reaching defined objectives (Albers et al., 2016, p. 101). Looking at the operation system in relation to the use phase data strategy that is being implemented can reveal, for example, that new processes are needed to support product development activities with use phase data. Applying process tailoring can help to identify the changes required, for example to the product development process (Hollauer et al., 2017, pp. 85–87). Afterwards, process tailoring can also help to design new process that fit to the use phase data strategy. Other implications might be that the company needs employees to hold certain skills or needs to hire additional employees. If the use phase data strategy builds upon a business model, using a business model canvas can help to document the underlying ideas (Osterwalder and Pigneur, 2013, p. 44). Overall, documenting the non-technical implications of the use phase data strategy is also important for the development of the roadmap in the next step.

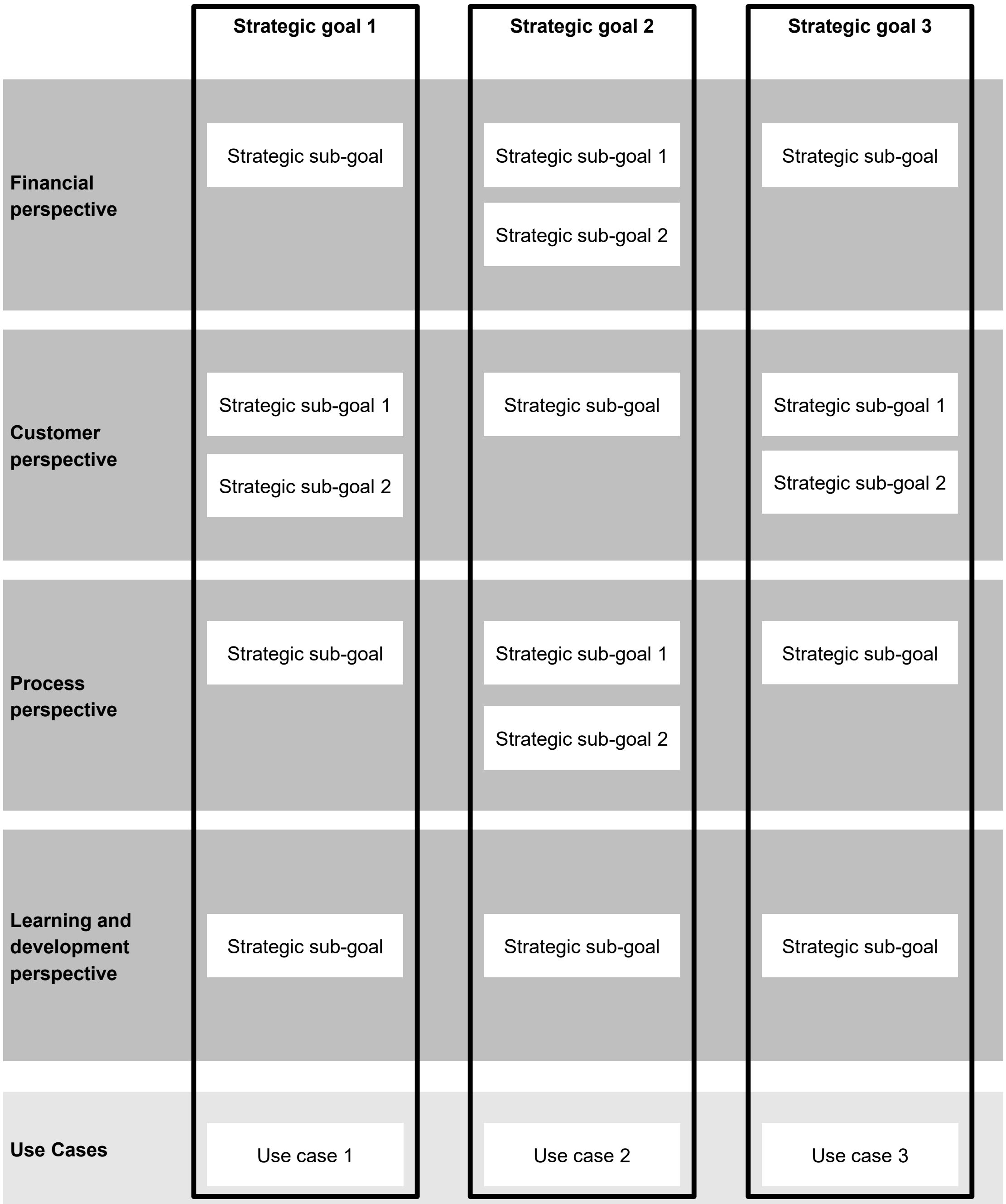


Figure 6-26: General template of a strategy map for the documentation of a use phase data strategy

Altogether, this task provides a textual description of the developed use phase data strategy. Based on the selection of use cases, the results also reveal how the strategy complements products, services, or the business model.

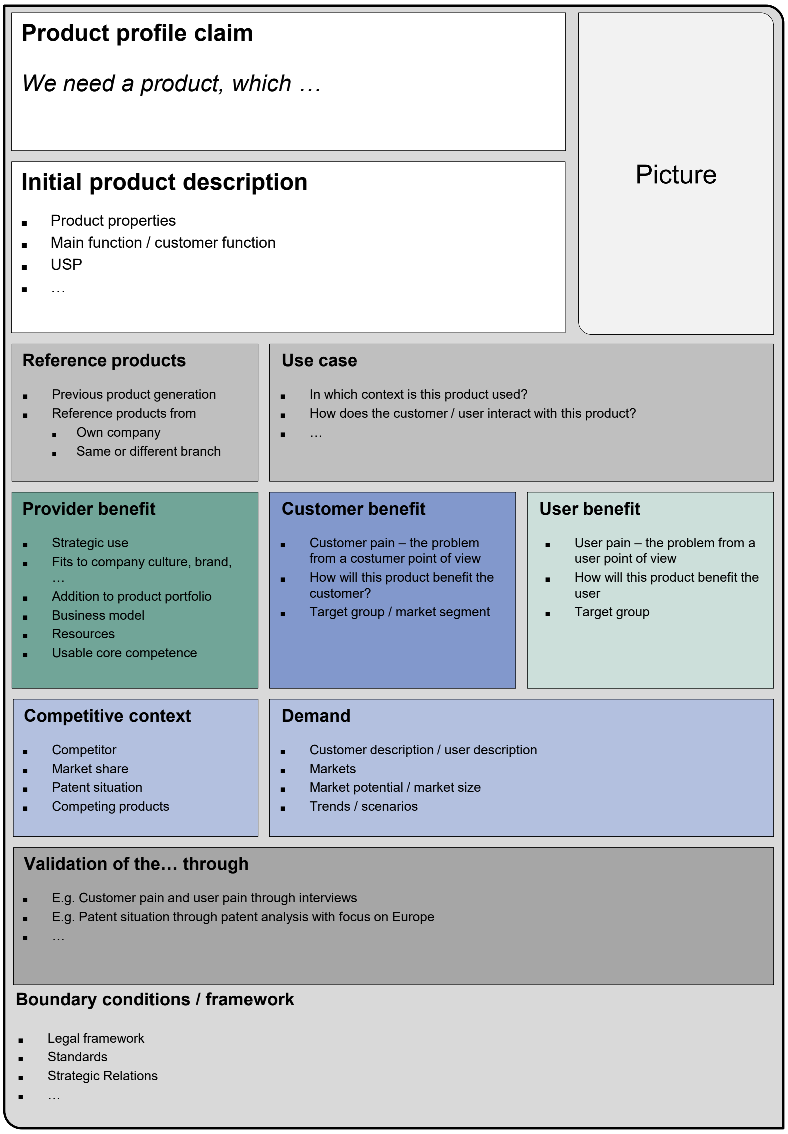


Figure 6-27: Product profile template to document a product idea (based on Albers et al. (2018b, p. 257))

The last task is to *establish a monitoring system* for the use phase data strategy. Defining key performance indicators (KPIs) allows for monitoring to which degree the main objectives are reached (Hille et al., 2016, p. 10). Furthermore, based on the uncertainty that a use phase data strategy faces, timed reviews help to ensure that the strategy fits to the internal and external conditions (Courtney et al., 1997, p. 79). Afterwards, it is essential to define who is responsible for the use phase data strategy and who is allowed to make decisions, because the use phase data strategy might require adjustments (Neilson et al., 2008, pp. 63–64; Schwaninger, 1987, p. 82). The last activity is then to *communicate the developed use phase data strategy* to relevant departments, projects, or stakeholders (Neilson et al., 2008, pp. 65–66).

After finalising the formulation of the use phase data strategy, the last task is to **derive a roadmap for the implementation concept**. The development of a strategy does not only require the definition of objectives, but also a description of a path towards achieving them. A clear plan is important for the implementation in order to estimate efforts, define milestones, and set deadlines (Schwaninger, 1987, p. 82). A main obstacle for analytics initiatives is that companies do not follow a systematic approach for the implementation (Colas et al., 2014, p. 7). As mentioned earlier, a use phase data strategy covers technical aspects (e.g., required IT infrastructure or use cases) and business aspects (e.g., service concept). Because a use phase data strategy is developed for a technical product and connected services, a clear link between the product strategy and the use phase data strategy is important.

A product-technology roadmap is a tool that addresses the aforementioned requirements because it combines business and technology strategy (Albright and Kappel, 2003, p. 31; Groenveld, 1997, p. 48). Roadmapping in general is used in many industries to support innovation and strategic management on a corporate and department level (Phaal et al., 2007, p. 3). This flexibility is ideal for use phase data strategies because they can address different parts of a company based on the organisational structure. Another important aspect is that roadmaps provide a cross-functional perspective (Groenveld, 1997, p. 48), which is especially relevant for use phase data strategies because they require that stakeholders with different perspectives work closely together.

Different types of roadmaps exist in literature, but technology roadmaps are one of the most commonly used ones (Phaal et al., 2004b, p. 6). Within the context of developing a use phase data strategy, use cases play a key role during the formulation of an implementation roadmap. The two main tasks of technology roadmaps are to analyse and communicate the links between technological resources, organisational objectives and environment (Phaal et al., 2004b, p. 9). Therefore, roadmapping helps to merge different perspectives that are required for the implementation of a use phase data strategy. In general, a technology roadmap consists of different vertical layers that are interlinked, but can also evolve individually (Phaal et al., 2004b, p. 14). Nevertheless, existing roadmaps from literature present only a starting point because a roadmap must always be tailored to the application and company context (Phaal et al., 2004a, p. 26). To prepare for the implementation of a use phase data strategy it is important to link the product strategy with the use cases. In addition, the roadmap should also highlight the internal changes that a strategy requires for implementation. Figure 6-28 depicts an exemplary implementation roadmap for a use phase data strategy. The developed roadmap consists of five different layers which can be further separated into internal and external ones (Wilberg et al., 2018b, pp. 9–10). The external layers (product and service, and application) are visible to customers and users. The application layer contains the use cases that the company plans to implement. The internal layer contains required tasks that need to be carried out to prepare the organisation for the use phase data strategy. The roadmap also describes the required changes to software and hardware. Lastly, one layer describes when certain data points will be accessible. A main benefit of this graphical representation is that it increases the transparency concerning the links between use cases, product strategy, and required activities for the implementation of the strategy. The roadmap also allows for the identification of a critical path that determines the implementation timeframe.

Nevertheless, the presented roadmap can only be a starting point because each company requires a tailored roadmap. Phaal et al. (2007, pp. 5–6) suggest a six-step process that uses workshops to derive a roadmap. For the development of the implementation roadmap, all relevant stakeholders should be involved that also participated in the strategy and use case development. Depending on the number of use cases, it might be helpful to derive roadmaps on different abstraction levels. One roadmap should include all use cases in order to highlight the dependencies among the use cases. However, this roadmap should be complemented by roadmaps for each use case that highlight required activities and time planning for each one on a more granular level. A roadmap however can only support the implementation if it is kept updated and therefore provides a current perspective (Phaal et al., 2004b, p. 21). Overall, the different implementation roadmaps for the use phase data strategy should provide a clear description of the time horizon, responsibilities, required activities, and the critical dependencies for an implementation. Because a roadmap represents the status at a specific point in time, it is important to update them in order to ensure, for example, that all prerequisites for a use case are fulfilled before it is implemented.

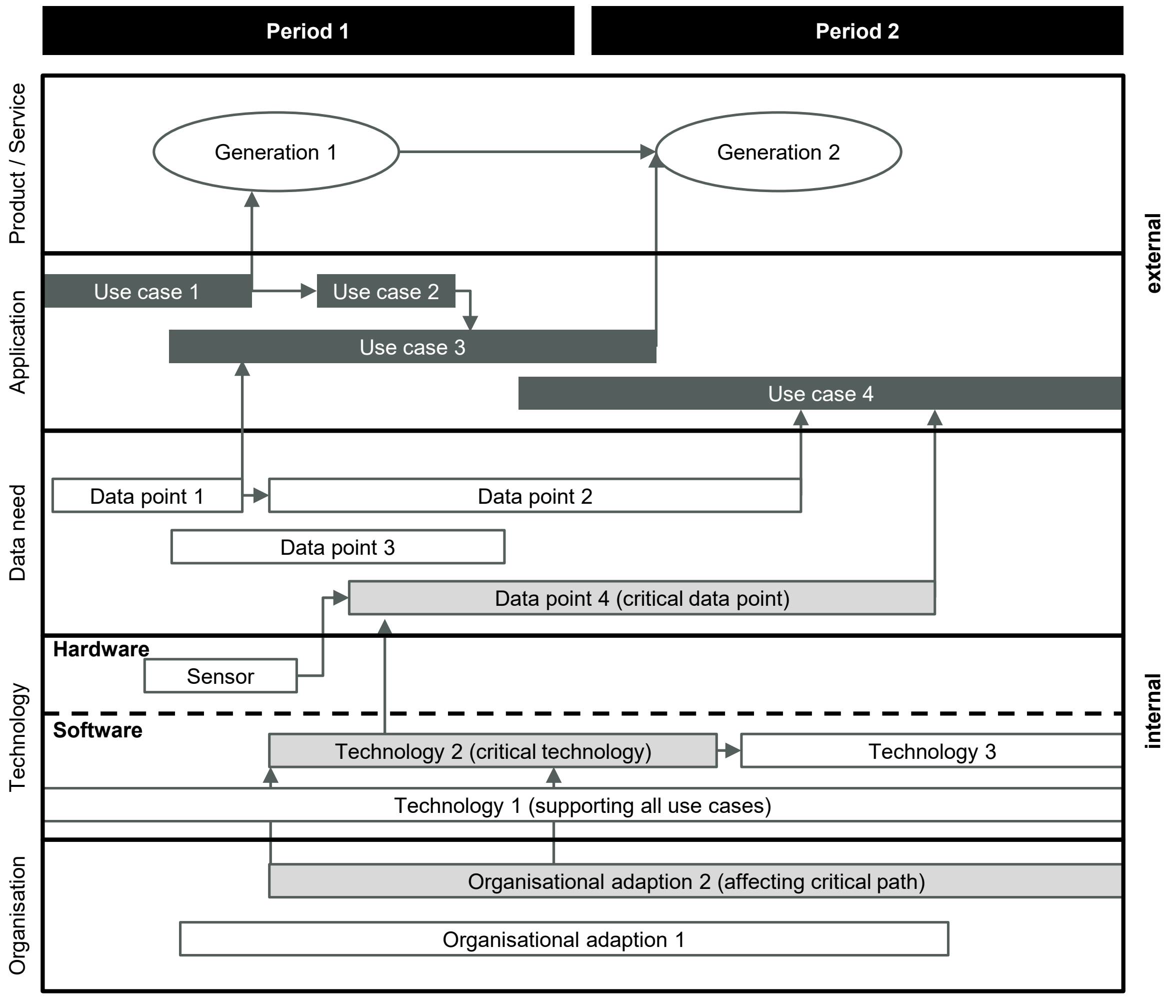


Figure 6-28: Exemplary implementation roadmap for a use phase data strategy (based on Wilberg et al. (2018b, p. 10))

The **main outcome** of Step 6 is a comprehensive use phase data strategy, which concludes the development process for the strategy and therefore provides important input for the following activities and tasks. The outcome is not only a written use phase data strategy, but also its depiction using a strategy map. In addition, implementation roadmaps highlight required activities and changes. In addition, the roadmaps link the use phase data strategy and product planning, which helps to describe how use cases will be integrated into products and services. Thus, the result is a sound use phase data strategy and a corresponding implementation concept.

6.8 Summary of the process model

Offering connected products and services can open up a variety of new opportunities for engineering companies. However, theoretical and empirical data reveals that companies struggle to exploit use phase data transmitted by technical products and services. The obstacles that companies face comprise of technical and managerial ones. The development of a use phase data strategy is vital for companies in order to ensure that use phase data is exploited in a systematic way. Existing research findings and empirical data helped to derive the process model, which the previous sections of this chapter introduced. The process model provides guidance for companies that want to develop a sound use phase data strategy that fits to the internal and external circumstances of a company. Therefore, the process model helps the companies to explore the range of possible use cases in order to turn use phase data into value. In addition, the process model supports the evaluation of the different use cases and helps companies to understand the related implications on an organisational and technical level in order to provide a decision support for the use phase data strategy.

The developed process model consists of six steps, which build on each other. Step 1 and Step 2 prepare the strategy development by defining the objectives for the development of the use phase data strategy and building an understanding of the internal as well as external environments that influence the development process. Afterwards, Step 3 focuses on identifying internal and external application areas for which use phase data can provide additional value. Understanding the possible application areas then helps to derive concrete use cases that allow for the exploitation of use phase data. A detailed analysis of the required data for each use case and the consolidation of the set of use cases follows in Step 4. Then Step 5 focuses on gaining a detailed understanding of the use cases, which enables them to be evaluated in terms of attractiveness and feasibility in order to select the final set of use cases. The process model concludes with the formulation of the use phase data strategy and the development of a roadmap describing the implementation concept.

The main contribution of the process model is that it enables companies to develop a use phase data strategy in a systematic and methodical manner in order to benefit from use phase data. To achieve this, the process model fosters a structured collection, elaboration, and selection of use cases. Furthermore, the process model helps to reveal the gap between required and available use phase data, which provides companies with a clear understanding of the activities and efforts required in order to implement the developed use phase data strategy.

In summary, the process model provides comprehensive guidance concerning the development of a use phase data strategy. The complementary manual for the process model increases its applicability and provides a brief summary for each process step. The process model further supports the strategy development process by providing methods and tools that are tailored to the tasks. Applying the process model aims to facilitate engineering companies to derive a use phase data strategy that provides additional value for relevant internal and external stakeholders. Overall, the intention of the use phase data strategy is to lead to competitive advantages for companies and a successful exploitation of use phase data.

7 Industrial evaluation of the developed support

After introducing the developed process model and the supporting methods in the previous chapter, the objective of this chapter is to present the results of the industrial evaluation of the developed support. Section 7.1 therefore introduces the overall evaluation concept and briefly describes the industrial evaluation cases. Then Section 7.2 discusses the first evaluation case that involves the application of the process model for the development of a use phase data strategy at a provider for connectivity solutions for laundry rooms. Afterwards, Section 7.3 outlines the findings of the second evaluation case at the washing machine department of a home appliances manufacturer. The following Section 7.4 introduces the results of the third evaluation case at the dishwasher department of a home appliances manufacturer. Afterwards, Section 7.5 summarises the results of an interview-based evaluation with a railway company. Then, Section 7.6 concludes the industrial evaluation with a discussion of the evaluation results obtained during evaluation. In addition, the last section derives advantages and shortcomings of the developed process model.

7.1 Evaluation design and overview

The developed process model and the supporting methods address the identified research gap and aim to enable companies to develop a use phase strategy in a systematic and methodological way. The final research task is to perform an evaluation of the developed solution approach in order to show that the process model helps to overcome planning and managerial challenges. Therefore, the objective of this evaluation is to assess whether the process model and the methods fulfil the defined functional, formal, and application requirements (see Section 4.2).

In general, the evaluation of a solution approach aims to show that the support can be used within the intended context (**application evaluation**) and that the solution approach delivers the intended value (**success evaluation**) (Blessing and Chakrabarti, 2014, p. 181). Furthermore, the evaluation should outline the potential to further improve the process model and its methods. A prerequisite for an application and success evaluation is the support evaluation (Blessing and Chakrabarti, 2014, p. 184). The support application is part of the development process for the solution approach and aims to ensure that the approach meets the defined requirements (Blessing and Chakrabarti, 2014, pp. 176–177). Within the context of this work, the three orientating case studies helped to carry out the support evaluation and gain initial feedback (see Section 5.2). Because the support evaluation was already completed, this section focuses on the application and success evaluation of the developed process model and the supporting methods.

The **application evaluation** includes assessing the **applicability** as well as **usability** of the developed process model and its integrated methods (Blessing and Chakrabarti, 2014, pp. 184–185). Within the context of this thesis, the evaluation of the applicability should confirm that companies could apply the developed process model in the intended situation, which means the development of a use phase data strategy. The assessment of the usability should confirm that users are able to understand the developed process model and that users have all relevant information for its application. Afterwards, the next step is the **success evaluation**, which aims to investigate whether the process model is able to fulfil the defined objectives (Blessing and Chakrabarti, 2014, p. 185). Within the context of this work, that means to evaluate whether the developed process model helps companies to derive a use phase data strategy that allows them to better exploit use phase data. However, it is important to mention that the success evaluation is challenging because positive effects sometimes only occur after a long time (Blessing and Chakrabarti, 2014, p. 185). The process model supports companies in developing a use phase data strategy, but the effects (e.g., increase in turnover) only occur after the strategy has been implemented. Therefore, it will only be possible to perform an **initial success evaluation** that builds upon predictions about the positive effects of a developed use phase data strategy.

The overall research objective was to provide methodological support for companies in order to enable them to develop a use phase data strategy. Therefore, the decision was to evaluate the developed process model using **case studies** in order to assess whether the process model supports companies in the intended way and is applicable in practice. Although case studies cannot be as rigorous as formal experiments, they can nevertheless provide valuable insights about the benefits that a support provides (Kitchenham et al., 1995, p. 53). The decision was to conduct multiple case studies in order to assess of the applicability and usefulness of the developed process model under different conditions. Furthermore, using independent case studies helps to gain a differentiated picture of the benefits and drawbacks of the developed support, which helps later to derive suggestions for improvement. Overall, using different cases studies also allows for testing the process model in different company settings.

For preparing case study based research, the **selection of suitable case study partners** is important (Yin, 2014, p. 25). The process model is intended to support engineering companies that already are already having or planning to have connected products (see Section 4.2.1). Therefore, a selection criterion was that the case study partner must sell a mechatronic product that already has a connectivity module or will have such a module in the future. Furthermore, it was important that the potential case study partner was willing to collaborate closely and provide access to relevant, internal information in order to ensure a comprehensive application and evaluation of the process model. Table 7-1 provides an overview of the four industrial evaluation cases for this research, which were selected based on the afore mentioned criteria. The first three cases focused on a case study-based application and evaluation of the entire process model. The fourth evaluation case was an interview-based assessment of the process model. Due to confidentiality reasons, it is not possible to provide the names of the companies.

Each of the three case study based evaluations were part of a six-month long student project. During these case studies, each student worked fulltime for six months at the respective company and therefore was able to develop a use phase data strategy that was tailored to the specific context. Each student had access to the same version of the process model and the integrated methods. Using student projects for the evaluation cases helps to involve a stakeholder that was not influenced by the company environment or the research environment before, which helps aims to increase the objectiveness of the evaluation cases.

The company being part of the **first evaluation case** offers a connectivity solution for laundry rooms of apartment houses. It is also important to mention that the first case study partner is a subsidiary of the company at which the second and third evaluation cases took place. However, the first company develops products and services independently.

A collaboration with a large manufacturer for home appliances served as the input for the **second** (washing machines) and **third evaluation case** (dish washers). Even though the second and third case study were done at the same company, they serve as individual evaluation cases due to the following reasons. Firstly, each evaluation case took place within a different product division. Within the company, each product division has its own strategy as well as product roadmap. Therefore, each division has a certain degree of independence. Secondly, the product management department for washing machines provided the context for the second evaluation. The third evaluation case took place in collaboration with the predevelopment department for dishwashers. Each of the two departments has accordingly different roles and responsibilities as well as working on different products.

The three evaluation cases all took place within the home appliances sector. Therefore, the decision was to conduct an additional **fourth**, **interview-based evaluation** with a different industry sector in order to avoid that the characteristics of the home appliances sector influence the evaluation results. The partner for the interview-based evaluation was a large railway company from Germany. The interview-based evaluation used the same version of the process model in order to ensure a comparability with the three evaluation cases.

Table 7-1: Overview of the four industrial evaluation cases

Characteristics	Evaluation case 1	Evaluation case 2	Evaluation case 3	Evaluation case 4
Scope	Connectivity solutions for laundry rooms	Washing machines	Dish washers	Train repair and maintenance
Industry sector	Home automation	Home appliances	Home appliances	Railway
Evaluation format	Case study-based application of the entire process model and relevant methods for the development of a use phase data strategy			Interview-based discussion of the process model
Company size	15 employees	~ 50,000 employees	~ 50,000 employees	~ 300,000 employees
Department	Operations	Product management digital services	Pre development	Connected production system
Business relation	B2B	B2C	B2C	B2C
Availability of use phase data	Yes	Yes	Yes	Yes

The intention of the **first three evaluation cases** was to conduct the application and initial success evaluation. During each case study, a combination of methods (e.g., interviews, workshops, or presentations) helped to gain the relevant insights and information. A questionnaire and additional interviews allowed for an evaluation of the developed solution approach and the case study results. Appendix A8.1 illustrates the questionnaire that was used for all three case studies. The questionnaire consists of the following six sections: usability, applicability, usefulness, evaluation of the case study process and the case study results, evaluation of the supporting methods, and complementary open questions. The three evaluation dimensions (applicability, usability, and usefulness) (Blessing and Chakrabarti, 2014, p. 37) and the requirements for the solution approach (see Section 4.2) served as the foundation for the questionnaire. The evaluation of the developed methods was made based on their application during each case study. The questionnaire, however, also had open questions to analyse the main benefits, drawbacks, and learnings of the solution approach and case study. In addition, interviews with key stakeholders of the case study helped to elaborate on the evaluation results and clarify the feedback given. The **fourth evaluation case** used a semi-structured interview to evaluate the process model and the methods. Appendix A8.5 lists the guiding questions used for the interview at the railway company.

The following three sections describe the first three evaluation cases. At the beginning, each case study partner is briefly characterised in order to provide an understanding of the case study context and the motive of the company for developing a use phase data strategy. Afterwards, the main activities and the results for each of the six steps of the process model are described. The last part of each evaluation case discusses the evaluation results and the related learnings. Then Section 7.5 summarizes the findings of the interview-based evaluation.

7.2 Evaluation case 1 – Home automation sector

This section describes the first evaluation case at a company that offers connectivity-based solutions for community laundry rooms. Furthermore, this section summarizes the case study results and findings of the evaluation. The evaluation was six months long and was part of a student project (Koch, 2018). During the case study, all process steps were passed.

7.2.1 Introduction of the case study company

The case study partner is a German start-up from the IoT sector whose office is in Munich. The company was established in 2016 and is a subsidiary company of a large manufacturer of home appliances. Offering combinations of physical products and services for operating communal laundry rooms is the core business of the company. The product offered by the company is a device that connects the washing machine with the electricity plug and thus controls the power for the washing machine. At the time of the case study, the company had 15 employees that mostly work in sales, operations, and software development. Currently the company already offers connected products and therefore collects use phase data. In addition, the case study partner is still quite young and thus unused potential exists in many areas. One of the company’s main objectives of the case study was to explore how use phase data could improve current operations and how it could be exploited in general. Due to this, the company was well suited for a case study and an evaluation.

7.2.2 Step 1 – Initiate the project and determine the objectives

Setting-up the project and deriving the main objectives for the use phase data strategy development projects are the main intentions of the first step.

Initiate the project

During this case study, the student was the project manager. Due to the interdisciplinary nature of a use phase data strategy, employees from the operations, sales, marketing, finance, and software development department joined the project team. The stakeholders were not always involved in every activity. The project sponsor was the COO of the case study company, which ensured that the project also involved someone with the authority to make decisions. Hardware development is not part of the case study partner's tasks because the hardware originates from an external company. Therefore, nobody from hardware development became part of the strategy development.

Determine the objectives

The overall objective of the company is to provide a reliable solution for communal laundry rooms. However, the decision was to avoid constraining the search for use cases at this early point. Based on discussions with the management of the company, the main objective was to explore the wide range of possibilities for exploiting use phase data because the case study partner did not extract much value from data and therefore wanted to obtain an overview first. A reason for the lack of exploitation of use phase data was that nobody was assigned with this task. The only limitation for the project was that the strategy should contribute to the company's success. Concerning the search for suitable use cases, the decision was to focus on use cases that the company could implement within one year of the project's start in order to understand the benefits that an exploitation of use phase data can confer. The underlying objective was firstly to take advantage of available use phase data, but also to understand the potential of use phase data quickly, without getting lost in complex use cases. Overall, the objectives of the project for the development of the use phase data strategy are twofold. First, the project should help to outline the potential that use phase data offers for the case study company and to highlight the range of possible use cases. Second, the project should provide a use phase data strategy with concrete use cases that support internal and external stakeholders.

7.2.3 Step 2 – Analyse the system and structure the situation

The main intention of the second step is to create internal and external transparency (i.e., competitive situation or available data) in order to create a foundation for the strategy development.

Analyse the system

The analysis of the systems starts with an analysis of the environment and an internal analysis of the case study partner. The PESTEL analysis helped to assess the macro environment (see Section 6.3). Concerning the social factors, the analysis revealed that the data privacy concerns of users need to be considered during strategy development. Urbanisation also presents an important factor because more and more people will live in large cities and will not have their own washing machines, which increases the need for communal laundry rooms and related solutions such as those that the case study partner offers. Concerning legal factors, the analysis highlighted the strong impact of data privacy rules on possible use cases. The analysis also showed that legal and political factors could constrain possible use cases. Overall, the findings highlighted that it is important to assess interesting use cases in order to ensure that they comply with the legal framework and user acceptance.

Analysing the industry sector and the direct competitors was the next step. The focus here was on companies with similar products and services. A key finding was that competitors existed that offer a similar product, but it also became clear that their technical maturity and market share was low. At the same time, the analysis also showed that competitors offer similar functionalities, but use different technologies. Afterwards, the next step was to assess the technology and services of competitors on a detailed level. The solutions of the competitors are often integrated into the washing machine, which means that competitors can most likely access more data coming directly from the machine. Thus, competitors might be able to implement additional use cases (e.g., health monitoring of the washing machines). Accordingly, the competitors might be able to gain advantages due to the better access to use phase data.

Group	Stakeholder	Interests & activities	Influence on project	Involvement strategy for project
Internal Stakeholders	Management	Reach corporate targets Planning and leading	Exchange of knowledge Provision of resources	Active integration – expert interviews
	Controlling	Reduction of costs Increase of revenues	Exchange of knowledge Provision of data	Active integration – expert interviews
	Sales	Increase sales Understand customers	Exchange of knowledge Provision of data	Active integration – expert interviews
	…	…	…	…
External Stakeholders	Parent company	Profitable investment Use knowledge of subsidiary	Exchange of knowledge Provision of data	Active integration – exchange
	Customer – user	Good washing results, high comfort, low costs	Understanding of interests Acceptance	Passive integration – analysis of interests
	Customer – partner	Satisfied user, low effort, low costs	Understanding of interests Acceptance	Passive integration – analysis of interests
	…	…	…	…

Figure 7-1: Results of the stakeholder analysis during the first evaluation case

Afterwards, the focus was to analyse the market and customers. The case study company works in a B2B segment, which means that the customer (buyer) and user are not identical. Therefore, it is important to highlight that the customer and user have different interests and expectations. It is possible to group customers based on their service needs (e.g., washing machines available or full service needed) or responsibility for the community laundry room (e.g., low involvement or participation). The main factors that helped to distinguish users were data privacy concerns, technological affinity, and usage channel. Thus, the expectations concerning functions and usability of the solution differ.

In order to complete the analysis of the system, the next task was the internal analysis. At the beginning, the goal was to assess the company's products. The case study partner offers two product variants to address the different needs of the buyers. The available use phase data is the same for both variants because the case study partner cannot access the data of the washing machines and dryers. The product offering of the company consists of the following three parts: power control device (electric switch with connectivity), App (booking of washing machines, payment, and status information) and the partner board (services for the owner of the laundry rooms). The device has only one sensor, which measures the current. Furthermore, the case study partner provides services for users (e.g., claim management, repair, maintenance, and organisation of a cleaning service).

Understanding the product lifecycle was another important preparation for the search for use cases. The case study partner already had a customer journey and user journey that highlight important interaction steps. It became clear at which steps context data (e.g., location of the laundry room) and use phase data are generated. Context data about the customer and user often enables certain use cases and allows for interpreting use phase data. Afterwards, a stakeholder analysis followed in order to have a clear overview of internal and external stakeholders. Interviews at the case study company highlighted the critical internal (management, development, sales, operations, and marketing) and external (parent company, certifier, legislative body, customer, and user) stakeholders that influence the use phase data strategy. Figure 7-1 provides an excerpt of the stakeholder analysis. The analysis also included an assessment of the particular interests of the stakeholders. The findings of the stakeholder analysis provided an important input for the search of use cases. The findings also confirmed that internal stakeholders saw high potential in better exploiting use phase data.

Afterwards, a comprehensive analysis of the IT infrastructure was conducted. The analysis showed that one central database existed that connected different tools. However, different departments used additional software tools, for instance for customer service or sales processes. The analysis also revealed that the database had performance limitations. Another finding was that no data analytics tool was used at the case study company. Accordingly, the assessment of the case study company's use phase data maturity concluded that it has a comprehensive set of use phase data, but limited analytics skills.

The last task was to analyse the business model and the strategy of the company. Offering a comfortable and modern solution for the reservation and billing of washing machines is the core value proposition. The key finding was that a use phase data strategy can contribute to the company's strategy and can help to improve the experience of customers and users.

Structure the situation

The last task was to merge the findings of the internal and external analysis in order to obtain a comprehensive picture of the current situation. The case study company already collected use phase data stemming from the products and services. At the same time, context data concerning products and users was available, which complemented the use phase data and helped to enable additional use cases. Figure 7-2 shows the data map, which is an abstracted visualization of available data. The depiction shows that the company already has a complex IT infrastructure. Even though the company enables the comprehensive storage of data, many databases were not connected. In addition, the analysis also indicated that relevant data points were not collected and very little value is currently extracted from use phase data.

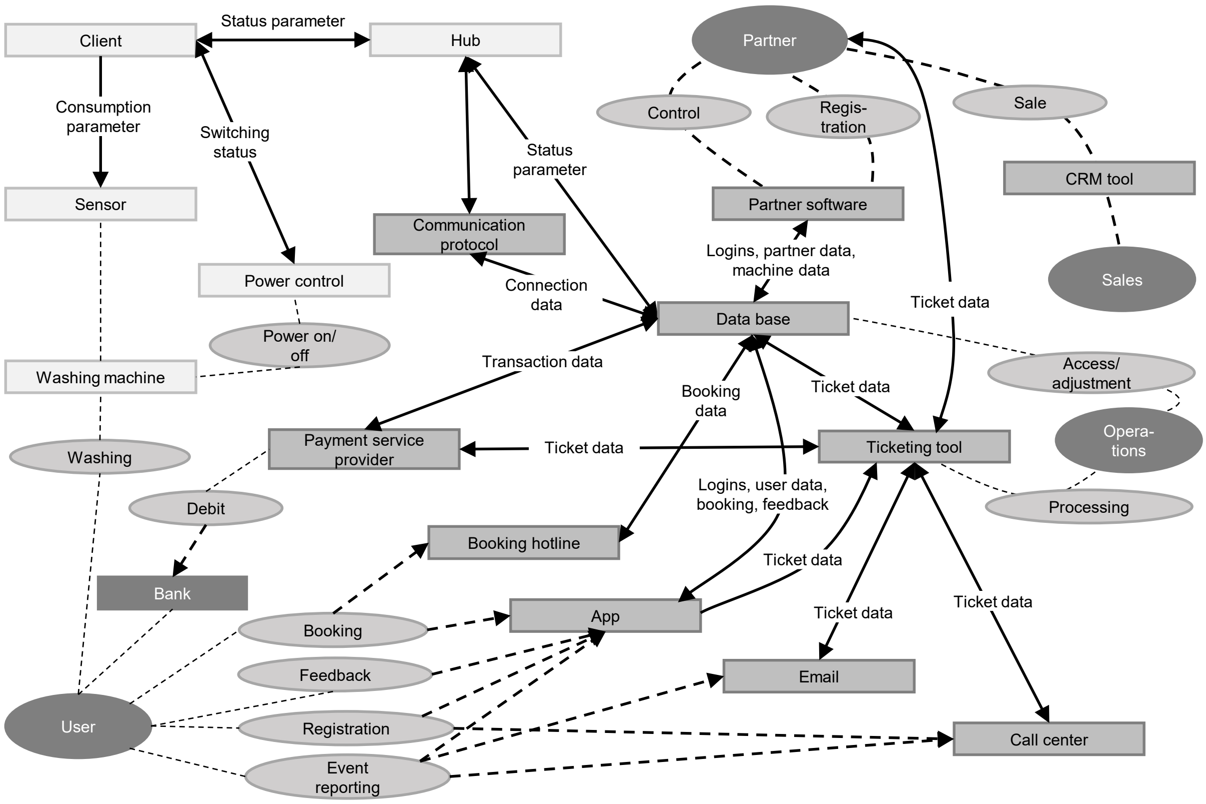


Figure 7-2: Depiction of the developed data map

The last task to conclude this step was to perform a SWOT analysis. A main strength of the case study partner was that a variety of use phase data was already available. However, a clear weakness was that little value was extracted from the available use phase data, which was also because of missing data analytics experience and the limitation of the IT infrastructure. From an external perspective, an important opportunity was that competitors did not have a technological lead. The case study partner also faces risks because data privacy rules and a lack of user acceptance can significantly hinder the exploitation of use phase data.

Overall, the comprehensive internal and external analysis was very valuable for the case study partner because it became clear that much data was already available, but so far, little value was extracted from it. Interviews also confirmed the potential of a use phase data strategy to provide additional value for internal and external stakeholders. However, the findings of the analysis confirmed that a structured approach for the development of the strategy is important in order to make use of the limited resources.

7.2.4 Step 3 – Identify application areas and derive use cases

The conclusions of the previous steps set the scene for the search for application areas and derivation of use cases. Thus, the overall objective of this step is to provide a list of potential use cases for the use phase data strategy.

Identify application areas

Due to the lack of experience in exploiting use phase data, one central goal of the case study was to make the range of possible use cases visible. Therefore, in order to obtain an initial holistic overview no application area was per se excluded from the search. Accordingly, the intention was also to follow both a data-first and use-case-first approach in order to make use of available use phase data, but also to think about additional use phase data. The results of the stakeholder analysis provided important input for the search for application areas because the findings highlight the important interests of internal and external stakeholders (Figure 7-1). In order to obtain a broad selection of possible application areas, the following sources were analysed: competitors, companies from other industry sectors, literature, and online resources. In addition, the developed use case catalogue (see Section 6.4) provided suggestions for additional application areas and was used in a workshop. These findings from external sources were important for preparing the ideation because they allowed for analogy building later on.

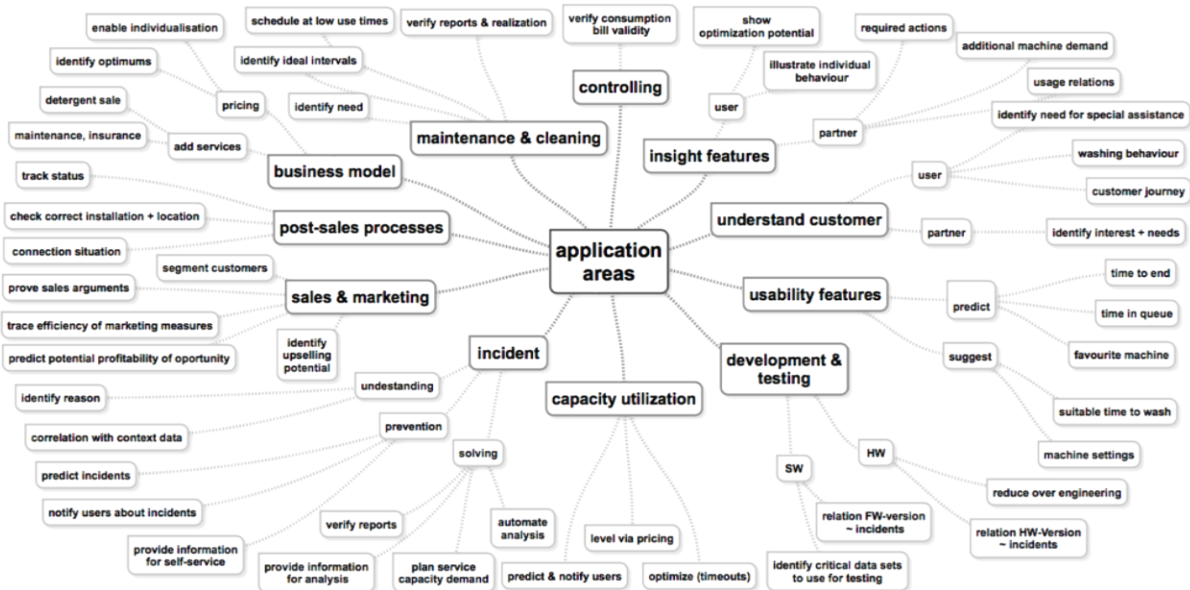


Figure 7-3: Overview of identified application areas

The ideation process included interviews with eight internal stakeholders and used different methods to stimulate idea generation. The main rule for the interviews was that the stakeholders should not think about technical and financial feasibility in order to avoid that relevant use cases are overlooked. At the beginning, each stakeholder was asked about their own ideas for application areas that would benefit from exploiting use phase data. Afterwards, each interviewee was introduced to the main findings of Step 2 (e.g., SWOT analysis, available use phase data, or data map) and was asked to derive ideas from them. In addition, the overview of external application areas supported the interview partners in generating additional ideas. The last step of the ideation process was to structure the ideas for application areas. Figure 7-3 summarizes the results of the ideation process and shows the ten application areas. The results show that the ten application areas address internal and external stakeholders.

Derive use cases

The next task was to derive concrete use cases. Many application areas were still quite broad and connected ideas sometimes very vague. An additional set of interviews with internal stakeholders helped to derive concrete use case based on the application areas. The outcome of these interviews was a list with 55 use cases. Appendix A8.2 provides a list with all use cases derived during the first evaluation case. The decision was to document each use case in a template by providing the following information: use case title, short description, and expected value for stakeholders. Due to the different maturity levels of the use cases and their complexity, additional interviews helped to ensure the uniform selection of use cases. The selected use cases stem from the following sources: 34 ideas from the team, 18 external application areas, 17 discussions about current problem areas, 11 ideas from the use case catalogue, and 6 external use cases. The numbers show that the ideas for use cases combine internal and external ideas. It is important to mention that some use cases belong to multiple categories or originate from a combination of ideas.

Altogether, it was possible to gain a comprehensive overview of possible application areas. Furthermore, the interviews with internal stakeholders allowed for the identification of 55 use cases that require additional detailing in order to assess their value for the strategy.

7.2.5 Step 4 – Determine the data needs and consolidate the use cases

The ideation for possible use cases led to 55 ideas for possible use cases. Therefore, the main objective of this step is to assess the use cases and identify dependencies among them.

Determine the data needs

Due to the small size of the company, the decision was to reduce the number of use cases before determining the data needs for the remaining ones. The first task for filtering the use cases was to group them based on the needs that each use case fulfils. Table 7-2 summarizes the allocation of the use cases to one of the ten need clusters (e.g., customer understanding, increase utilization, or sales optimization). However, the assignment of the use cases to different clusters did not help to reduce the number of use cases. Narrowing the focus of the use phase data strategy was the consequential task. A review of the company's strategy map revealed the following topics as especially important: turnover and income growth, good user experience, providing a reliable service, customer centricity, and sales efficiency. A discussion with the team further showed that the service quality is not adequate, the system stability needs improvement, and internal processes require too much manual work. These findings helped to define three benefit clusters that the use phase data strategy should address: improving the understanding of incidents during operations (1), reduction of manual effort when dealing with incidents (2), or increasing the turnover and the sales numbers (3).

Table 7-2: Number of use cases for each need cluster

Need cluster	Number of use cases
Customer understanding	6 use cases
Usability features	5 use cases
Insight features	6 use cases
Business model	5 use cases
Increase capacity utilisation	4 use cases
Machine operation	7 use cases
Development	4 use cases
Sales optimisation	5 use cases
Internal processes	7 use cases
Customer service	7 use cases

Afterwards, it was possible to reduce the set of use cases by applying two criteria. The first requirement was that every use case had to address one of the three benefit clusters. This evaluation led to 26 remaining use cases. The second requirement was to focus on use cases that mostly follow the data-first approach and do not require the integration of new sensors or other data sources. Afterwards, 17 use cases remained for a detailed analysis. Due to the allocation to one of the three benefit clusters, the numbering of each use case was changed (e.g., UC 1.3). The first number indicates to which one of the three benefit clusters a use case belongs. The second number was used to number the use cases within each benefit cluster. The list with the use cases in Appendix A8.2 also contains the new numbering for the remaining 17 use cases.

The remaining use cases underwent detailed discussion with internal stakeholders in order to determine the data needs for each use case. Each use case and its data needs were documented using the developed use case template (see Appendix A6.8). To address the needs of the case study partner better, the template was adjusted. For the company it was especially important to document the underlying process for the use case and describe possibilities for enhancement. Furthermore, the template contains two areas to describe the pains that a use case addresses and the gains that a use case intends to provide. The last task was to document, for each use case, which use phase data is missing. One use case that aimed to identify anomalies among reported incidents required additional data when the incident was reported. The use case further required context data that provided more information about the washing machine. Overall, it was possible to determine the required data points and the data quality for all use cases.

	Use phase data								Context data						
UC	Reservation	Appliance	Error data	Connection data	Ticket	Threshold	User	Partner	Hub	Location	User	Partner	Appliance	Sales	External
1.1	X	X	X	X			X								
1.2	X	X	X	X						X					
1.3	X								X				X		
1.4	X			X											
1.5	X	X	X										X		
2.1	X									X					
2.2	X	X					X				X				
2.3	X				X		X				X				
2.4	X	X	X	X					X	X			X		
2.5	X	X	X										X		
2.6	X	X	X			X			X	X			X		
2.1	X		X				X				X				
3.2	X						X			X	X				
3.3	X	X	X				X	X		X		X		X	X
3.4	X		X				X				X				X
3.5	X	X	X		X			X				X		X	
3.6	X	X												X	X

Figure 7-4: Matrix approach for the identification of use phase and context data requirements

Consolidate the use cases

The next task was to consolidate the use cases and to identify dependencies among the use cases. The developed matrix-based approach helped to analyse the dependencies between the use cases, use phase data, and context data (see Section 6.5). Figure 7-4 illustrates the matrix that describes the dependencies between the use cases and data points. To ensure readability, the matrix only shows clusters of data and not the individual data points. The depiction highlights that data about the reservation (e.g., time, state, and user) is necessary for every use case. The results further show that appliance and incident data is a prerequisite for many use cases. Based on this analysis, the conclusion was that the use cases mostly complemented each other. Finally, each use case was assigned to one of the three benefit clusters: improving the understanding of incidents during operations (5 use cases), reduction of manual effort when dealing with incidents (6 use cases) and increasing the turnover and the sales numbers (6 use cases). The last task was to derive service blueprints for service-oriented use cases in order to prepare the evaluation.

In summary, this step led to 17 relevant use cases that seemed to have a positive impact on the company and value proposition. The results also created transparency about data needs.

7.2.6 Step 5 – Evaluate the use cases and select

After assessing the remaining 17 use cases, the task is now to evaluate the remaining use cases and select final ones. The main objective is therefore to prepare and conduct a structured evaluation in order to derive a set of use cases that should be incorporated into the strategy.

Evaluate the use cases

During the case study, the decision was to conduct the evaluation based on the use case specific benefits and efforts. The main requirement for the use phase data strategy was that it provides solutions for current problems in an efficient way. However, a decision was made not to assess the efforts concerning costs and complexity because this seemed too time consuming for the case study company. Based on the maturity level of the use cases, the decision was to conduct a qualitative evaluation of the effort required for each use case. In order to have a more detailed understanding, each use case should also be assessed in relation to the data delta and its data quality requirements. Concerning the benefits of a use case, the decision was to use two evaluation criteria. First, a qualitative evaluation of the contribution to the three benefit clusters. Secondly, the monetary impact of a use case, which includes additional turnover and potential savings. In order to reduce the evaluation effort, each use case was assessed on its contribution to the three benefits clusters. Based on the results, it became clear that six use cases did not provide enough value for one of the three clusters, which led to a final list of 11 use cases.

For some of the remaining use cases, the required use phase data was already available. Therefore, it seemed suitable to pursue a prototypical implementation in order to obtain in-depth insights about the related benefits and efforts. Thus, some use cases were tested using simple prototypes. The test confirmed the feasibility and highlighted the potential that use phase data offers for the case study company. To evaluate the use cases, a weighted point assessment was used to reflect the varying importance of the evaluation criteria. Table 7-3 provides an overview of the final evaluation criteria and its weighting. Furthermore, each criterion for each use case was assessed using school grades (1 – very good and 6 – insufficient).

Table 7-3: Selected evaluation criteria for the use cases and their weighting

Category	Evaluation criteria	Weighting
Benefit	• Impact on the benefit clusters (e.g., improve the understanding of incidents) • Monetary impact (additional turnover or cost reduction)	6 4
Effort	• Qualitative assessment of effort drivers (e.g., development of analytics model) • Data delta (gap between available and required data) • Data quality requirements (deviation of the current data quality)	6 2 2

Interviews with corresponding stakeholders helped, for instance, to evaluate the impact of certain use cases on the benefit clusters. For the monetary impact, simple rough calculations helped to evaluate the potential effects in euros. The analysis showed that one use case had the potential to save approximately 100,000 € in labour costs for service. This rough monetary result was afterwards translated into a school grade. For the assessment, developed tools (e.g., data quality template and approach for cost-benefit analysis) were used to rate the different use cases together with the internal stakeholders.

Select use cases

In order to select the final use case, each use case was assigned one grade for every evaluation criterion. Based on the individual grades, an average grade was calculated for each use case, which then helped to derive a ranking of the use cases. Among the 11 remaining use cases, the best average grade was 1.9 and the worst was 3.5. Figure 7-5 depicts the portfolio matrix that summarizes the evaluation results. The portfolio compares the effort and value related with each use case. The decision within the strategy development team was to select six use cases in order to have two use cases for each benefit cluster. The selected use cases are marked in the portfolio with dashed lines.

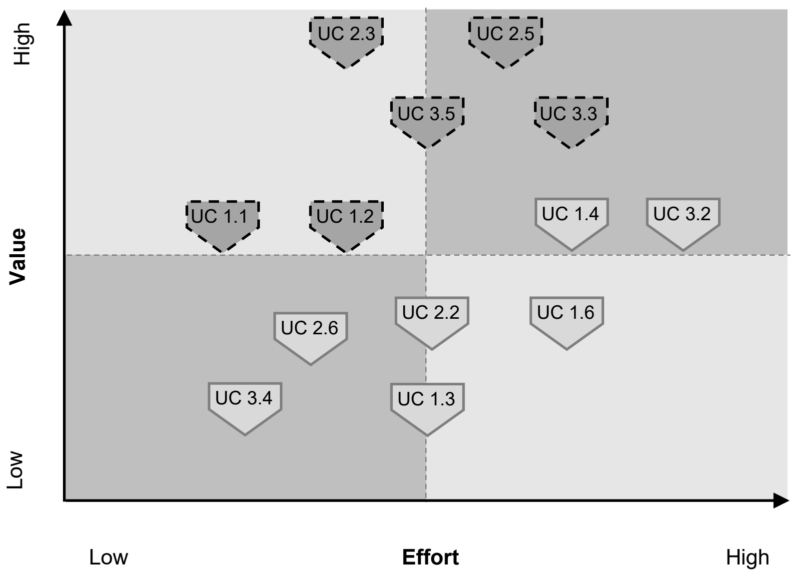


Figure 7-5: Portfolio with the results of the use case evaluation

Afterwards, the project team assessed the risk of each use case during a workshop in order to ensure that no business, technology, or project risks were overlooked. The analysis indicated that the project risks are the driving ones because implementing the use cases will consume a considerable amount of resources. Because the case study company does not have many employees, the implementation could consume resources that other projects need. The evaluation of the use case also revealed that use cases could have three different expansion stages depending on the implementation: simple tool integrated into the database, independent tool, and fully automated algorithm. A higher implementation complexity often increases the value, but at the same time, the time required for the implementation also increases. Figure 7-6 illustrates how different expansion stages impact the value und implementation time.

In summary, the project team used five evaluation criteria to assess the predicted benefits and efforts of each use case. Based on the evaluation results, the project team selected six use cases.

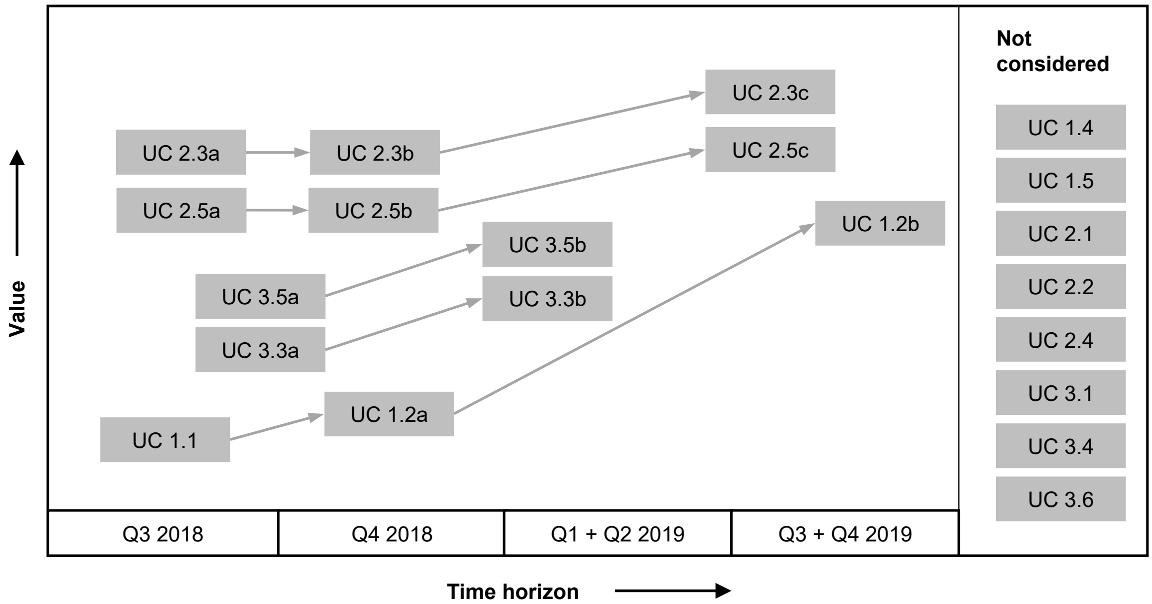


Figure 7-6: Visualisation of the different enhancement levels for use cases

7.2.7 Step 6 – Formulate the data strategy and derive the roadmap for implementation

The previous step revealed that six use cases seem especially promising in providing value for the case study partner. The objective is therefore to derive the overall use phase data strategy and formulate an implementation concept that describes important implementation tasks.

Formulate the data strategy

The selected use cases provide the foundation for the use phase data strategy. The derived use phase data strategy is “The exploitation of use phase data aims to support especially the overall success of the company by increasing the service reliability, ensuring the scalability of operations, and fostering growth of sales and turnover.” In order to complement the strategy definition, the Balanced Scorecard was used to give a detailed description of the underlying strategic objectives for each use case. Afterwards, a strategy map (see Section 6.7) helped to visualise the overall strategy and outline the main objectives that the strategy wants to achieve. The project team adjusted the strategy map by including the six use cases and three benefit clusters in the strategy map. Due to confidentiality, it is not possible to show the strategy map here. Overall, it was possible to derive a structure and clear description of the developed use phase data strategy.

Derive roadmap for the implementation

After formulating the use phase data strategy for the case study partner, the last task was to derive an implementation concept. During the case study, it became clear that a combination of different visualization methods helps to describe the implementation concept. The first visualization was a depiction of the expansion stages for each of the six use cases. Based on the previous assessment of the use cases it became clear that each use case had three expansion stages that are mainly based on the complexity of implementation. The analysis however also showed that it is not possible to have a fully automated tool for two use cases. The second part of the implementation concept was a roadmap that summarizes the implementation of use case clusters and expansion stages. Figure 7-7 depicts the roadmap and the implementation concept for the different use cases. The third part of the implementation concept was the development of an individual roadmap for each use case. Deriving these roadmaps enables the case study company to identify important activities and milestones for an implementation of the use phase data strategy on a product, technology, and organisational level. The last part of the implementation concept was a strategy roadmap based on the roadmap template for a use phase data strategy (template is depicted in Appendix A6.16). A main challenge during the development was that the case study partner is currently moving quite fast in order to improve their product and grow. Therefore, objectives and available resources can shift frequently, which led to a high degree of uncertainty for the implementation concept. The last task was to derive a product profile as suggested by Albers et al. (2018b). The profile allowed for the integration of the use cases into the product concept. The profiles further summarized the desired value of the selected use cases for the provider, customers, and users.

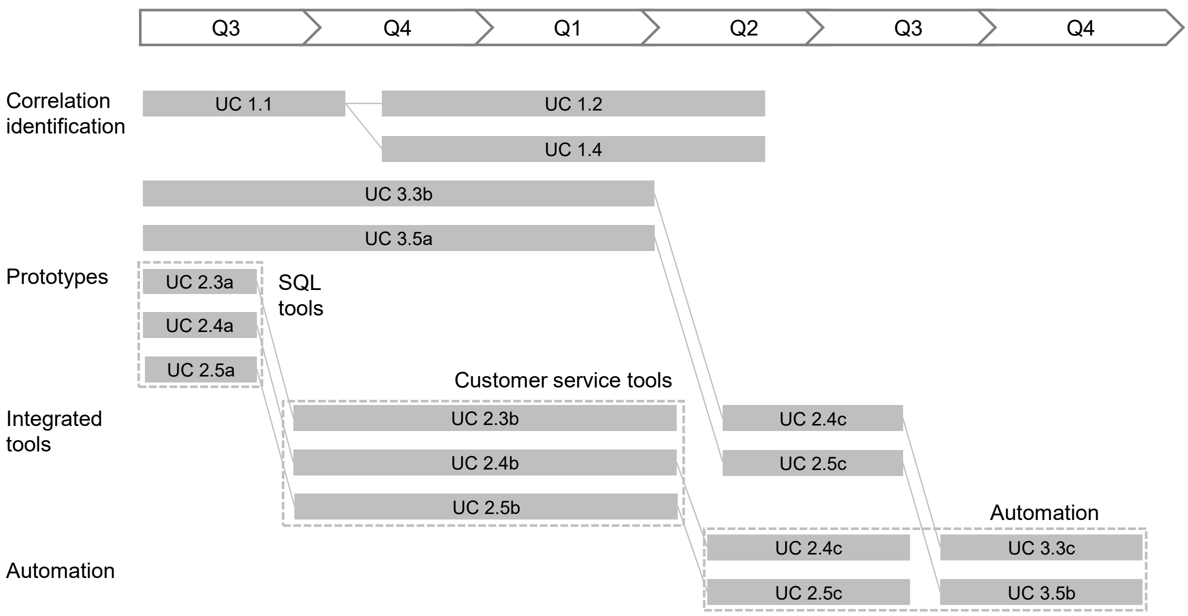


Figure 7-7: Roadmap for the implementation of the use cases and the planned expansion stages

Overall, the process model enabled the case study partner to derive a sound use phase data strategy. The case study also helped the company to identify more than 50 use cases that can potentially provide value for the company and its customers. The findings also confirmed the company that an exploitation of use phase data can be beneficial and should be further pursued. Additionally, the case study results also increase the transparency concerning available use phase data and the competitive situation because current strengths and weaknesses of the company became clear. In the end, six use cases appeared to be especially valuable and an implementation was planned after the case study ended. The relevant internal stakeholders received the results of the case study and will work on the implementation of the strategy.

7.2.8 Evaluation results for the process model and case study results

The questionnaire (see Appendix A8.1) and additional discussions helped to evaluate the developed process model, the supporting methods, and case study results. A presentation at the end of the case study summarized the case study process and the main results. Four stakeholders from technology operations, data operations, customer operations, and management attended the final presentation. Each participant filled out one questionnaire to evaluate the solution approach and the results.

Concerning the **usability**, the evaluation results confirm that the process model helps to develop a use phase data strategy in a structured way. However, the results indicate that the manual for the process model does not include all information required to develop a use phase data strategy. A discussion of the evaluation results indicated that the manual requires a certain amount of knowledge in order to be applicable. Based on oral feedback, the process model should also highlight the importance of the promotion of the results in order to ensure that the use cases and the strategy are incorporated into the company`s overall strategy. In addition, the results also show that the manual should be more comprehensible.

In general, the case study showed that the process model and the developed methods are **applicable** in industry. The evaluation results also show that the process model supports both a data first and use case first approach. Furthermore, the participants confirmed that the process model builds upon available information. Nevertheless, the participants stated that the process model is less applicable for the development of a strategy for external stakeholders. The comments of the case study partner reveal that users and customers should have been involved in the development process. At the same, the discussion of the evaluation showed that the involvement of customers requires a high amount of effort because it must be done very systematically.

Afterwards, the participants were asked to evaluate the **usefulness** of the process model. The findings show that the support especially helps to obtain a comprehensive overview of possible use cases. The results also confirm that the stakeholders believe that the process model helps to find use cases that provide additional value for a company. Furthermore, the results indicate that the process model helps to integrate different stakeholders into the development process. The results, however, also indicate that the analysis done during step 2 requires adjustment in order to provide a better foundation for the strategy development. Based on the oral feedback, an analysis is important, but at the same time, more support is needed to help decide which topics are relevant in order to avoid that the analysis focuses on irrelevant aspects. Another aspect to discuss is the quality of the use case evaluation because the results show that a more comprehensive assessment would be preferred. Due to time constraints it was not possible to perform an in-depth evaluation of benefits and costs at this point. The feedback further revealed that the process model needs to better highlight the implications of the use phase data strategy.

Besides the process model, the developed **methods** also play an important role in strategy development. Feedback shows that the use case template is seen as very helpful for documenting use cases and creating transparency. The same can be said for the data map, which also helps to provide a better overview. Concerning the use case catalogue, the feedback indicates that the catalogue can help to trigger ideas for use cases. However, the participants believed that the implementation needs improvement.

After discussing the process model, the participants were also asked to evaluate the **case study results**. The results indicate that all relevant stakeholders were involved in the strategy development. Furthermore, the participants stated that the implementation of the use cases would improve the product and service quality. The feedback further shows that the case study helped the company to improve their understanding of the complexity of exploiting use phase data. However, it also became clear that the stakeholders believed that the efficiency of the process model requires improvement. A suggestion was to define sprints for each step-in order to avoid that too much time is spent for a single step.

The analysis of the **open questions** provides additional insights. The case study was able to raise awareness about the need for additional resources in order to extract more value from use phase data. Another contribution was that the case study triggered a creative process for thinking about possible ways in which use phase data can provide additional value. Therefore, the results supported the stakeholders in understanding the value of use phase data. One person mentioned that the process model should focus more on data related topics before deriving a strategy. A central learning for the company was that available use phase data could already help them to improve their operational processes.

7.3 Evaluation case 2 – Home appliances sector (washing machines)

This section describes the second evaluation case. The case study, done in collaboration with a large manufacturer for home appliances, lasted six months and was part of a student project (Curraj, 2018). Due to the large range of products at the company, the collaboration took place together with the washing machine division. The following sections introduce the case study partner, present the case study, and summarise the evaluation results of the second case study.

7.3.1 Introduction of the case study company

The case study partner is one of the largest manufacturers of home appliances in the world and has more than 50,000 employees around the world. The company offers a wide range of different products (e.g., washing machines, fridges, and dishwashers), which include special variants that address the needs of different markets. In addition, the case study partner has a portfolio of different brands in order to provide products that meet varying customer expectations. Connected products have been part of the regular product portfolio for many years. However, only washing machines of a certain value class have connectivity features. The overall vision is to provide a comprehensive solution for connected kitchens. An app for mobile devices already allows customers to monitor and control their appliance. The products and app already transmit many different data points via wireless LAN, which has resulted in a high amount of available use phase data. The strategy of the case study partner is to further advance their product and service offering using connectivity. Therefore, the company is a suitable partner for developing a use phase data strategy and evaluating the process model. Due to the large variety of products, a decision was made to collaborate only with the department focusing on washing machines. Within the department, the collaboration took place with a team that focuses on digitalisation (e.g., development of new services or features).

7.3.2 Step 1 – Initiate the project and determine the objectives

Due to the large size of the case study company, the objective of the first step was to identify suitable stakeholders for the project team. Furthermore, it was important to derive objectives for the use phase data strategy project and to identify other projects within the organisation that work on similar topics.

Initiate the project

Two people became part of the core project team. The product manager for digital services and the student became the project managers. The product manager also became the sponsor of the project. However, the decision was to then identify additional stakeholders during the subsequent steps after organisational structures became clearer.

Determine the objectives

Working on a use phase data strategy within a large company that has many product divisions and already offers connected products requires an understanding of the company's internal project landscape and that clear objectives are derived in order to communicate the project. Offering connected products and related services is part of the corporate strategy. The initial analysis helped to identify other projects on a corporate and divisional level that work on related topics that might become relevant for the development of the use phase data strategy. An example is a corporate project that works on providing additional data analytics competences for the company. The placement of the project within the project landscape of the company made dependencies visible and highlighted the need for coordination.

The final task of this step was to formulate objectives for the project that ensure that the use phase data strategy fits to the corporate strategy. The first objective was that the project should aim to identify between 40 and 50 use cases during step 3. Furthermore, the use cases should provide value for internal and external stakeholders. The second objective was that the use phase data strategy should include approximately six use cases that appear to be especially valuable for the case study partner or the customers. Furthermore, the use phase data strategy should help to advance the digitalisation of washing machines. The third objective was to focus on use cases that require only a short-term or medium-term implementation. The fourth objective was that the project should reveal operational and organisational needs for action in order to implement the use phase data strategy. The fifth objective was to develop use cases only for connected washing machines. The project should therefore consider data coming from the product, app, and customer service when deriving use cases. Lastly, the decision was to derive a use phase data strategy that addresses the European market and its customers.

In summary, the first step laid the foundation for the development of the use phase data strategy by setting up the core team and defining a clear focus for the strategy development project.

7.3.3 Step 2 – Analyse the system and structure the situation

After defining the boundary conditions of the project, the main objective of the second step was to create internal and external transparency for the case study company in order to derive conclusions for the development of the use phase data strategy.

Analyse the system

Understanding the macro environment was the first task for the system analysis. The DESTEP analysis helped to obtain an overview of the environment (Runia et al., 2011, pp. 57–58). Compared with the PESTEL analysis (see Section 6.3), the DESTEP analysis treats political and legal aspects as one factor. Overall, the analysis showed that customers could choose from an increasing number of services for a connected kitchen. At the same time, customers prefer individualized products and services (social cultural aspect). The analysis also highlighted that new energy directives and data privacy rules have an impact on the development of connected products and services. A further important learning was that customers expect low entry costs but also flexibility. The analysis results helped to provide a clear understanding of the boundary conditions for the strategy development.

Afterwards, the objective was to obtain a better understanding of the market and the customers. For this task, marketing knowledge was very helpful because the department had detailed information about the two topics. The company uses different brands of washing machines to address different customer needs. Therefore, the decision was to focus on two main brands that already offer connected washing machines. At first, it was important to understand the attitude of the customers towards connectivity and data privacy. The analysis indicated that the customers of each brand had their own characteristics and thus demand specific use cases.

Based on the understanding of the customers, the concluding task was to analyse the market for smart home appliances using market studies and interviews with marketing. A general finding was that the market for smart home appliances is gaining more traction. Therefore, new competitors are also entering the market and offering innovative solutions. It is therefore important for the case study partner to offer new connected solutions in order to stay competitive. A detailed analysis of competitors' products revealed that they offer similar solutions, which mainly allow for monitoring and controlling products. However, it also became clear that some competitors have a technological edge. A strength-weakness analysis (see Section 6.3) allowed for the comparison of the case study partner with a main competitor. A key finding was that the development of a use phase data strategy could help the case study partner to gain competitive advantages by better exploiting use phase data.

After gaining an understanding of the company's environment, the internal analysis came next. The analysis helped to provide an understanding of how departments currently work together to implement use phase data-based use cases. The finding was, that the data analytics team takes over central responsibility when analysing data. Understanding the internal processes was very helpful for gaining an overview of the interaction between different stakeholders and departments. A following stakeholder analysis helped to advance this understanding. The analysis assessed which stakeholders can help to identify, evaluate, and implement use cases.

The last aspect of interest was to understand which use phase data was available. The two main sources for use phase data were the washing machine itself and the app for mobile devices. Modern washing machines have multiple sensors (e.g., turbidity sensor). However, it is possible to calculate additional data points using sensor data. Furthermore, washing machines also transmit, for example, the following data points: selected program, start time, and end time. The app also provides information about the location of the user and the selected program. The case study company already collected a lot of use phase data. The data quality, however, was not always sufficient because transmission was sometimes incomplete. A key finding was that it is not possible to connect different data sets because a unique identifier is missing which is required in order to comply with data privacy rules. Therefore, it is not possible to derive user or machine specific conclusions. A data map was used to visualize the different databases within the company. Overall, the findings highlighted that the company has quite a high maturity level because it has experience in data analytics as well as available use phase data.

Structure the situation

A SWOT analysis then summarized the findings of the internal and external analysis. A clear strength was that the case study partner has offered connected products for a long time now, which means that the required skills and IT infrastructure are available. It is also beneficial that offering connected products and services is part of the corporate strategy, which means that the topic receives the required attention. However, the external threats are data privacy rules and new competitors. Interviews with internal stakeholders helped to complement the SWOT analysis. The analysis revealed that technical, organisational and personnel-related obstacles exist. It became clear that employees must learn to share data and to understand the organisational interfaces. Data often exists in a fragmented way across the company. Therefore, it is important to foster new collaborations. From an organisational perspective, more standardisation for the names of data points is needed, as well as more transparency about available data.

Having a lot of use phase data is a great opportunity for the case study company. However, it became clear that a lack of transparency and increasing competition required the case study company to act in order to better exploit use phase data and to remain innovative.

7.3.4 Step 3 – Identify application areas and derive use cases

The previous step highlighted that opportunities and challenges relating to the exploitation of use phase data exist at the case study partner. Therefore, the objective is to identify application areas within and outside the company in order to derive use cases.

Identify application areas

The definition of objectives helped to narrow the focus of the use phase data strategy development project. However, the scope was still quite wide because the use phase data should provide additional value for both internal and external stakeholders. The decision was therefore to consider the following internal application areas marketing, sales, customer service, washing machine product development, washing machine product management, and local brands. Complementary external application areas to consider were customers and energy suppliers.

Derive use cases

The next challenge was to derive use cases for internal and external stakeholders. In order to obtain a wide perspective, the decision was to use three different sources for use cases. First, interviews with internal stakeholders helped to gain a detailed understanding of other projects that work on the exploitation of use phase data. Second, two workshops with employees from different departments allowed for the identification and detailing of potential use cases. The third source was idea generation by means of searching the developed use case catalogue (see Appendix A6.6).

The stakeholder analysis during the second step helped to provide an initial overview of stakeholders that worked on exploiting use phase data in parallel projects. The additional interviews during the search for use cases highlighted that one project was working on predictive maintenance at the time of the case study. Based on the interview it was possible to derive one use case. However, the decision was made not to focus on other related use cases in order to avoid duplication. One other use case was derived from the results of a previous innovation workshop. Another project was working on providing customer specific guidance and suggestions to the customers using the mobile app and emails. Because the project did not search for washing machine specific customer guidance, it was possible to derive 16 use cases that built upon usage-based assistance. Altogether, the interviews provided 18 use cases.

Two workshops with internal stakeholders were the second source. The first workshop was two hours long and involved employees from different departments (e.g., product management, customer service, product development, data analytics, and mobile app). The underlying idea was that bringing different disciplines together is beneficial for the ideation process. To ensure a similar understanding amongst the stakeholders, an overview of data currently generated by washing machines and dryers was presented. In addition, it was shown alongside the sensors that a washing machine has. After laying the foundation, four interdisciplinary teams started searching for use cases. Each use case received a use case one-pager template for documentation. Each one-pager consisted of different sections (e.g., required use phase data, value of the use cases, relevance for the case study partner, and effort-value portfolio). Afterwards, the teams presented their use cases in order to discuss them with the other teams. The outcome was 22 use cases and corresponding one-pagers. Overall, the discussion highlighted that ‘value’ for the case study partner means, principally, additional turnover. It also became clear that accessing data and data privacy rules are central causes for effort.

A second workshop followed that lasted 1.5 hours. An analysis of the previous workshop results showed that five use cases were rather high-level ones. Therefore, the objective was to detail the use cases from the previous workshop and to derive additional use cases. Figure 7-8 shows the main process of the second workshop. The five high-level use cases were the starting point and the task was to derive at least three concrete use cases for each high-level use case. To support the ideation process, the use case catalogue and the data journey were used during the workshop. Overall, the two workshops helped to derive 27 use cases. In addition, it was possible to derive seven clusters for the use cases, which Figure 7-9 summarizes.

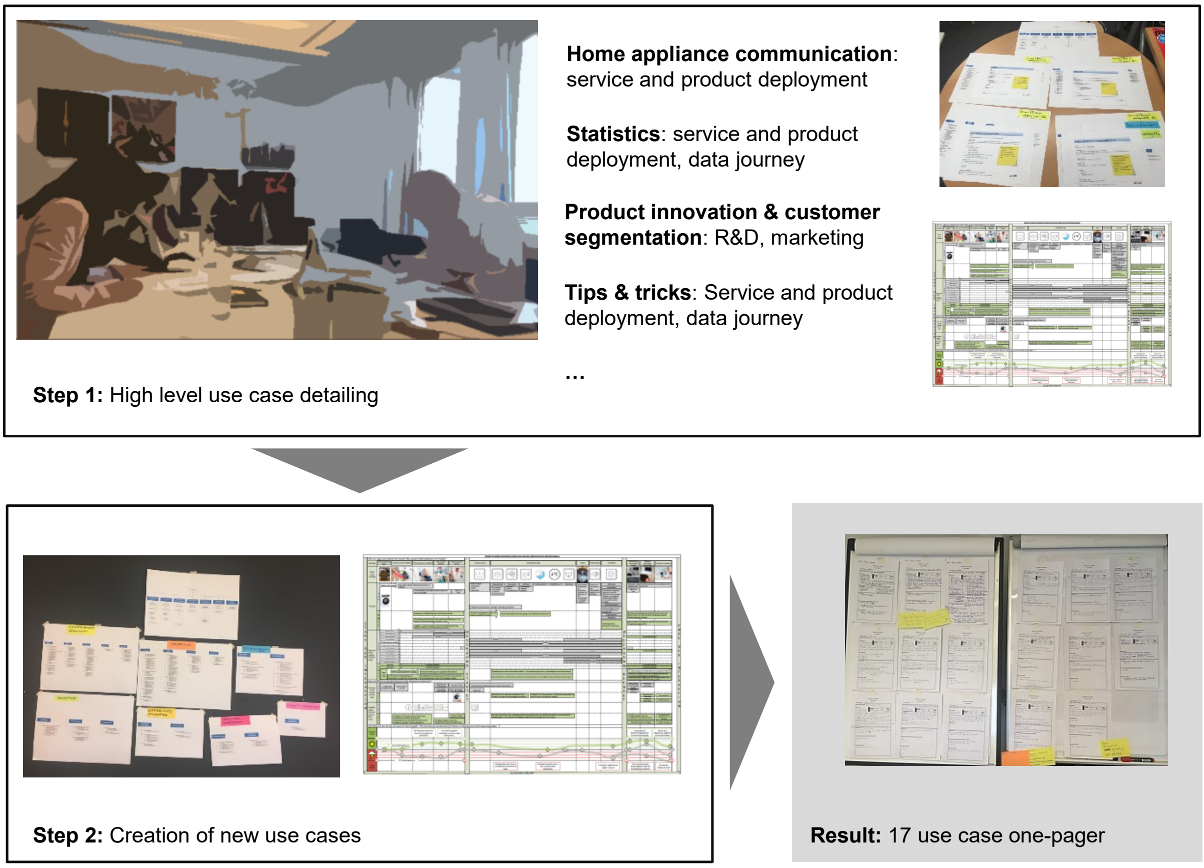


Figure 7-8: Structure of the second workshop for the search for use cases for washing machines

The third source was the developed use case catalogue (see Appendix A6.6). A detailed individual review of the use case catalogue by the student at the company helped to identify six additional use cases. The catalogue was especially helpful for thinking outside the box because new ideas about connecting different home appliances arose. In addition, the review helped to generate ideas about new data sources. In summary, the search for use cases concluded with a list of 51 different use cases stemming from the three sources. Appendix A8.3 provides a list with all identified use cases.

The third step started with an identification of possible application areas and the results highlighted the broad range of possibilities. Using three different sources and integrating various disciplines helped afterwards to derive a comprehensive collection of 51 use cases that present the main input for the next steps.

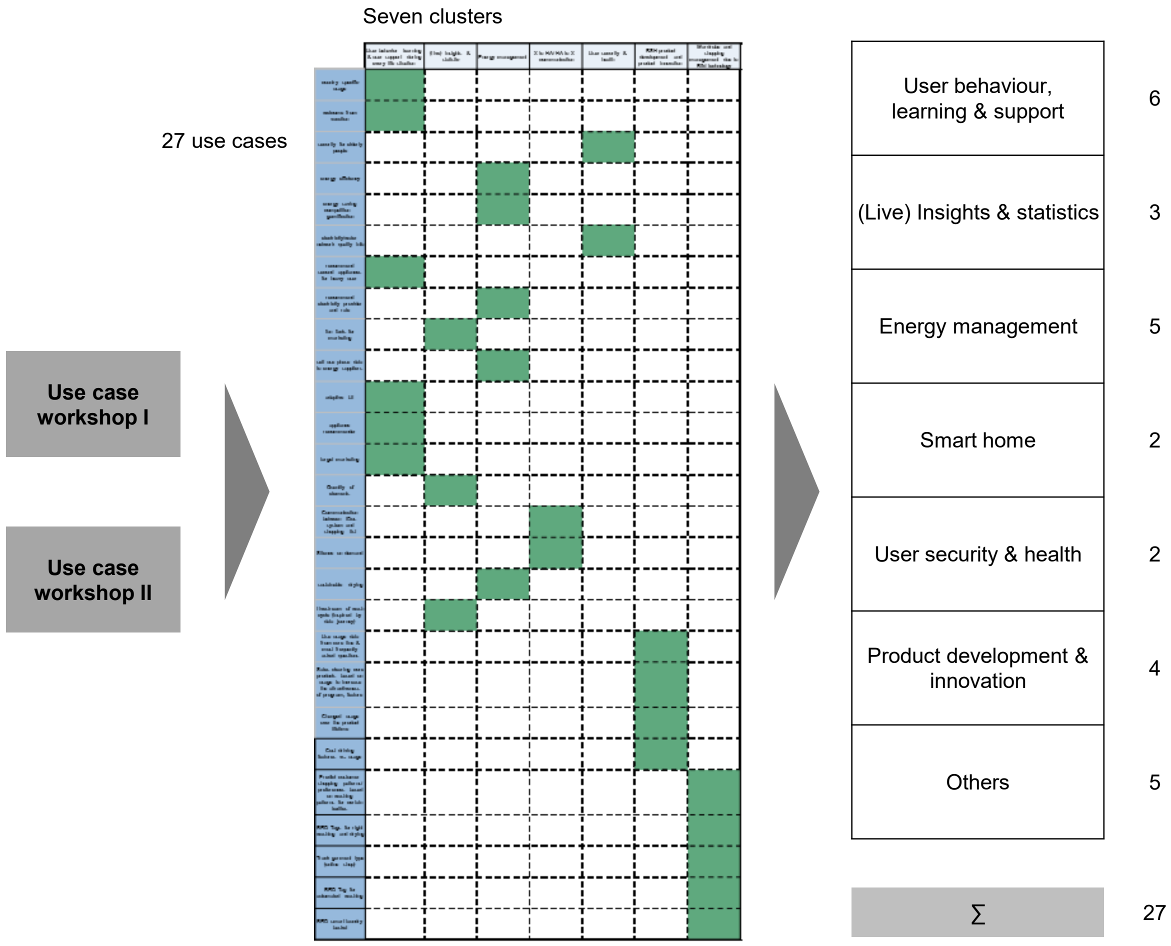


Figure 7-9: Results of the two workshops

7.3.5 Step 4 – Determine the data needs and consolidate the use cases

Different sources helped to derive 51 use cases during the previous step. Therefore, the objective was to identify relevant use cases in order to focus on a reduced number of them afterwards. Due to the organisational setting at the company, the decision was to consolidate the use cases first before discussing the data needs with the digital transformation department.

Consolidate the use cases

The high number of use cases and the limited availability of data analytics experts required an initial consolidation of the use cases. The first task was to identify clusters that summarize the different use cases. The decision was to derive clusters based on the benefits that the use cases provide. Based on the analysis, it was possible to identify 14 different benefit clusters (e.g., wardrobe management, customer clustering, or live insights & statistics). A DSM based approach then helped to identify dependencies among the clusters and to combine clusters (see Appendix A6.11). Thus, it was possible to reduce the number of clusters by four. Afterwards, the participants evaluated the importance of the clusters for the case study company and the company's customers. The evaluation highlighted that the cluster "perfect washing results" had the highest importance for customers. The approach did not help to reduce the number of use cases.

Therefore, the next step was to use knock out criteria to reduce the number of use cases. Based on the discussions within the project team, the decision was to exclude use cases that require high investment for their implementation or have a long implementation time have been implemented already at the case study company provide no added value for the case study company (e.g., additional turnover) or for the customers (e.g., improved user experience)

Interviews with internal stakeholders helped to evaluate the use cases concerning the three knock out criteria. It was possible to eliminate nine use cases using this approach. However, the number was still too high to proceed. Another detailed evaluation of the individual use cases was therefore necessary. Relevant stakeholders at the company were then asked to rate the value for the company and the value for the company's customers on a scale from zero (no value) to ten (high value). Figure 7-10 summarizes the outcome of the detailed assessment and shows that the focus was on use cases with a high value for the company and its customers. Overall, the decision was to continue the next task with seven use cases (e.g., preventive maintenance).

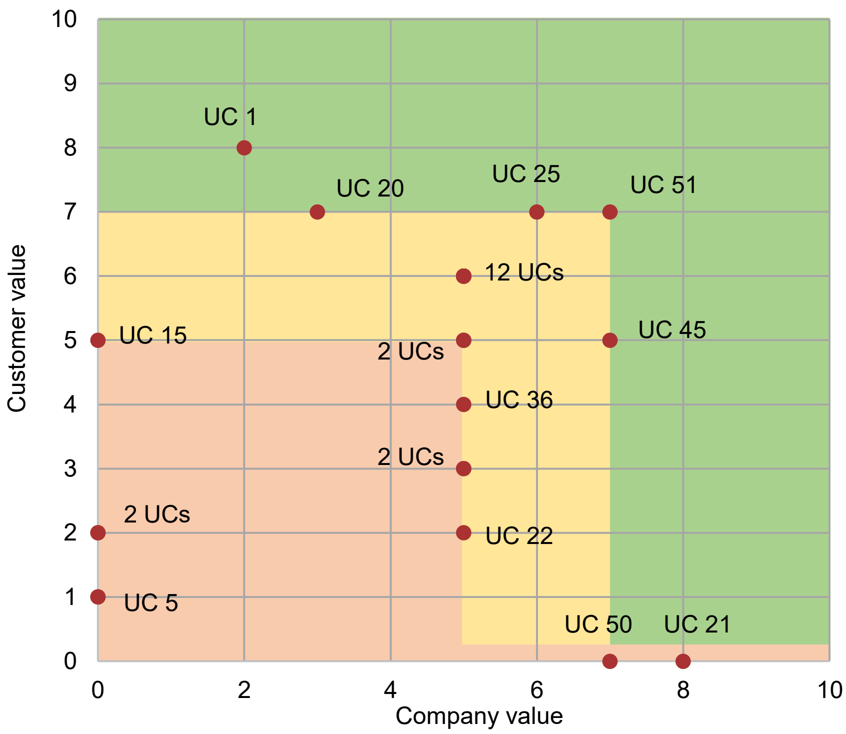


Figure 7-10: Portfolio matrix for the evaluation of the use cases

Determine the data needs

After reducing the number of use cases, the next task was to improve the understanding of the data needed for the use cases. An initial workshop with the IT department focused on the refinement of the use cases, which helped to define prerequisites, identify the required IT infrastructure, and assign suitable data analytics approaches. The discussion highlighted that it is difficult to assess the effort needed for the IT infrastructure due to the complexity of some use cases. Applying a matrix-based approach further helped to analyse the data needs and to highlight missing data points (see Section 6.5). A key finding was that many data points were already accessible. In addition, almost all use cases also required use phase data from the mobile app, which is already available or accessible with little effort. The integration of new sensors needs a detailed assessment due to the comprehensive efforts for an integration. Connecting different databases presented another obstacle for use cases because although the data might exist, different organisational responsibilities make it challenging to aggregate the data. At the time of the case study, the decision it was to derive data quality requirements later on.

The detailed consolidation of the use cases helped to identify seven use cases that could potentially provide great value for the company and its customers. The results of this step further helped to detail the use cases and to better understand their requirements.

7.3.6 Step 5 – Evaluate the use cases and select

The development of the use phase data strategy requires selecting a final set of use cases for implementation. Therefore, the objective of this step is to prepare and conduct a final evaluation of the remaining use cases in order to select the most promising ones.

Evaluate the use cases

The evaluation of the use cases requires a detailed assessment concerning their efforts and benefits. The previous evaluation used the same categories for an evaluation but did not look into any details. Therefore, the decision was to derive additional criteria for the effort and the value. To determine the effort, the effort categories of the developed cost-benefit analysis served as a foundation (see Appendix A6.14). The decision was to focus on effort related to data analytics and implementation efforts. Discussions with experts led to the following set of criteria for assessing each use case: data availability, IT infrastructure requirements, data integration effort, need for additional functions, implementation time, and costs for operationalisation. In contrast, the following criteria for evaluating the value were defined: turnover generation, additional benefit for the brand, cost saving potential, and provision of a unique selling point. Interviews with internal stakeholders helped to assess each use case in relation to the different criteria. A value-effort portfolio helped to summarize the results (see Section 6.5).

Even though the evaluation provided a detailed understanding about the benefits and drawbacks of each use case, the objective was to evaluate the use cases further. Therefore, a data analytics expert assessed the innovativeness, complexity, and costs of each use case. In order to obtain a better estimation of possible implementation costs, the idea was to determine the required implementation time. It became clear that the product development and data analytics related activities affect the implementation time especially. The findings highlighted the differences between the use cases because the lowest implementation time was a few days, whereas the highest one was several months. Overall, use cases that required new sensors had the highest implementation time. The last task to prepare for the selection of use cases was to perform a risk analysis. The findings indicated that customer acceptance presented the main risk because it is crucial to convince the customer to connect their washing machine and to share data. Therefore, it is important to ensure that the customers understand the value of the use cases.

Select the use cases

Based on the detailed evaluation of the remaining seven use cases, the next task was to select the use cases that should form the use phase data strategy. The findings of the value-effort comparison provided the foundation for the selection of the use cases because the detailed analysis of the hours required for an implementation confirmed the previous results. Finally, the project team selected four use cases (UC 20, 21, 45, and 51) that seemed especially promising.

Applying different criteria helped to gain a detailed understanding of the benefits and efforts connected with each use case. In the end, it was possible to identify four use cases in order to derive a use phase data strategy.

7.3.7 Step 6 – Formulate the data strategy and derive the roadmap for implementation

Translating the four use cases into an overall use phase data strategy is the last important step for providing a clear direction. It is also important to have clarity about the required tasks.

Formulate the data strategy

A key criterion for the selection of the use cases was that they provide value for the case study partner and for its customers. Therefore, the developed use phase data strategy should help to reach the following three objectives: customer centred product development, analysis, connection, and exploitation of available data and data lakes, and additional insights about individual users.

Overall, the use phase data strategy and its objectives aim to help the company to reduce development costs and to develop products that are better tailored to the needs of customers. The benefits for the customer are individualised products and improved user experience. The strategy therefore should lead to competitive advantages. The application of the strategy map (see Section 6.7) further helped to document the overall use phase data strategy by linking use cases to the objectives of the four perspectives of the Balanced Scorecard.

Derive the roadmap for implementation

Especially for a large company like the case study partner, it is crucial to have an overview of required tasks and collaborations between different stakeholders. Thus, the decision was to use a combination of Gantt charts and roadmaps to visualize the implementation concept. On a use case level, the Gantt chart allowed for the documentation of efforts related to programming, IT infrastructure development, data analysis, knowledge collection, technical implementation, and training. Afterwards, the Gantt charts for each use case provided the main input for developing an overall implementation roadmap. The visualisation of the implementation concept strongly increased the transparency concerning the required tasks on a technical and organisational level. The analysis revealed that the implementation of two use cases could start immediately and would take only a short period of time. The roadmap also highlighted that the other two use cases build upon a technology that is currently in development, which means that the implementation needs to wait until then. Nevertheless, an important finding was that all use cases are independent, which allows for more flexibility during the implementation. Lastly, a product profile was derived for a use case that adds a new functionality to the product. The profile helped to develop an understanding of how the use case complements the current product and which benefits might arise for the company and its customers.

In summary, the last step derived a use phase data strategy that focuses on better understanding products' users in order to develop products tailored to the user's needs. The implementation concept also showed that the implementation of two use cases could start immediately. Overall, the case study enabled the industry partner to obtain an overview of possible use cases and available use phase data. Furthermore, the use phase data strategy provides a clear direction for the future and helps the product division to align their activities accordingly. The comprehensive analysis also helped the company to uncover existing data analytics skills within the organisation and to identify parallel projects working on related topics.

7.3.8 Evaluation results for the process model and case study results

This collaboration with the industry partner also ended with an evaluation of the developed solution approach and the case study results. Individual meetings with five key stakeholders at the end helped to summarize the development process for the use phase data strategy and to outline the key results. All five employees participated in the development of the use phase data strategy. The participants also represented different perspectives because they worked in product management as well as data analytics. In order to assure comparability, the employees had to fill out the same questionnaire for the evaluation at the end of the meeting.

The first evaluation criterion was the **usability** of the developed process model. Four participants either agreed or strongly agreed with all three statements. One participant stated that the process model could contain additional information. The results especially indicate that the stakeholders believe that the process model enables the user to develop a use phase data strategy. Furthermore, the feedback confirms that the process model is comprehensible.

It was further important to obtain feedback concerning the **applicability** of the process model. The overall results show that the applicability was rated less positively than the usability. The participants agreed that the process model provided methods and tools to derive use cases for internal stakeholders. In contrast, the results indicate that the methods and tools are less applicable to derive use cases for external stakeholders. The feedback however confirms that the process model is applicable for a bottom-up and top-down approach. Participants stated that the process model could be more flexible to allow an application in different contexts. One comment was that the process model should better respect the different starting points when developing use cases for internal and external stakeholders. Concerning the efficiency of the process model, the answers show a high variation, because one participant evaluated the effort as too high in relation to the results whereas another one stated that the efficiency of the process model is good. Another comment highlighted that the diverse evaluation criteria for the use cases help to assess the use cases from different angles.

After discussing the application evaluation, the next step is to assess the **usefulness** of the process model. Overall, the results show that for eight out of ten criteria, the average value is between agree and strongly agree, which indicates that the process is useful. On a detailed level, the responses indicate that the process model is especially useful for obtaining an overview regarding possible use cases and for fostering the integration of different stakeholders. Furthermore, the answers highlight that the process model creates transparency about available and required use phase data. Other useful features are that the context of the strategy development becomes clear and that the evaluation process ensures an informed selection of use cases. Nevertheless, the feedback also reveals potential for improvement. Based on the results, the process model is only slightly useful for generating new use cases. The comments indicate that the process model especially helped to collect and detail use cases that were spread within the organisation. In addition, the feedback emphasizes that the process model has limited usefulness for deriving use cases that add additional value. A clear benefit, however, is that the process model supports the entire process, from the ideation until the implementation concept.

The participants also provided feedback concerning the **use case catalogue**. Two participants highlighted that the catalogue is useful for triggering new ideas. Based on their perspective, providing ideas from other companies helps to make users think outside the box in order to come up with new use cases. The feedback also indicated that users must translate use cases into the company's domain first before an application is possible. Another participant mentioned that an implementation of the catalogue as a website would increase its usability.

Besides discussing the process model, the feedback also covered the **results of the case study**. Participants highlighted that each process step was useful for the development of the strategy, meaning that the case study did not generate unnecessary information. The feedback also confirms that all relevant stakeholders participated in the development process. Nonetheless, the results also show that the ratio between time invested and result achieved could have been better. However, the participants believe that the use cases will help the company to understand the usage of their product and to increase customer satisfaction. The overall grade for the results was between good and very good, which supports the positive feedback.

The answers to the **open questions** provide additional insights about contributions, drawbacks, room for improvement, and learnings. Based on the feedback, a main contribution of the process model is that it provides a structured and systematic approach, which helps to bring the different stakeholders together. Furthermore, the process model seems to be a communication and guidance tool. Based on the comments, the drawbacks of the process model are the high resource consumption and the effort required for its application. Adding more flexibility and providing best practise cases would help to improve the process model. The participants mentioned that the case study helped to collect and detail use cases that were spread within the company. Based on the evaluation, the business relevance and feasibility are also clearer. A key learning was also to understand the different perspectives on use cases and to identify requirements for future product generations in order to exploit use phase data better.

7.4 Evaluation case 3 – Home appliances sector (dishwashers)

This section describes the application of the process model at the dish care division of a large manufacturer for home appliances. The third evaluation case was six months long and was part of a student project (Evers, 2018). The objective was not only to apply the process model, but also to obtain evaluation results in order to identify potential for improvement.

7.4.1 Introduction of the case study company

The industry partner for the third evaluation case was the same partner as for evaluation case two. Therefore, Section 7.3.1 already introduces the basic characteristics of the company. Two main differences distinguish this evaluation case from the previous one. First, the collaboration took place together with the division that develops dishwashers, which means that the products use different technologies and face different customer expectations in comparison to washing machines. Secondly, the case study took place at the pre-development group. The task of this group is to develop product enhancements and new technologies. Therefore, this group is an enabler for future product generations, which rather follows a technology push approach. The product division has also offered connected products for many years and therefore already collects use phase data. In addition, the division wants to take better advantage of the digitalization and connectivity of their product. The company is a suitable case study partner.

7.4.2 Step 1 – Initiate the project and determine the objectives

The strategy development took place at a large organisation with different departments and stakeholders. It was thus important to ensure a structured definition of the project.

Initiate the project

The starting point for the project was the definition of the core team that will be responsible for the development of the use phase data strategy. Overall, the project team consisted of three members including the student working at the company during the time of the case study. However, the decision was to include other stakeholders during the later steps.

Determine the objectives

Two approaches helped to define the objectives of the project. First, discussions with the project sponsor helped to identify possible abstract objectives, which turned out to be insufficient. The second approach was to define 10 exemplary use cases, which allowed for narrowing the scope of the project. The overall objective of the strategy was that use cases must fit to the required focus areas that the pre-development group had for the development of dishwashers, which meant focusing on improving cleaning results instead of production improvements. In addition, the use cases should aim to provide an additional benefit for customers. Furthermore, the objective was to search for use cases that have a short, mid, and long implementation time. The strategy should thus comprise of use cases from these different categories.

Summing up, this step defined the key stakeholders working on the use phase data strategy. Furthermore, the defined objectives provided a clear understanding of the scope of the project.

7.4.3 Step 2 – Analyse the system and structure the situation

Having a foundation and scope for the strategy development project enabled the company to proceed with the internal and external analysis. It is important to understand the context for the use phase data strategy in order to derive a strategy that provides benefits.

System analysis

During the case study, the internal analysis focused on the analysis of the company, product, customers and users. The external analysis assessed the micro and macro environment in order to understand the context for the strategy. A combination of different sources (e.g., interviews, market reports, and online searches) helped to take advantage of available knowledge during the system analysis.

The analysis focusing on the company context confirmed the findings of the second evaluation case. A main strategic objective of the case study partner was to advance its products and services further using digitalization and the IoT trend. One benefit was that the company already provides a single interface that connects the differed home appliances. In addition, the company already offers an app and digital assistant. The company therefore has an IoT infrastructure to build upon. However, the sales numbers for smart home appliances and dishwashers indicated that potential for market growth exists. Based on the customer profile for the group (see Section 6.3), a key learning was that specific skills for digital solutions would help the group to develop innovations.

The next task of the internal analysis was to better understand the dishwasher product itself. In general, the case study partner offers more than 1,000 different variants using multiple brands. On the product side, two components enable the smart ability. The control module allows for controlling the different functions and the communication module sends and receives settings. At the time of the case study, an app allowed the user to monitor and control the dishwasher remotely (e.g., select a program). Use phase data therefore stems from the product and app. Discussions with engineers helped to derive a list of the 25 data points stemming from the product and app. Furthermore, it was possible to describe the data quality for each data point. However, it also became clear that the case study partner does not extract many insights from the data because projects working with the data started only shortly before the case study. At the time of the case study the IoT functionalities were monitor and control, which corresponds with the second IoT maturity level suggested by Porter and Heppelmann (2015).

The next task was to characterise the users. An analysis of an existing user journey revealed that choosing a program and missing program options are two key pain points. The application of a customer profile helped to summarize the findings of the user analysis.

An analysis of the micro and macro environment followed in order to finalise the analysis of the system. The first task was to understand the competitive situation. The case study company was one of the biggest manufacturers of dishwashers at the time of the case study, but a high number of experienced and new companies competed for market share. A comparison with the closest competitors revealed that all companies offer apps to monitor and control dishwashers. In addition, it became clear that none of the companies were offering outstanding use cases based on connectivity and use phase data. Therefore, the development of the use phase data strategy could help the case study partner to gain a competitive advantage. A strength-weakness analysis and Five Forces analysis helped to provide additional insights (see Section 6.3).

Structure the situation

Combining the findings of the internal and external analysis enabled the project team to gain an understanding of the current situation. A key learning was that different stakeholders exist that have interests and skills related to the development of the use phase data strategy. The overview of the relevant stakeholders helped to plan their integration into the next steps. Furthermore, the case study partner already stored use phase and context data at the time of the case study. Different responsibilities and systems led to a fragmented storage of data. The creation of a data map therefore helped to visualize the IT architecture and different systems. It became clear that no singular data lake existed that allowed different stakeholders to access different datasets. Instead, it was very difficult for one department to access data from another department, which is an important obstacle to overcome in order to exploit use phase data. A SWOT analysis helped to finalise the structuring of the system. The findings highlighted that the case study partner targets customers that are not as price sensitive and therefore most likely to be willing to pay for additional functionalities. Furthermore, the company already offers connected products and a platform connecting them, which provides a foundation to build upon. A weakness was that the case study partner needs to become faster in developing and implementing data-driven use cases. At the same time, new competitors are entering the market, which leads to an increase in competition.

Overall, the findings helped to gain a detailed understanding of the company, product, customer, and competitive environment. The findings indicated that the use phase data can help to give a competitive advantage and to address customer needs better.

7.4.4 Step 3 – Identify application areas and derive use cases

Starting with the identification of possible application areas helps to narrow down the scope of the use case search. Afterwards, the main challenge is to derive use cases that provide value.

Identify application areas

Based on the analysis during Step 2, it was possible to identify two possible application areas that also fit to the overall objectives of the strategy development project. The first application area was the development process of the pre-development group. Use cases within this area, for example, support the engineers in better understanding customer preferences and needs. The second application area was the customer itself because use phase data has high potential to improve the experience of the customer when using the dishwasher.

Derive use cases

The next task was to identify use cases that lay within the application areas. During the third evaluation case, a combination of five different sources helped to derive use cases. The use cases stemmed from an innovation day, internal documents, two workshops, and a search of the use case catalogue.

The first source for use cases was the innovation day of the dishwasher product division that took place at the beginning of the case study. The innovation day provided 17 potential use cases. The second source was internal documents. Prior to the case study, different workshops and meetings took place that conducted searches for possible use cases. It was possible to access the documentation of the results and it became clear that little time was spent on detailing these use cases. In addition, many use cases originated from the laundry care division, which is understandable because customers of these products have similar needs (e.g., clean clothes compared with clean dishes). In total, these internal documents provided 55 use cases.

Two workshops were an important source for generating additional use cases. Both workshops were part of the case study and therefore focused only on the identification of use cases. Each workshop was two hours long and used different methods (e.g., data memory and wargaming) to support the ideation process. Five engineers of the pre-development group attended the first workshop and had to apply two methods (data memory and data-driven process optimization). The main idea of the data memory method is to provide workshop participants with cards that list current and future data points in order to allow stakeholders to combine data points to derive use cases. The focus of the second method was to assess the pre-development process and identify potential for use phase data-driven improvements. The first workshop led to 41 use cases, but it is important to mention that the first method was responsible for 40 of these ideas. The second workshop involved stakeholders with different functions. During this workshop, the participants used data wargaming and a customer journey for idea generation. The first method asked the participants to imagine that they had access to the use phase data of competitors. Based on this scenario, they had to describe what they would do with the data to obtain competitive advantages. The other approach during the second workshop was to analyse the customer journey in order to identify potential ways in which data could improve the user experience. These two methods helped to generate another 27 use cases.

Overall, it was possible to derive 129 use cases, which includes 11 use cases derived from the catalogue and two from a discussion with other product divisions. It was possible to derive eight categories based on the benefit that a use case provides. Table 7-4 provides an overview of the categories and the number of use cases for each category. The table shows that supporting users through providing recommendations is the category with the highest number of use cases. Due to the high number of use cases, the next task was to organise and review them. Therefore, similar use cases were merged, multi-level use cases were split, and duplicates were removed. Furthermore, use cases that did not lie within the responsibly of pre-development were removed. In the end, 118 use cases remained on the list. Appendix A8.4 shows the list with the use cases. Lastly, the task was to document the use cases, describing the main functionality, use case category, main beneficiary, and source of each use case.

Step 3 helped to obtain an overview of 118 possible use cases within the dishwasher division. Many ideas for use cases already existed in fragmented way, but the application of the process model led to a comprehensive overview of potential use cases for all stakeholders.

Table 7-4: Overview of use case categories derived during the third evaluation case

Category	Details	# of Use Cases
Remote control	The dishwasher can be controlled remotely without using the control panel.	7
Remote monitoring	Usage data and other status variables can be assessed remotely.	14
Nudging/ Help	Based on use phase and context data, the consumer receives recommendations.	28
Automatisation	Through data not directly stemming from consumer interaction, the machine (and its program) is optimised.	22
Customer knowledge	The company can uncover new customer information.	12
Error recognition/ prevention	A machine error is recognised, prevented, or solved.	16
Customer Adaption	The machine adapts to the customer through direct consumer interaction data.	13
Business Model	New business models are enabled by the data.	8
Else	All use cases not fitting in the other categories.	9

7.4.5 Step 4 – Determine the data needs and consolidate the use cases

Once a long list of use cases is available, the objective is then to understand the data needs of these use cases. Furthermore, it is important to consolidate the use cases in order to provide a reduced number of them for the next steps.

Determine the data needs

The workshop results and expert interviews allowed for an assessment of the data needs of the use cases. Based on the analysis, it was possible to identify 60 data points that the use cases require. Out of these data points, 25 data points were completely new and required new sensors or technologies. However, the findings show that available data points can also provide valuable input for use cases. Overall, the results showed that a data-driven and use case driven approach is possible for the development of the use phase data strategy.

Consolidate the use cases

Understanding the data needs of the use cases is an important prerequisite for the consolidation of the use cases. Analysing 118 use cases on a detailed level is very challenging and therefore it was crucial to reduce the number of use cases. The first step was to derive a use case and use phase data matrix (see Section 6.5), which helped to identify use cases with similar data needs. The matrix also enabled the identification of hierarchical dependencies among the use cases.

However, this approach only helped to gain additional transparency without actually reducing the number of use cases. Therefore, the project team defined four criteria to evaluate the use cases: pre-development fit, demand for additional technologies or sensors, customer benefit, and contribution to a hunting field. Firstly, two engineers assessed whether the pre-development department would be responsible for a use case. This analysis helped to reduce the number of use cases to 75. Secondly, the objective was to remove use cases that require special technologies or sensors. The task was therefore to understand what the underlying technologies for each data point were. This analysis helped to reveal technologies that are a key enabler for many use cases, which might justify their development. One key technology turned out to be responsible for 30 use cases. Based on this assessment, it was possible to eliminate technologies that enable only a limited number of use cases. This process led to 59 remaining use cases. Thirdly, it was possible to remove an additional 10 use cases that did not provide value for the customer. The final approach was to check whether each remaining use case contributed to at least one of the company's hunting fields. Overall, this concluded in a selection of 47 use cases.

The main contribution of this step was to have a detailed understanding of the data and technology needs of the use cases. This helped to reduce the number of use cases to 47, which constitute the main input for the concluding tasks.

7.4.6 Step 5 – Evaluate the use cases and select

The previous discussion of the data needs revealed that new technologies and sensors function as important enablers for multiple use cases. Therefore, the objective is to assess the effort required for the technology development and use case implementation. This knowledge allows for a cost-benefit analysis to be made in order to select suitable use cases.

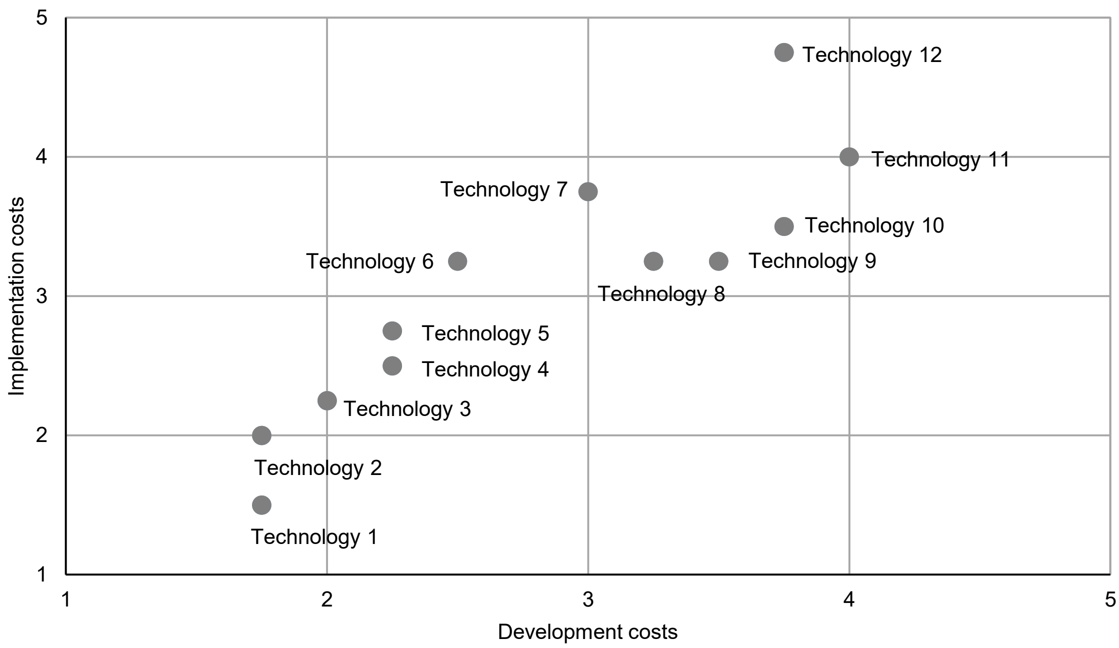


Figure 7-11: Portfolio illustrating the evaluation results for the technologies

Evaluate the use cases

A main finding of the previous step was that several use cases require 12 new data points, which entails the development of new sensors and their integration into the product. Therefore, the first task is to evaluate the technology needs before detailing the use cases. Five employees from different domains (i.e., physics, electronics, and digitalisation) helped to evaluate the technologies in relation to development costs, implementation costs, and timeframe for development. To evaluate the technologies in relation to their costs, the experts scored them on a scale of 1 to 5 (1 – very low costs and 5 – very high costs). For the evaluation of the implementation time they had to assign each technology to one of three categories: short- (within one year), mid- (between one and four years), or long-term (more than four years). Figure 7-11 summarizes the evaluation results concerning the costs, which indicates a correlation between both sets of costs. Altogether, the experts had similar opinions concerning the costs. Overall, the results showed that four technologies had a short implementation time, five had a middle one, and three had a long one.

Use cases	Formula 1	Formula 2	Formula 3	Formula 4	Formula 5	Formula 6	Formula 7	Formula 8	Formula 9	Average rank
UC 78	1	2	1	1	2	2	1	2	1	1,4
UC 113	4	1	2	4	1	1	4	1	2	2,2
UC 22	3	3	3	3	3	3	3	3	3	3,0
UC 114	2	4	4	2	4	4	2	4	4	3,3
UC 13	5	5	5	5	5	5	5	5	5	5,0
UC 124	6	6	6	6	6	6	6	6	6	6,0
UC 30	7	7	7	7	7	7	7	7	7	7,0
UC 66	9	8	8	9	8	8	9	8	8	8,3
UC 53	8	10	10	8	10	10	8	10	10	9,3
UC 7	10	9	9	10	9	9	10	9	9	9,3
UC 75	11	11	11	11	11	11	11	11	11	11,0
UC 108	12	12	12	12	12	12	12	12	12	12,0

Figure 7-12: Results of the sensitivity analysis for use cases with a short implementation time

Afterwards, the next task was to evaluate the use cases based on the evaluation results for the different technologies. First, the objective was to determine the implementation time for each use case. In the case that data was already available for a use case, the implementation time was set to short-term. For use cases that required new technologies, the maximum value for the implementation time of the technology determined the implementation time of the use case. A key finding was that technology development is the main driver for costs and complexity. In summary, 12 use cases were rated as short-term, 18 as mid-term, and 13 as long-term. Afterwards, four internal stakeholders evaluated the benefits of each use case in relation to three categories: newness, customer benefits, and business potential. The last challenge in conducting the cost-benefit analysis was to combine the evaluation results for the technologies and use cases. The team decided to use different formulas to derive an overall cost-benefit estimation. All formulas compared the cost-benefit ratio for each use case, but the different formulas weighted each of the three benefit categories differently. At the same time, each formula also calculated the overall costs differently based on the use case and technology-related costs. Figure 7-12 shows the results of the sensitivity analysis for short-term use cases, which helped to assess the impact of the formula on the rank of a use case. Overall, this approach allowed all use cases to be ranked within each of the three-time categories in relation to their cost-benefit ratio. The finding was that the different formulas had little influence on the rank of a use case.

Select the use cases

After obtaining a detailed understanding of the use case specific costs and benefits, the challenge was then to select suitable use cases. Based on the evaluation results, the project had selected 15 use cases. An adapted version of the use case template (see Appendix A6.8) helped to document the remaining use cases and add missing information. Afterwards, the project head reviewed all use cases one more time, which resulted in nine remaining use cases (UC 13, 21, 28, 30, 33, 61, 90, 95, and 112) for the use phase data strategy in addition to four optional ones (UC 29, 47, 49, and 124). A comparison of the use cases highlighted the following four benefits cluster: hygiene, automatic program adaption, ecological machine and consumer behaviour, and dishwasher flexibility.

Summing up, the results of this step provided detailed insights into the costs and benefits of the use cases. Furthermore, the evaluation of required technologies helped to uncover important efforts and concluded in the selection of nine use cases.

7.4.7 Step 6 – Formulate the data strategy and derive the roadmap for implementation

The evaluation of the use cases resulted in a set of nine remaining use cases. Therefore, the objective is to derive an overall strategy and a roadmap for the implementation concept.

Formulate the data strategy

Nine use cases from the previous step provided the foundation for the development of the use phase data strategy. The overall objective of the strategy was to foster customer centric development projects within the pre-development group. A comparison of the use cases highlighted that they provide the following benefits: improved environmental friendliness, dishwashing simplification, flexible usage of the dishwasher, hygiene improvements, and better reliability. Deriving a strategy map (see Section 6.7) helped to provide a comprehensive understanding of the use phase data strategy. It was possible to describe the benefits of the strategy in all four domains of the Balanced Scorecard. The strategy map highlights that the strategy can provide value for the case study partner (e.g., additional turnover or cost savings) and its customers (e.g., better dishwasher performance or easier program selection). However, it also became clear that the company needs additional skills (e.g., data analytics). In addition, a product profile for one use case highlighted the value that a use case adds to an existing product. Implementing the use cases requires more time and therefore the next generation of dishwashers might be different, which means that the product files require updating.

Derive roadmap for implementation

After deriving the strategy, the last task was to formulate a roadmap for the implementation concept. The decision was to formulate two types of roadmaps. First, an overall development roadmap outlined the implementation concept for all use cases. The roadmap consisted of three lanes: required technology, planned use case, and available data. This roadmap helped to highlight the dependencies between all three domains. The visualization was helpful for pointing out the technological prerequisites of the use cases. Based on the roadmap, the implementation of certain use cases will not be possible before 2023 due to missing technology. Second, an exemplary roadmap for one use case enabled a description of the development process on a more granular level, highlighting required tasks and stakeholders. However, the use cases require further detailing in order to define all responsibilities and tasks.

Altogether, the evaluation case supported the pre-development group in deriving a use phase data strategy that consists of nine use cases enabling improved customer centric development. However, it was not possible to derive a use case that would help the company to dominate the market.

7.4.8 Evaluation results for the process model and case study results

This case study also ended with an evaluation of the solution approach and the results. The use of the same questionnaire helped to ensure that the results were comparable. The evaluation followed the final presentation of the case study results. Five employees with an average employment time of four years filled out the questionnaire.

The first part focused on the **usability** of the process model and the manual. The overall results show that the participants either agreed or strongly agreed with all three statements. Therefore, the results confirm their usability, especially highlighting their comprehensibility.

Afterwards, the objective was to assess the **applicability**. The results of the evaluation show a differentiated picture. The participants believe that the process model is applicable in the engineering context. Furthermore, the results indicate that the process model offers the means and methods to derive a use phase data strategy for internal and external stakeholders. Lastly, the process model seems also applicable for a data-driven and a use case driven approach. Nevertheless, the results also highlight room for improvement. The answers indicate that the flexibility and information needs did not meet the expectations of all stakeholders. A point of critique is the high effort required for an application of the process model.

Another important dimension in focus was the **usefulness** of the process model. Altogether, the results indicate that the process model is useful for certain aspects, but also that there is potential for improvement. Based on the answers, the process model is especially helpful for obtaining transparency about available and required data. They also showed it to be helpful for providing an overview of possible use cases. Nevertheless, the feedback indicates that the process model seems less useful to generate new use cases. The comments show that it is not only the process model that is responsible for generating new use cases, but also the stakeholders. The answers however also confirmed that the process model helped to identify clusters of use cases. Concerning the usefulness of the cost-benefit assessment, the feedback is mixed. One comment indicates that a quantitative assessment of the cost-benefit ratio would have been beneficial.

The evaluation of the **methods** only covered the use case catalogue. In addition, oral feedback was provided concerning the four methods used during the two workshops in Step 3. The answers indicate that the use case catalogue is applicable and useful for the search for use cases. However, one participant mentioned that the interface of the catalogue should be improved. Concerning the four methods, the overall feedback was positive. Workshop participants stated that they helped to support idea generation and triggered innovative ideas for use cases.

Concerning the overall case study **results**, the feedback shows that it was possible to achieve a good outcome (average grade 2). The participants confirm that the use phase data strategy matched the objectives. Furthermore, all steps were necessary for the development of the use phase data strategy. However, the participants stated that the resource consumption was very high and that the case study did not involve all relevant stakeholders. Overall, the stakeholders believe that the strategy will have a positive impact on the product and service quality as well as customer satisfaction. Based on the comments, a drawback was that the case study did not reveal a ground-breaking use case. Nevertheless, the comments show that it was possible to obtain a structured overview of possible use cases.

The last aspect to discuss is the **open questions** on the questionnaire. Based on the comments, the main contribution of the process model was the provision of a structured approach for the strategy development. Furthermore, the process model helped to cluster use cases and derive dependencies between use cases and technology needs. Two participants also highlight that the process model led to new use cases. Concerning the drawbacks, the comments indicate that the process model involved too many different methods, which increased the effort required. Another participant mentioned that the development of a tailored evaluation approach required too much effort. The comments also indicated room for improvement, which involved reducing the complexity of the process model and providing approaches for evaluating use cases. The main learning for the stakeholders was that it helps to prioritise use cases and focus on selected ones. Furthermore, a scientific tool for the development of a use phase data strategy was positive for the stakeholders.

7.5 Evaluation case 4 – Railway sector

The motivation for the fourth evaluation case was to obtain evaluation results from a company outside the home appliance sector as well. The fourth evaluation partner is a large railway company from Germany that operates regional and long-distance trains. The decision was made to conduct interviews with this company because the company operates a large fleet of modern trains that produce large amounts of use phase data. At the same time, the company is currently working on the exploitation of use phase data in order to increase the reliability of the trains and to improve customer satisfaction. However, it is important to highlight that the railway company is not responsible for the development and production of the trains.

The company consists of different divisions due to the number of employees and different business sectors. The interview-based evaluation took place together with the division for long-distance traffic. Two employees of the division attended the evaluation. The first person had been working for the company for more than four years and was responsible for an initiative focusing on predictive analytics at the railway company. The second person was a data scientist who had been working for more than half a year at the railway company. However, the second participant worked at several other companies before and was therefore an experienced data scientist. The interview-based evaluation lasted 90 minutes and consisted of two parts. During the first 30 minutes, the process model was introduced including results from a previous application in industry. Afterwards, a semi-structured interview with both participants followed (see Appendix A8.5 for questions).

The interview started with some general questions and the answers confirmed that the process model and the manual were comprehensible. The two participants further confirmed that the process model appeared to be applicable to develop a use phase data strategy at the railway company. Afterwards, the discussion focused on the completeness of the process model and the order of the process steps. The interviewees confirmed that the process model contains all relevant steps for the development of a use phase data strategy. At the same time, the interview confirmed that the order of the steps appears to be logical. However, the discussion also highlighted that the company would start at step 3. One reason was that the project team only consists of a few people, which makes the definition of a team unnecessary. Furthermore, the objectives of the team are also clear because its focus is to develop predictive approaches. The interviewees also confirmed that step 2 is important in order to have a clear overview about the current situation, but due to existing knowledge and missing resources, the participants would skip this step. Nevertheless, the participants agreed that both steps are important in general.

The next part of the interview focused on the discussion of the potential benefits and drawbacks of the process model. The two interview partners mentioned different benefits. A central benefit would be that the process model provides a clear structure when planning to exploit use phase data. The data scientist highlighted that this is especially important for this topic because it is a rather novel topic for many companies. Many employees have not worked on analysing use phase data before and therefore experience regarding how to approach such a task is lacking. In addition, the participants mentioned that a systematic exploration of possible use cases leads to increased transparency about possible options and helps to derive a comprehensive list of use cases. They furthermore stated that the process model could help to foster an objective selection of use cases, which ensures clear understanding of the benefits related to each use case.

Concerning the roadmap and the strategy, the feedback indicated that both documents are useful. Firstly, to communicate the use case selection and secondly to gain an understanding of the required tasks for an implementation. The interview also provided insights about potential challenges. A main point of discussion was how comprehensible the process model is for stakeholders that have not worked on this topic before. Therefore, the suggestion was to review the process model prior to its application in order to use terms and methods for the strategy development that fit to the company context. The interviewees also pointed out that a clear understanding about the feasibility of use cases is only possible once the implementation has begun. It is therefore important to perform an extensive assessment of the use cases before the selection. Both stakeholders also mentioned that the assessment of the use cases is very challenging because during step 5 only a rather qualitative evaluation is possible. Lastly, the data scientist mentioned that the work for her would start after step 6 once the use cases are ready to be implemented.

Overall, the interview-based evaluation provided valuable input concerning the strengths and weaknesses of the process model. The railway company also highlighted that they would like to apply the process model to obtain an overview of possible use cases and select suitable ones. Altogether, the interview-based evaluation highlighted the advantages of the solution approach.

7.6 Conclusion derived from the industrial evaluation

The objective of this section is to derive an overall conclusion concerning the evaluation of the process model and the methods. Section 4.2 describes the formal, functional, and application requirements that set the scope for the development of the process model. Thus, the objective is to assess to which degree the process model is able to fulfil each requirement. At the end of each evaluation case, every participant filled out the same questionnaire (see Appendix A8.1 for the questionnaire). The first three evaluation cases allowed for a comprehensive application of the process model in industry. Therefore, the evaluation results of the industrial case studies serve as the main foundation for the final evaluation. In order to derive an overall conclusion, the answers from the questionnaire were converted into numerical values (-2 = strongly disagree and +2 = strongly agree). Afterwards, the mean value for each question was derived. The questionnaire contained at least one question that directly linked to one of the 12 requirements. Figure 7-13 summarizes the overall evaluation results and indicates the fulfilment of the different requirements. If the mean value for a certain requirement would had been at +2 then the bar would have been at 100 %. Accordingly, a mean value of -2 would result in a 0 % bar. Additional radar charts in Appendix A8.6 highlight the differences among the three evaluation cases concerning the results for each statement.

The first assessment focuses on the **formal requirements** for the process model. The results show that the process model is able to fulfil all four requirements to a high degree. The participant's answers to the open questions confirmed that the process model helps to foster a structured development of a use phase data strategy. At the same time, the overall results also showed that the process model and its manual help users to follow a step-based approach for the development of the use phase data strategy. However, the comments also highlighted that prior experience helps to apply the process model. Furthermore, the process model allows users to follow a use case driven and a data-driven approach. All three case studies used a combination of both approaches in order to derive use cases. Lastly, the case studies showed that the process model successfully helped companies to overcome managerial and planning challenges.

Figure 7-13: Overall results of the industrial evaluation of the process model

The next task is the discussion of the **functional requirements**. Figure 7-13 shows that the first requirement has a lower degree of fulfilment compared with the later three ones. First, the results show that the process model supports companies in obtaining internal and external transparency. The feedback during the case studies confirmed that it was very helpful for the companies, for example, to obtain an overview of available data pools and the IT infrastructure. The second and third evaluation case revealed that it is also important to create an organisational transparency in larger organisations first. However, gaining transparency also appeared to be a time-consuming task. Nevertheless, the findings show that the process model's fulfilment of the second requirement was rated slightly better. The process model was useful for obtaining an overview of possible use cases and for identifying dependencies among the use cases. However, a point of criticism was that the process model did not create many new use cases and that the evaluation was rather qualitative. In addition, more support could be provided for outlining available and required use phase data. There is, however, a difference between the first case study and the other two. The participants from the first case study partner stated that the process model did not help to create transparency about use phase data. Whereas the results from the second and third evaluation case indicate that the process model is very helpful for this task. Lastly, the evaluation results show that the process model led to a use phase data strategy and implementation concept that was suitable.

Concerning the **application requirements**, the results of the evaluation also show mixed feedback. The findings show that the participants believe that the process model is not fully applicable for every engineering company. A suggestion for improving the applicability was to review the process model before its first application in order to ensure that it fits to the company context. The second requirement focuses on the flexibility of the process model. The results also indicate that room for improvement exists. Findings from the case studies highlight that it is helpful that the process model suggests methods for the different tasks. However, the process model needs to consider the methods that already exist within a company. Furthermore, the industry partner requires more support to identify the most important tasks of the process model depending on their situation. Nevertheless, the evaluation results confirmed the importance of a collaboration between the different disciplines within a company in order to exploit use phase data successfully. A key strength of the process model is that it fosters and triggers collaboration between different stakeholders. The last requirement is the efficiency of the solution approach. Overall, the results show that the ratio between the value of the results and the time invested could be improved further. Based on the ratings for the results, it becomes clear that all three case studies provided good results. However, the participants believe that the effort involved was too high. The resource consumption during the identification of use cases was named as a possible aspect for improvement. A proposed solution would be to lower the number of stakeholders involved in the use case search. Furthermore, the process model should provide better guidance about how many use cases a company should identify in order to avoid that too many are discarded later on.

Overall, the evaluation results draw a positive picture and show that the process model is able to support companies in developing a use phase data strategy in a structured way. In addition, the developed methods (e.g., use case catalogue) further support the development process and were evaluated as useful. Nevertheless, the process model also had unintended effects, for example, by highlighting the value of existing use phase data or connecting stakeholders from different departments that have not collaborated before.

8 Discussion and contribution of this thesis

After outlining the findings of the industrial evaluation of the solution approach, the objective of this chapter is to discuss this thesis and outline the contribution that it provides. Thus, Section 8.1 first discusses the research approach and then the research results using the three research objectives as a foundation. Finally, Section 8.2 outlines the contribution of this work to research and industry.

8.1 Discussion

The starting point for this dissertation was the definition of research objectives (see Section 1.3). The intention of this thesis is to provide methodological support that enables companies to develop a use phase data strategy in a structured way. In order to achieve this, the overall objective was subdivided into three objectives. The foundation for the research approach was the DRM of Blessing and Chakrabarti (2014) (see Section 1.4.1).

8.1.1 Discussion of the research approach

The starting point for the research was a **review of existing literature** on digitalisation, data analytics, and connected products (see Chapter 2). A main challenge for this review was the diversity of terms used within the different publications. Publications that focus on connected products also use terms like IoT, smart PSS, or (smart) connected products. Accordingly, researchers and practitioners did not agree on a single term. Similar findings also occurred within the data analytics field. Furthermore, the discussion of the two research fields of connected products and data analytics illustrated how closely both fields are related when the focus is on certain topics (e.g., challenges and suggestions for an implementation). Another challenge was the popularity of the research domain for industry and research. The literature review revealed that a fair amount of publications that address organisational challenges related to the exploitation of use phase data stemming from consulting companies (e.g., KMPG or McKinsey & Company), industry associations (e.g., BITKOM), or companies providing technology for connected products (e.g., IBM). Publications about the technical challenges often stem from academia. Overall, the review of literature also pointed out that the number of publications focusing on data analytics and connected products is growing steadily. Therefore, it was important to constantly monitor new publications.

However, it was not only literature that provided important input to identify the need for additional research, but also **empirical studies**. The literature review provides a helpful overview of challenges and benefits related to the exploitation of use phase data. Nevertheless, it was important to gain a comprehensive understanding of the barriers that companies face when planning to exploit use phase data for this work. The first four initial case studies had a wider scope, so that it was possible to obtain an understanding of the activities and problems that arise when companies want to exploit use phase data (see Section 3.1). The main contribution of these four studies was an understanding of the importance of a use phase data strategy. At the same time, the initial case studies also revealed the challenges that companies face when planning to exploit use phase data.

Another important source for empirical data was an additional **interview study**, which allowed for the discussion of problems and opportunities related to data analytics in product development (see Section 3.2). A main motivation for this interview study was that many publications about data analytics do not focus on engineering companies in particular. However, the assumption was that engineering companies face special challenges, for instance due to the longer development cycle of a product compared to those of software. The interview study also helped to highlight the importance of a use phase data strategy and a structured approach for its development. Due to the strategic importance of this topic, it was very challenging to find interview partners from industry that were willing to talk about their strategy for exploiting use phase data. The experience during the interviews also showed that it was helpful to introduce the terms 'use phase data' and 'use phase data strategy' into this work. The introduction of these terms helped to set a clear scope of data that stems from connected products and services. The experience during the interviews showed that using a term such as 'Big Data' makes the discussion challenging due to the diverse understanding of the term among practitioners. Furthermore, the interviews also confirmed that companies see high potential in exploiting use phase data, but at the same time have not gained comprehensive experience of exploiting use phase data. Therefore, it was not possible to derive a best practice approach from the results.

In order to discuss the findings of the interview study and to detail the needs of industry for additional support, an **industry workshop** was conducted (see Section 3.3). The workshop highlighted that only a minority of industry participants would prefer a trial and error approach for the development of a use phase data strategy. In contrast, other participants stated that they could not afford to integrate sensors and collect data without a clear strategy. Nevertheless, the workshop confirmed that companies would like to have methodological support for the development of a use phase data strategy.

Afterwards, combining the findings of the literature review and empirical studies helped to outline the **need for a solution approach** (see Chapter 4). The analysis revealed that planning and managerial challenges present a main obstacle for companies when exploiting use phase data. Based on the understanding of the problems, it was not only possible to narrow down the scope of this thesis, but also to derive requirements for a solution approach that addresses the planning and managerial problems. Having a set of requirements was very helpful to evaluate existing process models for data analytics projects and to outline their shortcomings, which highlighted the research gap.

The following research step was the **development of the process model** and the **supporting methods**. For this task, this thesis used a combination of insights stemming from literature and empirical data. Therefore, it was possible to bring the academic and industrial perspective together. Combining existing process models for strategy and data analytics further allowed for the derivation of a process model for the development of a use phase data strategy that brings together the strategy and data perspective. Building upon existing work helped to make use of established approaches and, at the same time, to focus on the novel obstacles linked to the exploitation of use phase data. The application of the conceptual process model during three orientating case studies then provided important feedback concerning the design of the solution approach. Using an early version of the process model allowed for the collection of early user feedback. The findings help to reveal tasks (e.g., ideation for use case) that are particularly challenging for companies when developing a use phase data strategy.

Furthermore, the case studies provided a helpful foundation for the development of additional methods because it was possible to derive methods during the case studies at the same time that the need for additional support was occurring. Furthermore, it was also possible to apply and test the newly developed methods. A main challenge for the development of the process model and the methods was the diversity in company characteristics (e.g., availability of connected products or experience with exploiting data) that influence the application context for the process model and the methods. However, the empirical data that was gathered when working with different companies allowed for the design of a flexible solution approach. Due to the success of the case studies, they also marked the start of a continuing collaboration with the industry partners. Overall, the approach led to the development of the comprehensive process model and its methods, which support companies in developing a use phase data strategy.

The last research step was the **evaluation** of the methodological support. It was possible to conduct three independent evaluation case studies at two different companies. These circumstances allowed for a comprehensive application and evaluation of the process model. A fourth interview-based evaluation further completed the evaluation. In general, the DRM suggests evaluating three dimensions of a solution approach: usability, applicability, and usefulness. It was possible to evaluate all three dimensions. However, the evaluation of the usefulness was only initial. It was not possible to evaluate what the final benefits (e.g., increase in turnover) of the developed use phase data strategy will be because the benefits of a use phase data strategy will only become visible after its implementation. Nevertheless, it was possible to evaluate the usability and applicability of the process model.

Using a standardised and identical questionnaire for all case studies enabled a detailed comparison of the results. In the end, the follow-up interviews with case study partners provided additional information to better interpret the evaluation results. A main characteristic of all evaluation cases was that each company already had connected products. From a research perspective, it would have been interesting to conduct an evaluation with a company that did not offer any connected products in order to assess whether additional challenges occur.

An aspect to discuss is the comprehensive **use of case studies** for this research work. Figure 8-1 summarizes how case studies contributed to the different steps of the underlying research process. Overall, collaborations were done with eight different industry partners because one initial case study only happened in an academic environment and two evaluation cases took place at the same company. Nevertheless, the use of case studies provides valuable insights about the obstacles that hinder companies from successfully exploiting use phase data. Applying the process model in industry allowed for detailed feedback concerning the benefits and shortcomings of the methodological support to be obtained. Due to the collaboration with a broad spectrum of companies, which were diverse in terms of size, experience in exploiting use phase data, product type and customer, it was possible to derive insights from a variety of company contexts. Furthermore, the case studies included the identification and elaboration of use cases, which provide benefits for internal and external stakeholders. Altogether, this broad spectrum helped to derive a methodological support that was derived from different settings.

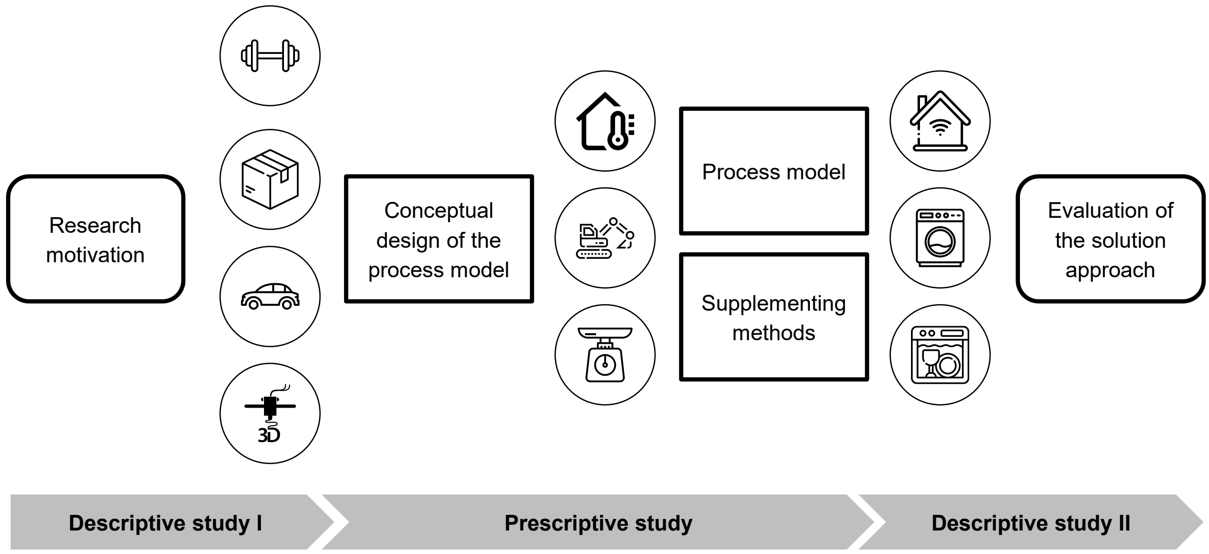


Figure 8-1: Case studies used over the course of the research project

8.1.2 Discussion of the research results

Having discussed the research approach, this section focuses on the results, which present the outcome of the research process. The overall objective of providing methodological support has been subdivided into three objectives, which will be discussed in turn.

The **first objective** was to gain an understanding of the problems that hinder the exploitation of use phase data. Based on the analysis of existing literature and empirical data, it became clear that planning and managerial challenges at the beginning of the data exploitation process present a major obstacle for engineering companies (see Section 4.1.1). Findings of the analysis confirmed that companies need to develop a use phase data strategy in order to have clear objectives. Furthermore, the results of the analysis revealed that certain tasks are especially challenging for companies (e.g., gaining internal and external transparency, or identifying use cases). The orientating and evaluation case studies confirmed the importance of overcoming the planning and managerial challenges. Due to the comprehensive description of the challenges, the research objective can be considered to be fulfilled. Additional case studies or an interview study might have helped to further prioritize the different challenges. Nevertheless, it was possible to outline problems that hinder companies in exploiting use phase data and to derive a set of requirements for a solution approach that would be able to overcome them.

The **second objective** was to provide operational guidance for the development of a use phase data strategy. The main input for the discussion of the process model stems from the evaluation results (see Section 7.6). The discussion of the formal requirements confirms that the process model provides a suitable structure and enables companies to develop a use phase data strategy step-by-step. The manual for the process model aims to make its application in industry easier due to the reduced complexity. However, the discussions showed that the application of the process model requires a certain degree of experience. Especially in the case of inexperienced companies, the manual can only provide a starting point. Therefore, it is important to use both the comprehensive textual description of the use phase model and the corresponding manual. Overall, the results confirmed that the process model is comprehensible.

From a functional perspective, the evaluation highlights strengths of the process model as well as room for further improvement. A main point of discussion in two evaluation cases was that the process model did not reveal “killer” use cases. Companies used this term for use cases that can provide outstanding benefits for external or internal stakeholders. It is important to highlight that the process model was not designed to function as a method of fostering creative thinking for deriving use cases. The objective of the process model is to provide a structure for the development of the use phase data strategy. An important task during the strategy development is the identification of use cases and, therefore, the process model suggests starting points for the search for use cases. Even though the process model might not have revealed outstanding use cases, the feedback from industry indicated that the process model was useful for collecting the various ideas for use cases that exist in a company in order to obtain an overview. The discussion regarding outstanding use cases also highlights an additional problem. Data analytics and connected products are very popular topics, which often lead to high expectations among practitioners. However, companies need to also question their expectations and should aim for less complex use cases at first. Different publications highlight the importance of a continuous extension of competencies and use cases. A good starting point is to focus on quick wins first, before getting lost in the search for outstanding use cases. In addition, during each evaluation case study it was possible to derive between 51 and 118 potential use cases. The sheer number of use cases does not say anything about the quality, but it does show that the process model helps to explore a large range of possible use cases.

Another point of discussion was how detailed the analysis during Step 2 of the process model should be. Two evaluation cases were conducted at one large company with more than 50,000 employees and one at a start-up. The interview with stakeholders from the large company highlighted how important it is to conduct a comprehensive internal analysis. A discussion at the start-up revealed that an internal analysis was considered less important. Accordingly, the scope and comprehensiveness of the analysis must be determined based on the situation and existing transparency at the company. At the same time, there is a certain risk that companies believe they already have an adequate overview and therefore skip this step. However, a thorough analysis of the internal and external environments provides an important foundation for the development of a use phase data strategy. A stakeholder from the large company confirmed that without the detailed analysis certain aspects would have been overlooked.

The last subject of discussion concerning the functional requirements was the assessment of the identified use cases. The challenge during the assessment is to ensure an adequate level of detail among all use cases. Without a certain level of detail, a comprehensive assent is not possible because advantages and disadvantages do not become visible. Selecting the final use cases that form the strategy is an important step. Therefore, stakeholders mentioned that it is important to provide guidelines for the selection and evaluation process. Nonetheless, the process model is able to provide suitable approaches for an assessment that companies then need to adjust according to their objectives for the use phase data strategy.

Concerning the use phase data strategy itself, stakeholders agreed that each strategy looked promising. However, it is difficult to assess the actual value of a use phase data strategy only shortly after it has been implemented. Therefore, an assessment of the outcome of the process model was only possible based on the estimations of the employees. The interviews that followed the evaluation confirmed that developed use phase data strategies provide clear objectives and outline a path towards exploiting use phase data more successfully.

Lastly, the evaluation confirmed the applicability of the process model. However, stakeholders from all evaluation cases mentioned that the efficiency of the process model should be improved. The efficiency is driven by the time invested in the strategy development and results. Many of the stakeholders provided good ratings for the results, although interviews with them also highlighted that the process time for the strategy development could be shortened. A participant from the start-up mentioned that it might be better to apply the process model in short iterations instead of spending six months on one iteration. This suggestion was also discussed with an employee that participated in the second evaluation case, where the clear feedback was that strategy development in large companies takes time and six months is rather quick. These contrary opinions highlight the challenge of providing a solution approach that fits all companies. A solution could be to better empower the user of the process model to decide themselves beforehand how much time each step should take.

A clear strength of the process model was that that it brought relevant stakeholders together in order to derive a use phase data strategy. The literature review and the empirical studies highlighted how important it is that the different disciplines collaborate in order to exploit use phase data. Based on the evaluation results, the process model was able to achieve this by integrating various disciplines right from the beginning of the strategy development.

Overall, the evaluation results confirm that the process model provides adequate guidance for the development of a use phase data strategy. Furthermore, the written feedback showed that the process model was helpful for creating an overview of potential use cases. Altogether, these results show that the second objective was achieved.

The final aspect of the discussion involves the **third objective**, which was to provide additional methods that support the application of the process model. Overall, it was possible to derive a set of 16 additional methods to complement the process model. Each method supports a certain activity during the application of the process model. Some methods (e.g., data journey) can be used during two steps of the process model. Furthermore, it is important to mention that the methods differ in complexity. The feedback provided for the overall methodological support was quite positive. However, some stakeholders mentioned that it was difficult to apply methods that they had not used before. A suggestion would be to adopt those methods suggested by the process model that correspond to the methods used at the company. Nevertheless, the general feedback was that the methods are helpful and support the application of the process model. The use case catalogue especially received positive feedback because it provides ideas gathered from other companies. Accordingly, the process model and its methods can foster the search for innovative use case ideas.

In summary, it was also possible to fulfil the third research objective as well. However, it would have been useful to conduct additional workshops with participants from industry to evaluate each method on a detailed level. Nonetheless, the evaluation results highlighted that the developed methods provide additional value for the process model and therefore support the development of a sound use phase data strategy.

8.2 Contribution of this thesis

Digitalisation, exploitation of data, and connectivity of technical products are currently three important topics for research and industry. The results of this thesis connect these fields in order to enable advances in academia and industry. Overall, the contribution of this work is to enable companies to develop a use phase data strategy in a structured way, which aims to foster a more successful exploitation of use phase data.

8.2.1 Research contribution

The results of this thesis mainly build upon existing work in the fields of data analytics and connected products. Therefore, the results contribute to these research fields in different ways, which are discussed in the following.

The main contribution of this thesis is the **process models**, which provides operational guidance for the development of a use phase data strategy (see Chapter 6). The starting point for the development of the process model was an analysis of existing process models for data analytics, problem solving, and strategy development. The research on data analytics highlighted the importance of a data strategy in order to derive clear objectives. At the same time, the research on strategy development provided general approaches for the development of a strategy. However, the existing work on strategy development did not take the specific challenges that arise when developing a data strategy into account. Therefore, existing work does not provide tailored solutions that address the specific technical and organisational challenges related to the development of a use phase data strategy. The developed process model therefore builds upon established work for strategy development and takes advantage of existing methods and approaches. Thus, the research results also foster a knowledge transfer between both research fields. Overall, the developed process model itself contributes to the research on exploiting use phase data because it addresses the need for additional methodological support. Current research on data analytics and connected products pays special attention to the technical challenges (e.g., development of algorithms or measures for data security) (Saltz, 2015, p. 2066), but the findings show that organisational challenges are also a key barrier to the exploitation of use phase data. Current support mainly consists of recommendations for the implementation of data analytics. Methodological support for companies that are planning to exploit use phase data is, however, missing. The process model provides an important starting point for companies that want to exploit use phase data, but additional steps need to follow afterwards in order to implement the strategy. Therefore, future research can use the process model to develop additional methodological support for the following steps.

The **developed methods** for the process model present another important contribution (see Appendix A6). The main input for the methods came from existing methods. Therefore, the results illustrate how existing work can be transferred into the domain of connected products. However, the results also show how future research can help to provide additional methods to support companies. Based on the evaluation, the developed use case catalogue presents an important contribution because it provides a structured overview of possible use cases for connected products. At the present time, many publications discuss individual or a limited set of use cases, but a comprehensive overview is missing.

Another important contribution results from the comprehensive analysis of existing publications and empirical data. The outcome is a description of the **planning and managerial challenges** that engineering companies in particular face when planning to exploit use phase data (see Section 4.1). Previous studies on data analytics did not focus on the special needs of engineering companies that arise, for example, from longer and less flexible product development cycles. Furthermore, the identification of opportunities related to the exploitation of use phase data confirmed the importance of this topic for research and industry. These findings also contribute to the results of the Collaborative Research Centre (SFB 768) because they indicate how PSS providers can use connectivity to design innovative solutions that take advantages of the advances in ICT. According to Saltz (2015, p. 2066), current research on Big Data pays little attention to the related sociotechnical challenges. The findings of this work therefore provide input for additional research on this matter.

In order to prepare for the development of the solution approach, this work derived a **set of requirements** (see Section 4.2). These requirements did not only serve as a starting point for the development of the process model, but they can also help future researchers to design methodological support in order to aid companies in overcoming organisational challenges related to the exploitation of use phase data. The list of requirements subsequently provided the foundation for the assessment of existing process models for data analytics projects. Therefore, the thesis also contributes to the research field focusing on process models for data analytics by providing a comprehensive overview of current process models. The discussion of advantages and disadvantages can help to provide a starting point for the development of new process models that consider the identified challenges.

The final research contribution is the **empirical data** that this work created. Wamba et al. (2015, pp. 234–235) highlights that empirical studies that analyse the benefits of Big Data are lacking. The empirical data describes the development of a use phase data strategy within six different settings and provides an overview of potential use cases that companies want to implement in order to benefit from the exploitation of use phase data.

8.2.2 Practical contribution

The desired practical contribution of this thesis is to support companies in completing projects relating to the exploitation of use phase data more successfully. A main aspect of the research approach was to achieve high practical relevance by working closely together with industry.

The **process model** is the main contribution for industry. Companies struggle to benefit from the opportunities that connectivity can provide. The process model therefore provides important operational guidance to companies by describing the overall tasks that companies should perform in order to derive a use phase data strategy. Therefore, the process model enables companies to develop a use phase data strategy independently. Accordingly, the process model provides methodological support, which helps companies to avoid or deal with the planning and managerial challenges that arise during the planning phase. Applying the process model therefore shows companies how to approach the exploitation of use phase data. Furthermore, the detailed description of the process model ensures that companies do not forget important tasks or develop a strategy that does not fit to the internal or external context. A common mistake based on the experience from the case studies was that companies start to collect data before exploring which purpose this data should fulfil. The structure of the process model urges companies to define objectives before starting to collect data, which can help to reduce the risk of being inundated with data that is not necessary. Feedback provided during the evaluation also indicates that the process model helps companies to escape the traditional ways of approaching this topic. Therefore, the application can help to derive a use phase data strategy that contains novel ideas. The process model also functions as an orientation guide for stakeholders, because it allows for the communication of the current state of the use phase data strategy development and makes additional steps visible.

A key learning from the case studies was that ideas for use cases existed within companies. However, these ideas were often only existent in the heads of individual stakeholders. The process model fosters a structured collection of use cases, which leads to improved transparency. Therefore, companies obtain a better understanding of their possibilities for exploiting use phase data. Having a detailed overview supports companies in making informed decisions about the use cases that should form the foundation of the use phase data strategy. Taking into consideration all of the different perspectives that are required for an exploitation of use phase data presents a central problem for companies. The developed process model therefore fosters the early integration of the different disciplines, ensuring that the use phase data strategy incorporates the skills and objectives of relevant stakeholders.

The second contribution is the developed **methods**, which, for example, support companies identifying the required data and data quality in order to ascertain the gap between the current and desired state. The matrix-based approach also enables companies to identify dependencies among use cases and to detect consecutive use cases that have similar prerequisites. Thus, companies can develop a use phase data strategy that builds upon a step-by-step integration of use cases and therefore supports companies in continuously expanding their skills. The use phase data strategy and the roadmap enable companies to formulate clear objectives and make the organisational as well as technical implications of the strategy visible. The roadmap also encourages the company to derive a link between the use phase data strategy, product strategy, and service strategy. The methods also support companies in documenting use cases in a structured way, which makes identified use cases accessible for potential follow-up projects. The use case catalogue also has important value for industry because it provides a comprehensive overview of use cases that have already been implemented by other companies. Thus, the use case catalogue can have a positive impact on the search for use cases because it can trigger ideas for novel use cases.

Lastly, the **empirical data** provides examples of how other companies have developed a use phase data strategy. These examples can therefore support inexperienced companies in applying the developed process model for the first time, which can reduce the risk of failure.

9 Summary and outlook

This final chapter concludes the thesis, which supports companies in exploiting use phase data. First, Section 9.1 summarises the underlying motivation and solution approach that was developed based on the identified research gap. Then, Section 9.2 provides an outlook that highlights open points and indicates potential starting points for future research.

9.1 Summary

Enabling engineering companies to exploit use phase data from connected products and services was the overall objective of this thesis. Use phase data includes all data originating from the product and related services during the use phase. Although connected products provide new opportunities for companies, novel challenges also arise at the same time. Therefore, a process model and supporting methods were developed in order to provide operational guidance for engineering companies and to enable them to derive a suitable use phase data strategy in a structured way.

The starting point for the development of the process model, was a **review of the literature on digitalisation, data analytics, and connected products**. Besides offering products and related services, an increasing number of companies already equip or will equip their products with connectivity. Connected products are, for example, able to communicate with other products or the manufacturer. The term ‘digitalisation’ is often used to describe the comprehensive changes that advances in information and communication technology have triggered in industry and society. A main consequence of digitalisation is an increase in data.

Connected products and services are important sources of use phase data. However, data itself does not provide any value without an exploitation. The use of data analytics approaches enables companies, for instance, to detect patterns (e.g., reasons for machine failure). Offering connected products often includes the application of data analytics and can provide novel insights into, for example, the actual usage of products or customer preferences. Companies can use these insights to develop new product functionalities, reduce over-engineering, or develop new business models. Besides these novel opportunities, additional technical and organisational challenges arise that hinder companies from exploiting use phase data successfully. A common recommendation of different publications was that companies need to develop a strategy before starting to collect use phase data or equipping products with connectivity. This work introduced the term ‘use phase data strategy’ for a strategy for connected products that describes which use phase data a company wants to collect and exploit in order to realise certain use cases.

In order to develop the methodological support, the first research objective was to gain a detailed **understanding of challenges linked to the exploitation of use phase data**. A detailed analysis of the body of literature provided an overview of opportunities and challenges linked to data analytics and connected products. Four initial case studies, an interview study, and an industry workshop provided additional empirical data that complemented the findings of the literature review concerning the challenges that companies face. The analysis of both sources confirmed that engineering companies face planning and managerial challenges, in particular when they start trying to exploit use phase data. The analysis further revealed a list of different challenges that hinder engineering companies from developing a use phase data strategy. The main obstacles were the missing internal and external transparency, the lack of collaboration between different disciplines, the assessment of the deviation between required and available use phase data, and difficulties with the identification of use cases. Overall, it became clear that companies require methodological support for the development of a use phase data strategy.

The findings of the analysis of existing publications and empirical data led to the **definition of requirements** that a methodological support should fulfil in order to help companies. Using these requirements allowed for the evaluation of existing process models for data analytics projects. Based on this analysis, it became clear that existing process models provide limited support for the development of a use phase data strategy even though some mentioned the importance of a strategy to the successful exploitation of data.

The shortcomings of existing support highlighted the need for additional **methodological support for the development of a use phase data strategy** in the form of a process model. Therefore, the second research objective was to provide operational guidance that enables engineering companies to develop a use phase data strategy in a structured way. Due to the fact that the required process model should be located at the interface of strategy development and data analytics, existing process models from both domains were analysed. Based on this, it was possible to derive the structural and functional fundamentals for the solution approach, which resulted in a conceptual design of a process model for the development of a use phase data strategy. An initial application of the conceptual design of the process model during three orientating case studies then advanced the understanding of the tasks required for the development of a use phase data strategy. These findings also led to a third research objective, which was the development of additional methods that supports the tasks of the process model. The following paragraph describes the developed process model and the included methods.

The **process model for the structured development of a use phase data strategy** consists of six steps and aims to support engineering companies in overcoming the identified planning and managerial challenges. The design of the process model aims to allow for a flexible and iterative application. A manual for the process model provides an overview of the important tasks, suggesting methods, and outlining results for each step. **Step 1** of the process model focuses on the initiation of the project, which includes, among other aspects, the definition of a project team. The second task of within this step is to define the overall objective that the use phase data strategy and the project should fulfil. Afterwards, **Step 2** focuses on a comprehensive internal and external analysis. The internal analysis aims to create transparency concerning the available use phase data, current IT infrastructure, and other aspects. The external analysis creates an overview of the competitive situation, use cases that other companies offer, customer needs, and further elements. The findings of both analyses then enable an assessment of the current situation in order to provide initial insights into how the exploitation of use phase data could provide additional value to a company. Identifying potential application areas for an exploitation of use phase data is the first objective of **Step 3**. Having an overview of application areas then allows the company to identify potential use cases. Because a company cannot implement all possible use cases, **Step 4** firstly focuses on determining the data needs, which includes identifying the deviation between required and available data. Afterwards an initial consolidation of the use cases follows. This reduced number of use cases then provides the main input for a detailed evaluation of the use cases in **Step 5**. The evaluation results provide the foundation for the final selection of use cases that should form the basis of the use phase data strategy. Lastly, **Step 6** derives an overall use phase data strategy based on the selected use cases. Another outcome of this step is an implementation roadmap that outlines the technical and organisational implications of the use phase data strategy. The process model concludes with a **Review** that assesses whether the developed use phase data strategy conforms to the defined objectives. Furthermore, a number of methods was developed that provide additional support for the different tasks related to the development of the use phase data strategy.

Afterwards, the process model and the methods were evaluated during three **evaluation cases**. Two evaluation cases took place at a large manufacturer for home appliances, each within a different product division. The third evaluation took place at a start-up for connectivity solutions for laundry rooms. An interview-based evaluation at a railway company further complemented the evaluation. The **evaluation results** indicate that the developed process model is able to address the defined requirements. Results highlight that the process model is able to foster the structured development of a use phase data strategy. The feedback also highlighted that the process model helps in obtaining an overview of potential use cases. Nevertheless, the evaluation also revealed some room for improvement. Feedback indicated that the efficiency of the process model should be improved because certain steps were described as too time consuming. The results also indicate that the process model should be adapted to the company's context prior to its application in order to better fit to the environment. Overall, the industry partner rated the results of the process model as valuable and helpful.

Altogether, the **discussion** highlighted the contribution that this thesis provides to academia and industry. From a research perspective, the results address the lack of methodological support for the exploitation of use phase data. Industry benefits because the process model and its methods provide clear guidance on how to develop a use phase data strategy in a structured way, which therefore enables a more successful exploitation of use phase data in the future.

9.2 Outlook

The developed process model provides methodological support for the development of a use phase data strategy. However, the learnings from the evaluation and the following discussion reveal additional possibilities and recommendations for future research.

Along with the process model, the developed **methods** represent a core contribution of this thesis. Many of the developed methods were derived based on the particular needs that arose during the collaborations with industry. The three evaluation cases also showed that the developed methods are applicable in an industrial environment. The participants from industry highlighted the value that the methods (e.g., use case catalogue) can provide for the strategy development process. However, the comments also showed that companies asked for methods that better fit to their context. Therefore, future research could focus on a **detailed evaluation** of the developed methods in order to provide a detailed overview of the benefits and drawbacks. Based on the insights, it would be possible to further **advance the existing methods** or **develop additional ones** that could be used in combination with the process model. The evaluation already indicated an additional need for methods that foster creativity during the search for possible use cases. An interesting starting point could be to derive a **workshop concept** for the application of the use case catalogue. Altogether, implementing the process model and the methods in the form of a **software application** could have benefits for its usability.

Another possibility for future research is to perform case studies that go beyond the development of a use phase data strategy. Due to the duration of the evaluation cases, it was not possible to conduct a **success evaluation**. The assessment of the use phase data strategy and its use cases was based on assumptions about their potential benefits. Therefore, conducting case studies that continue after the last step of the process model can help to evaluate the actual benefits of the use phase data strategy. Furthermore, the process model currently only provides a concept for the implementation. Gaining a detailed understanding about the related tasks and challenges helps to provide improved suggestions for the implementation. Future research could also work on **developing indicators** that enable companies to monitor the effects of a use phase data strategy. Being able to assess and monitor the outcome of a strategy helps companies to learn and improve the strategy development process in the future.

The development of **guidelines** for the application of the process model could also help to improve the flexibility and efficiency of the process model. For deriving such guidelines, additional case studies should be conducted in order to collect more empirical data on the strategy development process. An analysis of this data could potentially enable the identification of different company profiles based on certain characteristics (e.g., experience with use phase data or existence of a use phase data strategy). Based on these profiles, companies could perform a self-assessment prior to the application of the process model and, based on the results of this assessment, the guidelines could provide suggestions for the application of the process model and suitable methods. These guidelines could therefore help companies to identify tasks that require the special attention of the company. At the same time, the guidelines could suggest methods that are especially relevant.

Lastly, the overall research field of connected products is developing at a fast pace. Therefore, the experience gained over the course of the research project highlighted potential topics for future research. The discussions during the evaluation cases indicated that the data journey addresses an important topic by focusing on the **improvement of user experience** based on use phase data. Support for a data-driven design of user experience seems to be rather limited and therefore could be interesting for future activities. The collaborations with industry highlighted the potential that use phase data offers for supporting the **product development process**. Being able to collect use phase data provides valuable insights into the actual usage of the product. Companies usually develop products in generations and use phase data provides valuable insight into the product's usage. Therefore, subsequent research should investigate how use phase data can support product generation engineering (PGE) as suggested by Albers et al. (2015) in structured way. Future research could also focus the an integration of use phase data into existing approaches for product development (e.g., the integrated Product engineering Model (iPeM) (Albers et al., 2016) or Munich Procedure Model (Lindemann, 2009)). Use phase data can also help to **improve simulation models** used during the development process. The term 'digital twin' is often used for this use case. Altogether, the experience from industry collaborations highlights potential for further research and the unused value of use phase data.

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11 Additional lists

11.1 List of figures

11.2 List of tables

11.3 List of figures using third party icons

Figures	Sources
Figure 2-7	Figure uses icons made by Freepik, Pixel perfect, and Goodware from www.flaticon.com
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Figure 11-30	See Figure 6-10 for the sources of the icons
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11.4 List of student projects

The following 19 student projects were created in the context of this dissertation project. The author of this work in his role as supervisor defined the tasks and scope of these student projects and gave continuous input to the students. In frequent meetings, the methodology, objectives and results were discussed and coordinated. These projects in chronological order are:

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Appendix

A1 Initial case studies on value extraction from use phase data

A1.1 Case study 1 – Additive manufacturing sector

Description of the case study environment and research objective

The first case study was conducted in the form of a student project and lasted 6 months (Triep, 2016). The case study company is a large manufacturer of additive manufacturing machines for metals and polymers with more than 700 employees. Additive manufacturing, also often referred to as 3-D printing, is an important technology for Industry 4.0 because it enables small batch production and customized products (Rüßmann et al., 2015, pp. 4–5). The case study was conducted together with the business unit that develops machines that work with polymer.

The machines that the case study partner offers are mainly used for industrial application and therefore Industry 4.0 is an important trend that influences the operational context of the machines. However, the case study partner mostly focused on the development of machines from a traditional engineering perspective in the past without paying attention to use phase data. At the time of the case study, the machines already generated use phase data, but the accessibility for the manufacturer was limited due to confidentiality concerns of users.

Therefore, the research objective of the case study was to identify potential internal and external use cases that build upon use phase data. The intended outcome was a strategy that describes how use phase data should be collected and analysed in order create additional value for customers and the company itself. The intention was to take advantage of available use phase data so that efforts for changes to the products and services is at a minimum.

Execution and results of the case study

During the six months of the case study, different research methods helped to gather empirical data. Over the course of case study, interviews with different stakeholders from product management, IT, project management, and technical service provided the main input. At the end of the case study, an evaluation workshop was conducted with five stakeholders from different departments.

The starting point for the case study was analysis of the current situation. The company stated that they had not conducted a data analytics project until the collaboration started. Furthermore, an analysis of which use phase data was already available was done. It became clear that data was available on two levels. First, process information was available that characterized the manufacturing process (e.g., status of the machine or errors). Secondly, the machines recorded process parameters (e.g., temperature or atmosphere). However, most of this use phase data was mainly accessed when a service technician conduced a diagnosis of the machines. After understanding the current situation, the next task was to identify use cases that can provide additional value for the company. Based on interviews it became clear that increasing the efficiency of additive manufacturing was the main interest and a decision was made to focus on production rejects. The following methods helped over the course of the case study to derive, detail, and select use cases: Goal-Question-Metrix, fault tree analysis (FTA), failure modes and effect analysis (FMEA), cost-benefit-analysis, and roadmapping. The use of the methods was required in order to identify relevant use cases together with the different stakeholders. The

FMEA, for instance helped to identify especially critical failures that should be avoided with the exploitation of use phase data.

Additional interviews with employees helped to formulate further use cases. Overall, the identified use cases fit into three categories. First, use cases that increase the efficiency of the production process and therefore provide additional value for the customers of the case study partner. The other two categories rather provide additional value for internal stakeholders. On one hand, use phase data can improve the service of machines by providing detailed insights about them in terms of errors and malfunctions. On the other hand, use phase data can support engineers in developing machines that better fit to the actual use of the customer.

Learnings of the case study

The main contribution of this case study is that it provided a detailed understanding of the opportunities that use phase data could provide for the case study partner. The case study also highlighted the barriers that the companies faced when exploiting use phase data.

The interviews with stakeholders from different departments showed diversity of possible use cases, which the company was not aware of before the case study. The case study partner saw clear potential that use phase data can increase the efficiency of the production process by reducing the amount of production rejects. In addition, use phase data can help to identify patterns in machine failure and would therefore help to predict breakdowns.

However, the case study also showed that the company extracted little value from use phase data even though the interviews revealed the broad range of potential use cases. The case study company confirmed having almost no experience with data analytics. Therefore, the internal stakeholders had little experience in identifying potential use cases and consequently struggled to name use cases that build upon use phase data. Thus, nobody was responsible for identifying and implementing use cases. The case study also revealed that use cases are very stakeholder-specific because their needs differ quite a lot and thus drive different possible use cases. A key problem was that the implementation of several use cases was not possible because required use phase data was not available. Some interesting data points were only recorded in paper format. The findings further show that additional context data must be recorded to better interpret use phase data. Due to the missing experience, additional methodological help was needed to select and detail suitable use cases. Combining traditional engineering methods (e.g., FMEA or FTA) and strategy development methods (e.g., roadmaps) turned out to be helpful in order derive a use phase data strategy. To exploit value from use phase data in the future, the case study partner needs to clearly formulate the data needs and define processes that implement the intended use cases. Overall, the case study partner required especially guidance in order to identify suitable use cases and formulate the required steps to prepare their implementation. The lesson for the case study partner was that the company needs to start collecting use phase data in a more structured way in order to implement the identified use cases. Furthermore, the case study also showed that changes to machines and processes are unavoidable if the company wants to implement the identified use cases.

A1.2 Case study 2 – Workout device sector

Description of the case study environment and research objective

The second case study was also conducted as part of a five-month long student project (Zerwes, 2016). The company is a relatively young manufacturer of mechatronic workout devices with more than 300 employees (founded in 2010). The case study partner develops and manufactures fully electronic products with related digital services (app and online platform). All products are connected with a cloud in order to facilitate a personalized training experience. The company therefore operates in a market that uses new technologies to develop novel products.

The products of the case study partner use connectivity as a main enabler for the enhanced functionalities of their products. Use phase data was therefore already collected by the case study partner and stored. The collected data is especially used to provide a novel training experience for the users of the workout device. However, based on the initial discussion with the partner, it became clear that at the time of the case study, little value was extracted from data in order to improve product design or support tasks during the product development process.

Discussions with engineers of the case study partner at the beginning of the collaboration revealed that they had ideas about how to use phase data can provide extra value for internal stakeholders. From the case study partner's perspective, use phase data can help to increase internal knowledge about machine failure. Therefore, the research objective was to derive an approach that enables the case study partner to reduce the number of failures and to maintain their products in a more proactive way based on an analysis of use phase data.

Execution and results of the case study

Over the course of the case study, interviews and workshops with employees from the mechanical engineering and business intelligence departments served as a main input for the empirical data. Furthermore, the available (use phase) data helped to assess the potential to improve maintenance and reduce downtimes.

At the beginning of the case study, it became clear that understanding the failure modes and the related drivers was important to achieve the case study's objectives. The hypothesis was that available use phase data can provide insights concerning this cause-and-effect chain, which results in failures. The first step therefore was to derive a clear understanding of available data. Due to the fact that failures do not only occur due to wear, the decision was to also include production and vendor parts data. The analysis revealed that different stakeholders store relevant data in different systems, which did not always have a connection. To increase transparency, a data map was derived that visualized available data at the case study company. In addition, the product lifecycle and data perspective were merged to describe the data creation over time. Afterwards, available use phase data was assessed on a more detailed level. At the time of the case study, use phase data contained information about the training method, training time, machine id, and service reports. In addition, context data included information concerning the customers (e.g., fitness studios or sports centres) and users. Furthermore, the quality of the use phase data was assessed by nine criteria based on Hinrichs (2002, p. 69). The analysis revealed that the data quality only allowed for the identification of trends because the accuracy was not high enough to derive complex prediction models. Furthermore, it became clear that only a manual analysis of the data is possible, but overall the use phase data was evaluated as suitable to detect failures. To prepare the analysis, available data was imported into one analysis tool.

After obtaining an understanding of the available data and merging the different data sources, the next step was to identify machine failures and connect them with causes. Five root causes for a failure are possible: wear, production defects, defects of vendor parts, misuse, and defects in design. During the case study, it was possible to identify three of the five causes for failures in analysing use phase data. For the first step, a product component was selected of which failure would make the use of the product impossible. The analysis of the correlation between the number of conducted training sessions with the machine and the time of failure showed that a remarkable number of components failed after a few thousand sessions. An additional analysis of the batches that failed revealed that a problem with the quality of a supplier part was most likely the cause. For two other components, a similar analysis revealed that a correlation between the number of training sessions and wear exists. The wear of the selected components only reduced the training experience, but the results helped to define maintenance intervals for these components. The last analysis of the use phase data revealed that the design of a product component led to a failure of the machine. However, a discussion with engineers revealed that this issue had been fixed in the meantime. In the end, the data quality was the main reason why it was not possible to implement a predictive maintenance use case or to optimize the maintenance.

Learnings of the case study

Compared with the first case study, this one started with the definition of a use case (predictive maintenance) that the case study partner wanted to implement. Another important characteristic of the case study was that the company already had more comprehensive use phase data.

Overall, the case study showed that use phase data of a connected workout device is very helpful for identifying different causes for failure. The results raised the awareness of the case study partner of the potential of use phase data. For a young company, such insights can increase the understanding of their own products and improve their design in the long run.

However, the case study also showed that the overall goal was not reached because it was not possible to come up with a predictive maintenance concept. During an early discussion, the case study partner mentioned that they believed they had almost all the data required to develop a predictive maintenance concept. However, the analysis of the data quality revealed that the use phase data was not suitable for such a use case. In addition, missing transparency around the different data sources required a comprehensive analysis at the beginning in order to describe the data inventory. Initial discussions revealed that engineers already had vague ideas of how use phase data can provide additional value. The company already used data to provide data-driven services to their users. However, none of the employees was responsible for identifying and implementing use cases that address internal needs. Furthermore, different departments only had access to limited parts of the data. Data was therefore fragmented and limited exchange happened among the stakeholders. The main contribution was to guide the company through the process of concretising a desired use case (predictive maintenance), revealing current limitations, and formulating actions in order to improve the situation.

A1.3 Case study 3 – Packaging machine sector

Description of the case study environment and research objective

The third case study was part of a research project that investigated the potential of use phase data to support proactive cost management in engineering design (Wilberg et al., 2016). The theoretical research findings indicated that use phase data could help to achieve more proactive cost management because insights about the actual use of a product can help to improve the functionality-cost ratio. After the development of a theory model for use phase data based proactive cost management, a two-month long case study was conducted with an industry partner and was parts of a student project (Gökdemir, 2016). The company designs and manufactures thermoforming machines and welding systems to process plastics. At the time of the case study, the company had more than 500 employees and was part of a larger group of companies.

The products of the case study partner are part of large production lines that consist of different machines. Due to the Industry 4.0 trend, connectivity of production lines is currently an important topic for the industry. The case study partner was therefore interested in examining the potential that use phase data can provide for their cost management. The case study partner did not work with use phase data before the case study and therefore the desired outcome was to derive measures that help to improve the data strategy and data infrastructure.

Execution and results of the case study

The main foundation for the third case study was the developed theory model. The case study partner offers a broad range of products. The decision was to focus on a forming and punching unit because this unit is one of the bestsellers and thus more data was available.

During the case study, interviews were conducted with all responsible persons along the entire design process, starting with order confirmation and ending with the final inspection. The first task was to derive a data map that visualizes available data and data sources within the company. The analysis revealed that (use phase) data was stored in different formats (e.g., Word documents, Excel files, or loose paper). Available use phase data was not very comprehensive and mostly contained information concerning failures of units, service reports, or customer feedback. Data generated by the units was not accessible. Afterwards, the cost structure of the unit was analysed. At the time of the case study, the available cost information only contained direct costs without considering, for instance, maintenance or individualization costs. The next step was to derive dependencies between the bill of material and the cost structure. To define the target-data, discussion with engineers helped to identify use phase data that could improve the cost management of the case study partner. However, the results are only hypothetical due to the limited availability of use phase data. The findings of the case study helped to formulate a data strategy that contains measures to improve the current situation. The important suggestions were to store data in a uniform format, define desired use phase data that provides additional value for cost management, and to improve the accessibility of data for the different stakeholders. Overall, the results helped the case study partner to identify weaknesses in their current practice.

Learnings of the case study

The third case study was much shorter than the two previous ones and therefore the data collection was limited. However, the case study helped to test a theoretical approach for a proactive cost management approach that builds upon use phase data. The case study partner confirmed the potential value that use phase data can provide for tailoring the cost structure of a product more towards its actual usage and user needs. In addition, the case study helped the company to better understand the potential that an analysis of use phase data could provide.

Interviews with two senior engineers of the case study partner highlighted that the accessibility of use phase data was a main problem for the company at the time of the case study. Further identified barriers were missing transparency and a large amount of data. The company further lacked knowledge about possible use cases that provide additional value. Little experience with use phase data is potentially the main reason for this. During the case study, the company also highlighted that they struggle to determine the technical and operational implications of promising use cases. The discussion with the interview partners further highlighted that analytical approaches are important to derive meaningful results from use phase data, but a key requisite is a clear data strategy. The case study showed that transparency about available and desired data is essential to realise the full potential of use phase data.

A1.4 Case study 4 – Academic project on customisation in cars

Description of the case study environment and research objective

Following the three industrial case studies, the fourth case study was conducted in an academic environment at the university and was part of a student project (Benta, 2016). Over the course of six months, a team of graduate students with engineering backgrounds worked together on this project under the supervisor of research associates. The overall objective of the project was to develop innovative product concepts for a BMW Mini that integrate the trends of individualization and digitalization into the car. To ensure that the concepts have a high maturity and practical relevance, the students had access to a real BWM Mini and were allowed to modify the cockpit to test their concepts.

The overall project consisted of different subprojects. For this research work, the subproject, which focused on the development of the related data-based business model for its concept, is of special relevance. The objective of the entire project was not only to develop physical prototypes of the derived concepts, but also to design the corresponding business model. Besides coming up with prototypes, the case study was also used to propose additional methods that help in designing use phase data-driven business models. Details of the developed methodological support can be found in Benta et al. (2017).

A2 Interview study on data analytics in product development

The next two sections present questionnaire and the list of interview partners for the empirical study on data analytics in product development. The results are summarized as well as discussed in Section 3.2 and in Wilberg et al. (2017a). All interviews were conducted in German.

A2.1 Questionnaire for the semi-structured interviews

The following part outlines the questions that were discussed during the interview study. Due to the fact that all interviews were conducted in German, a translation in English is given.

Grundlegendes Verständnis von Big Data und Entwicklungsprozess – *Basic understanding (Big Data and product development process)*

1. Was verstehen Sie unter dem Begriff „Big Data"? Wie ist der Begriff im Unternehmen definiert?
   How do you define the term „Big Data "? How is the term defined at the company?

2. Inwiefern stimmt das oben beschriebene Stage-Gate-Modell mit dem in Ihrem Unternehmen verwendeten Produktentwicklungsprozess überein?
   To which extent does, the Stage Gate model described above match the product development process used in your organization?

Aktueller Stand und Verwendung von Big Data im Unternehmen – *Current status and practice in using Big Data at the company*

3. Nutzen Sie aktuell Big Data in Ihrem Unternehmen? Wenn ja, in welchen Bereichen wird Big Data bereits verwendet?
   Are you currently using Big Data at your company? If so, in which areas is Big Data already being used?

4. Welche Art von Daten(-quellen) verwenden Sie aktuell im Unternehmen?
   What type of data (sources) do you currently use within the company?

5. Das Vorgehen zur Einbindung von Big Data in der Produktenwicklung besteht aus vier Schritten: *Entwicklung einer Datenstrategie*, *Sammeln der Daten*, *Korrelieren und Analysieren der Daten*, und *Ableiten von Erkenntnissen*. Bitte beurteilen Sie die Wichtigkeit der jeweiligen Schritte für eine erfolgreiche Umsetzung einer Big Data-Initiative in der Produktentwicklung.
   Skala: 1 – Sehr unwichtig; 2 – Unwichtig; 3 – Wichtig; 4 – Sehr wichtig
   The process of embedding Big Data in product development consists of four steps: developing a data strategy, collecting the data, correlating and analysing the data, and deriving insights. Please assess the importance of each step for successfully implementing a Big Data project in product development.
   Scale: 1 - Very unimportant; 2 - Not important; 3 - Important; 4 - Very important

6. Gibt es bei Ihnen eine Nutzungsdatenstrategie für die Produktentwicklung?
   Do you have a use phase data strategy for product development?

7. Wie werden die Nutzungsdaten Ihrer Produkte derzeit gesammelt, verarbeitet und analysiert?
   How is the use phase data of your products currently being collected, processed and analysed?

8. Was sind die wichtigsten Werkzeuge und Methoden, die Sie aktuell in den verschiedenen Stufen des Produktentwicklungsprozesses verwenden?
   What are the most important tools and methods you currently use in the different stages of the product development process?

9. Wie zufrieden sind Sie mit den bisherigen Ergebnissen der Big Data-Anwendung?
   How satisfied are you with the results of the Big Data application so far?

Zukünftige Anwendung von Big Data in der Produktentwicklung – *Future application of Big Data in product development*

10. Wo sehen Sie in Zukunft vielversprechende Ansatzpunkte für Big Data in Ihrem Entwicklungsprozess?
    Where do you see promising application areas for Big Data within your development process in the future?

11. Aus welchen Datenquellen könnten die verwendeten Daten stammen? Was ist für die Erschließung nötig?
    From which data sources could the data come from? What is needed for the implementation?

12. Welche Probleme könnten zwischen der Erfassung und der Verwendung der Daten auftreten?
    What problems could arise between the collection and use of the data?

13. Wie könnte Sie die Forschung dabei unterstützen, Big Data noch gezielter in der Produktentwicklung einzusetzen (Forschungsbedarf)?
    How could research help you to use Big Data more effectively in product development (need for research)?

A2.2 List of interview partners

Overall, it was possible to conduct 15 interviews. The following list summarizes some characteristics of each interview partner and the corresponding company.

Company / interview partner	**Length / format of the interview**	**Position of the interview partner / department**	**Product**	**Value chain position / number of employees / turnover**
C1 / IP1	35 min / via telephone	Industry 4.0, Product Owner Process Analytics / Products & Innovation	Machine tools	OEM / 1,000 - 4,999 / < €1 billion
C2 / IP2	45 min / via telephone	Senior Director Product / Development System Solutions	Industrial trucks	OEM / ≥ 10,000 / €5 - 9 billion
C3 / IP3	60 min / face-to-face	Mechanical Engineer	Fitness devices	OEM / n.s. / n.s.
C4 / IP4	32 min / face-to-face	Product Sales Manager / Software Solutions	Machine tools	OEM / 5,000 – 9,999 / €1 - 4 billion
C5 / IP5	60 min / via telephone	HR	Engineering and technology	OEM / ≥ 10,000 / > €10 billion

C6 / IP6	60 min / face-to-face	Product Manager	3D Printer	OEM / < 1,000 / n.s.
C7 / IP7	69 min / face-to-face	IoT Program Manager	Machines	OEM/ ≥ 10,000 / €1 - 4 billion
C8 / IP8	41 min / face-to-face	Machine technology / Development department	Machines	OEM / 1,000 – 4,999 / < €1 billion
C9 / IP9	62 min / face-to-face	Head of Research and Development	Heating systems	OEM / ≥ 10,000 / €1 - 4 billion
C10 / IP10	46 min / face-to-face	Innovation Management IT / IT	Tools	Tier 1 / 1,000 - 4,999 / €1 - 4 billion
C11 / IP11.1* (11)	67 min / face-to-face	Relationship Manager (Marketing) / Smart Factory	Construction equipment	OEM / 1,000 – 4,999 / €1 - 4 billion
C11 / IP11.2* (11)	67 min / face-to-face	In-House Consultant / Smart Factory	Construction equipment	OEM / 1,000 – 4,999 / €1 - 4 billion
C12 / IP12	56 min / via telephone	Division Manager Development	Machine tools	OEM / 1,000 – 4,999 / < €1 billion
C13 / IP13	60 min / face-to-face	Leader Services PLM, IMDS, Change management	Machine components	Tier 1 / > 10,000 / > €10 billion
C14 / IP14	49 min / face-to-face	Portfolio Manager	Power engineering	Tier 1 / 1,000 – 4,999 / < €1 billion
C15 / IP15	32 min / face-to-face	Technical Manager CNC / IT	Manufacturing robotics	OEM / n.s. / €5 - 9 billion

A3 Process models for data analytics projects

Process model of Almquist et al. (2015)

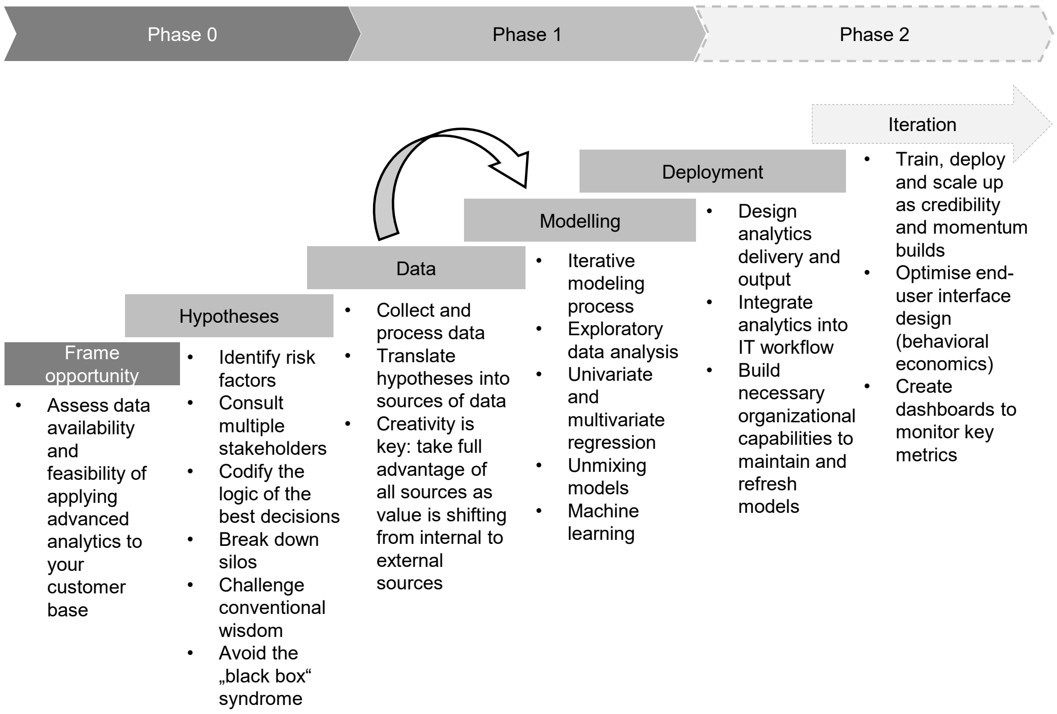


Figure 11-1: Phases approach to advanced analytics (Almquist et al., 2015, p. 2)

Process model of BITKOM (2013)

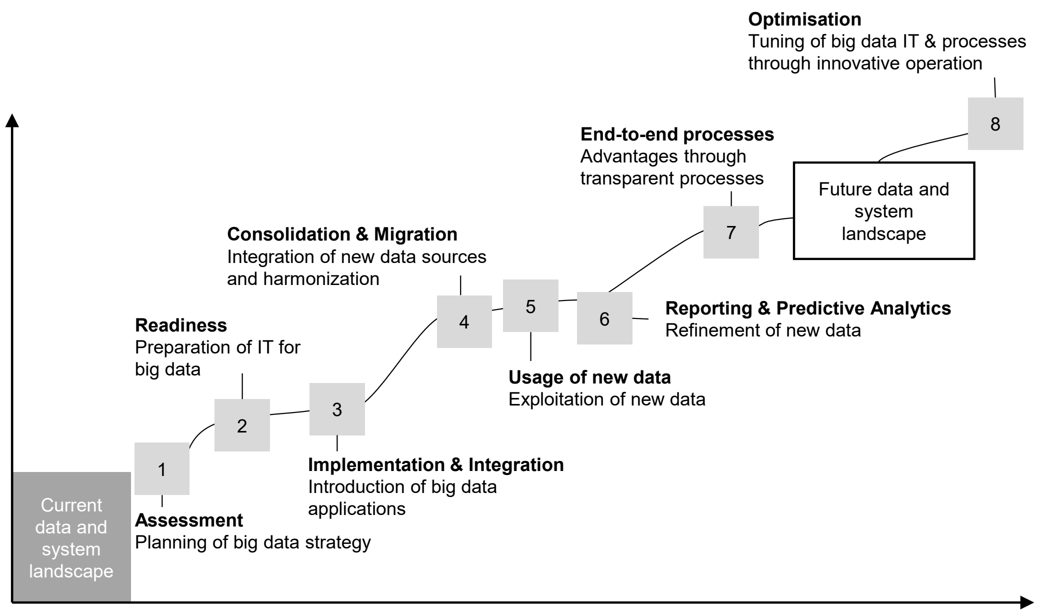


Figure 11-2: Process model for the implementation of Big Data projects (BITKOM, 2013, p. 30)

Process model of Chapman et al. (2000)

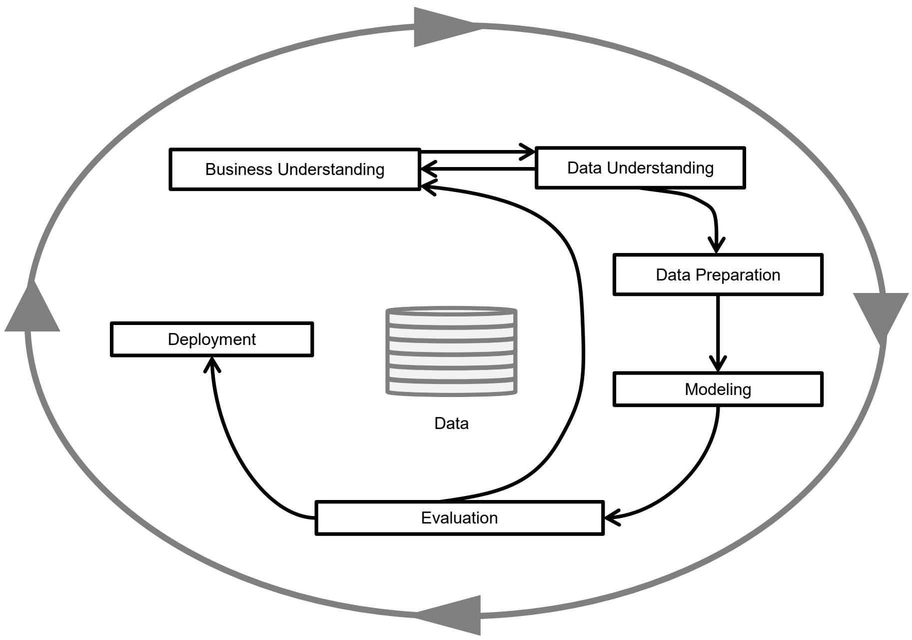


Figure 11-3:CRISP-DM process model (Chapman et al., 2000, p. 10)

Process model of Dutta and Bose (2015)

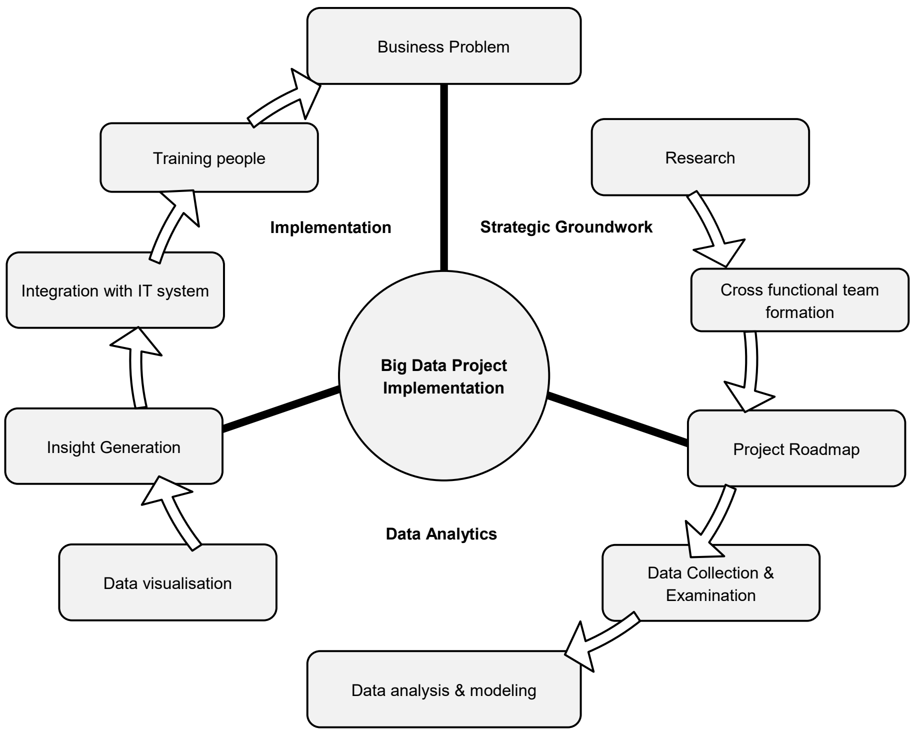


Figure 11-4: Framework for implementation of Big Data projects (Dutta and Bose, 2015, p. 295)

Process model of EMC Education Services (2015)

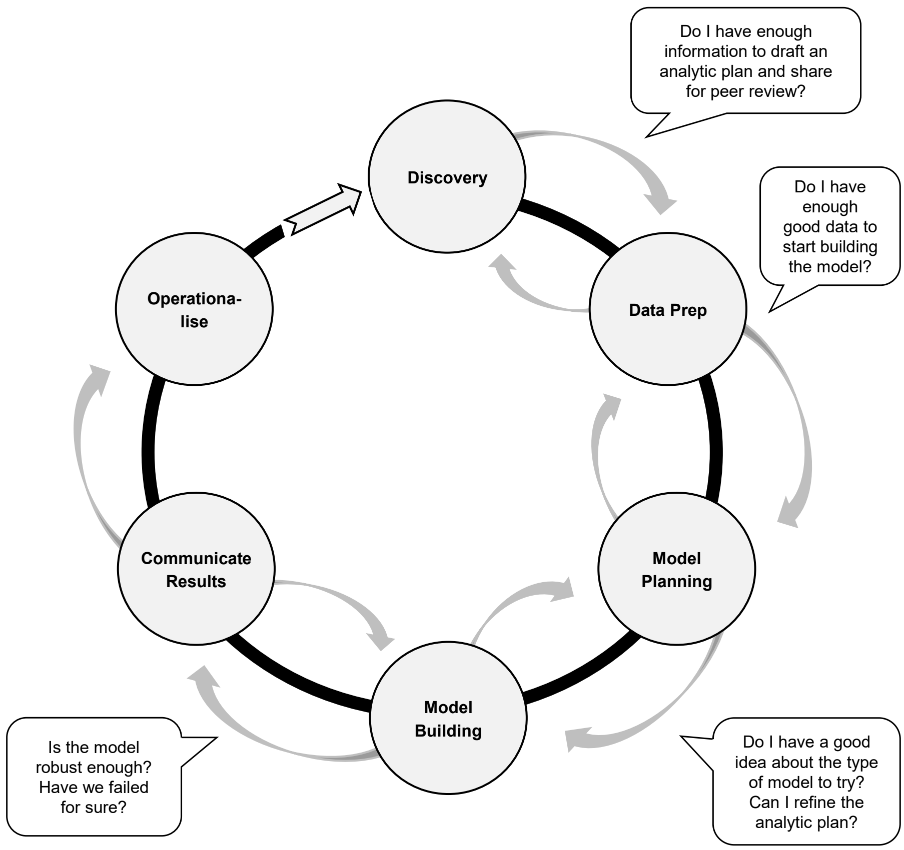


Figure 11-5: Data analytics lifecycle (EMC Education Services, 2015, p. 29)

Process model of Fayyad et al. (1996a)

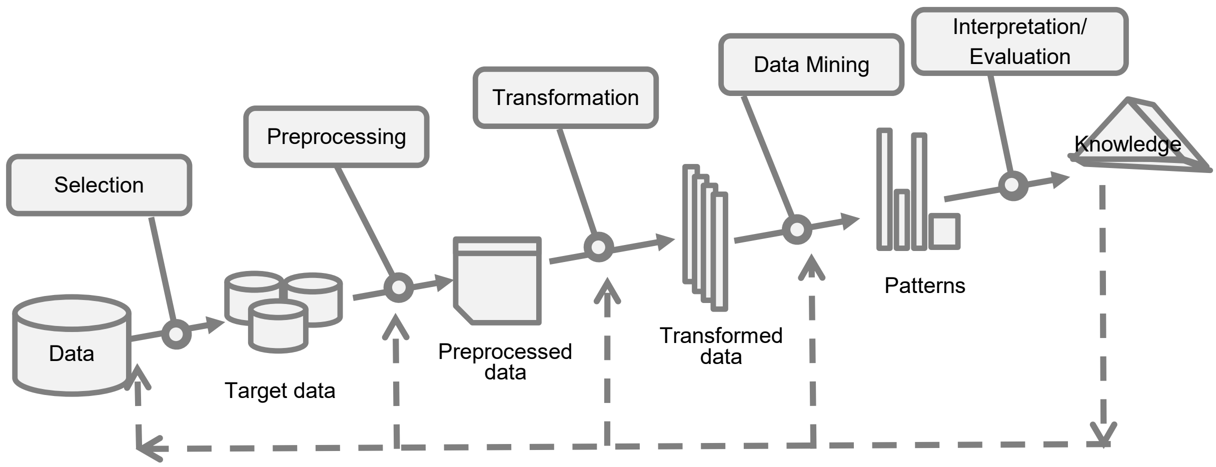


Figure 11-6: Knowledge discovery in databases (KDD) process (Fayyad et al., 1996a, p. 41)

Process model of Miller and Mork (2013)

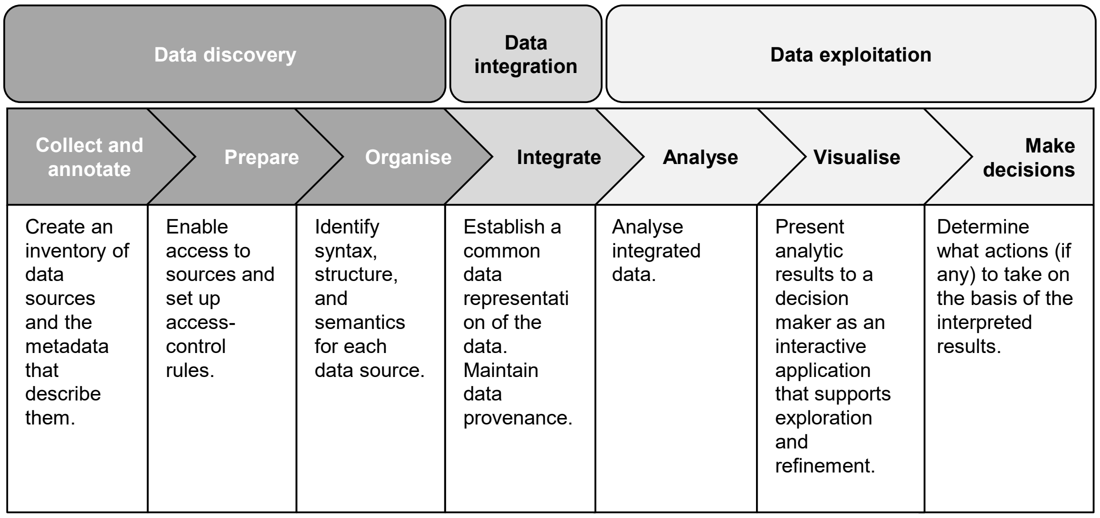


Figure 11-7: The data value chain (Miller and Mork, 2013, p. 58)

Process model of Morabito (2015)

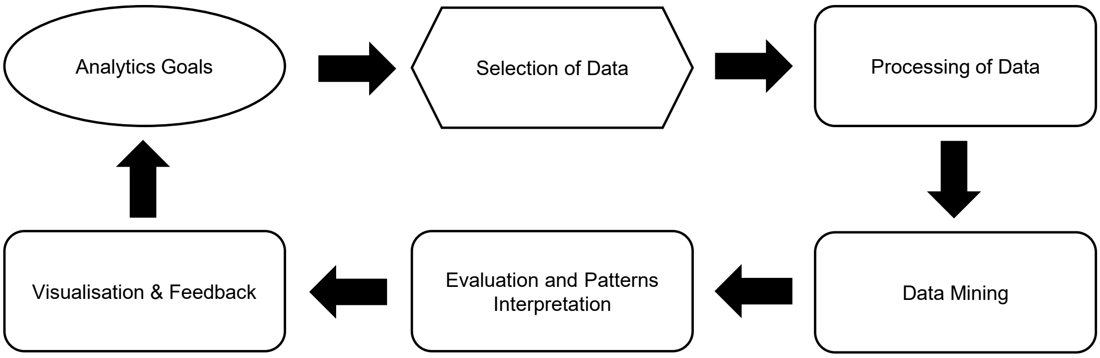


Figure 11-8: Big Data analytics process (Morabito, 2015, p. 107)

Process model of Rajpurohit (2013)

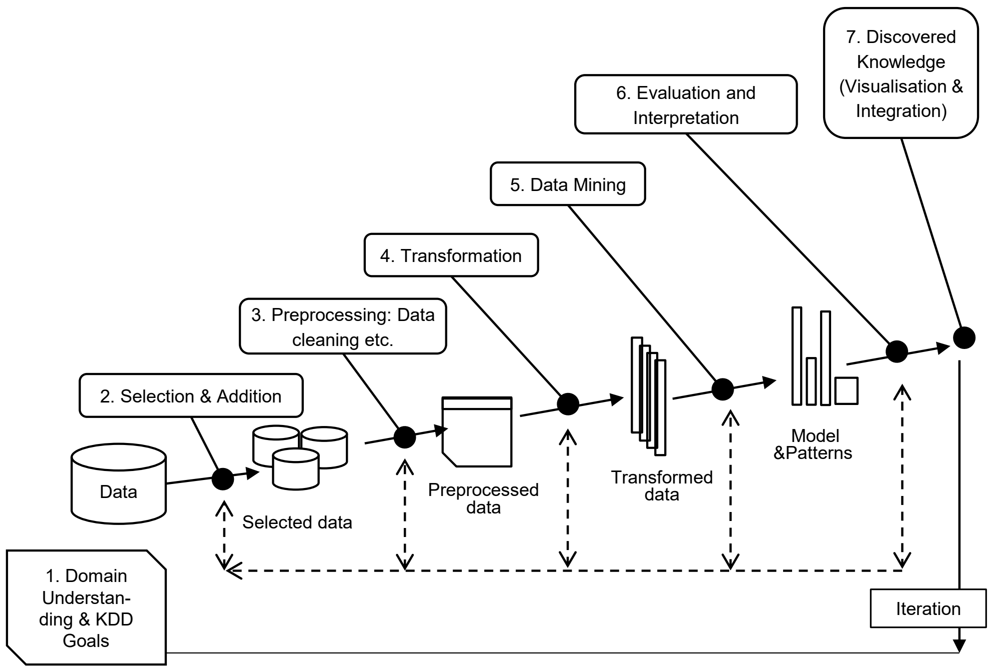


Figure 11-9: Big Data implementation (Rajpurohit, 2013, p. 30)

Process model of Gao et al. (2015)

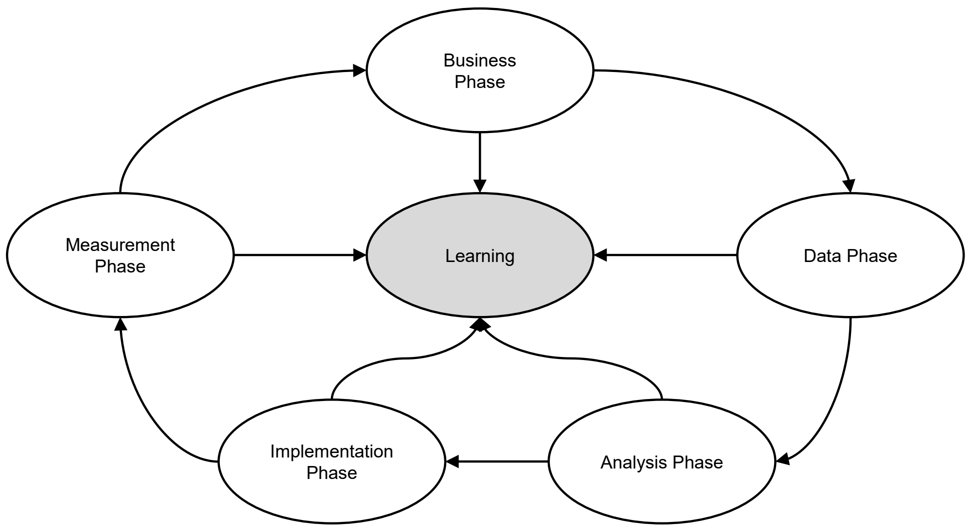


Figure 11-10: Business analytics process model (Gao et al., 2015, p. 5)

Process model of Jagadish et al. (2014)

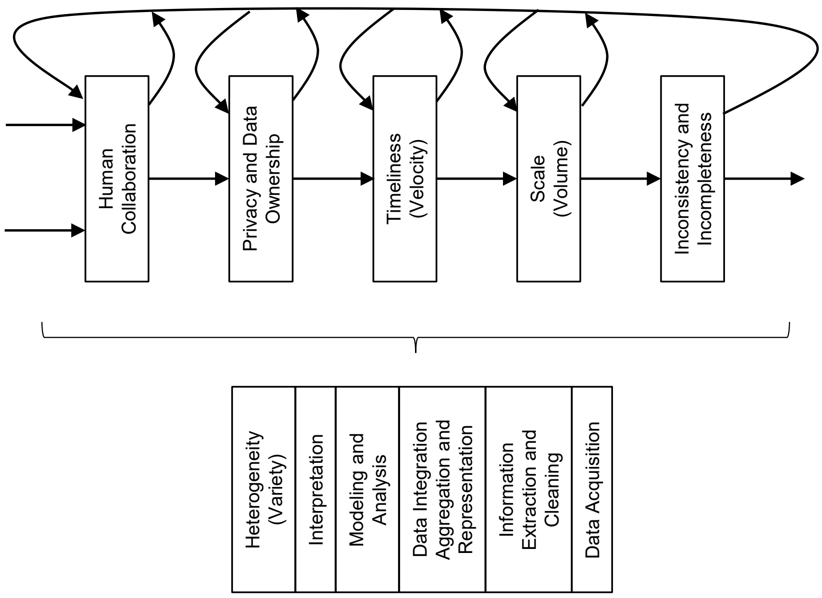


Figure 11-11: The Big Data analysis pipeline (Jagadish et al., 2014, p. 88)

Process model of Köhler and Meir-Huber (2014)

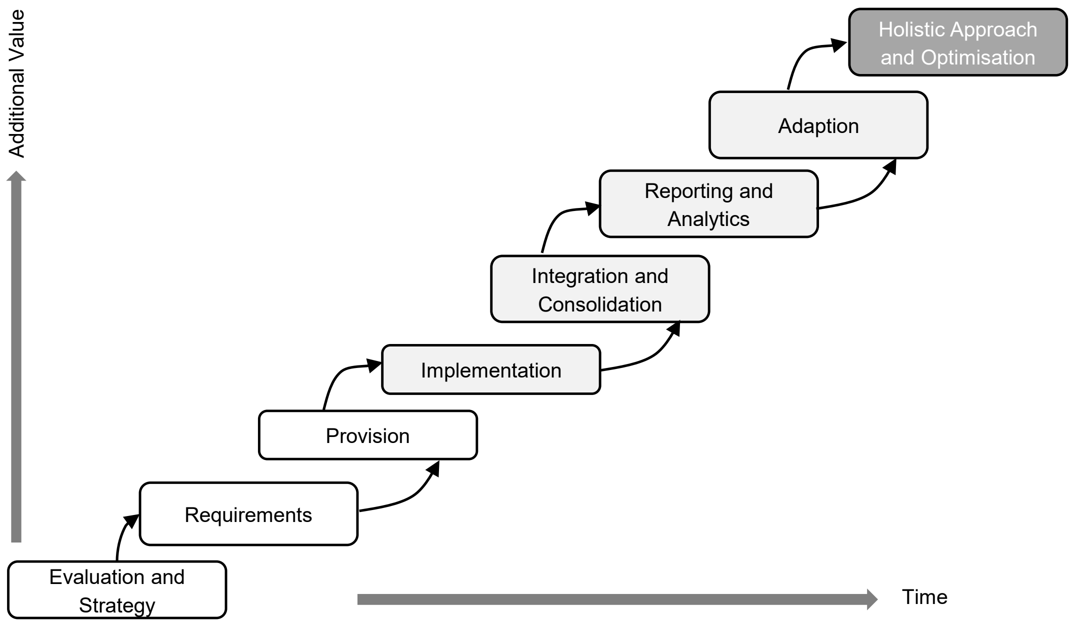


Figure 11-12: Process model for Big Data projects (Köhler and Meir-Huber, 2014, p. 120)

Process model of Vanauer et al. (2015)

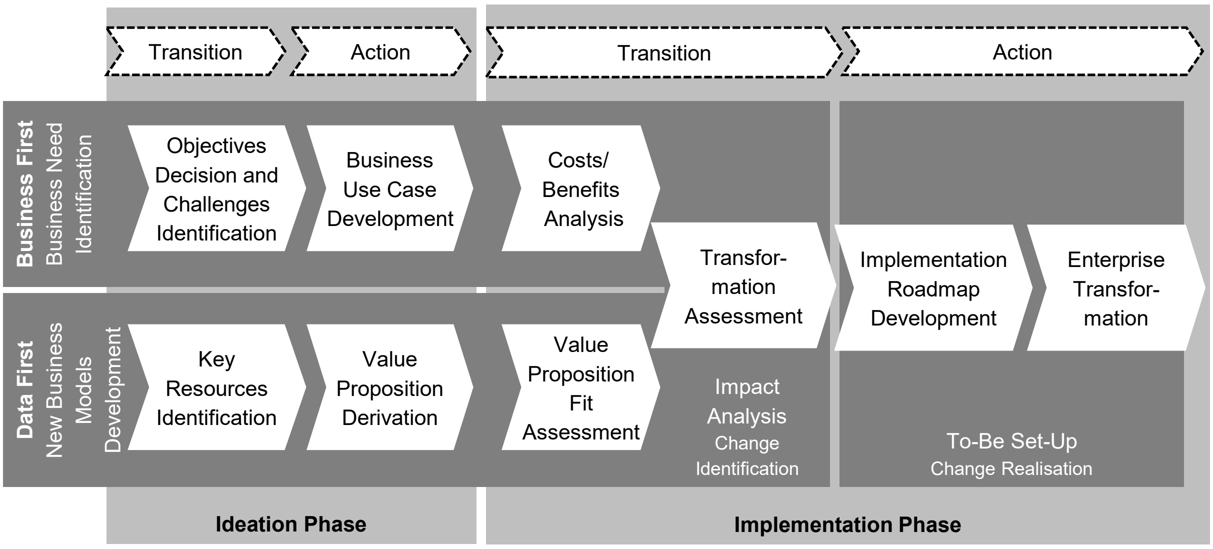


Figure 11-13: Methodology for big data idea generation, idea assessment and implementation management (Vanauer et al., 2015, p. 911)

A4 Process models for strategy development

Process model of Kaplan and Norton (2009)

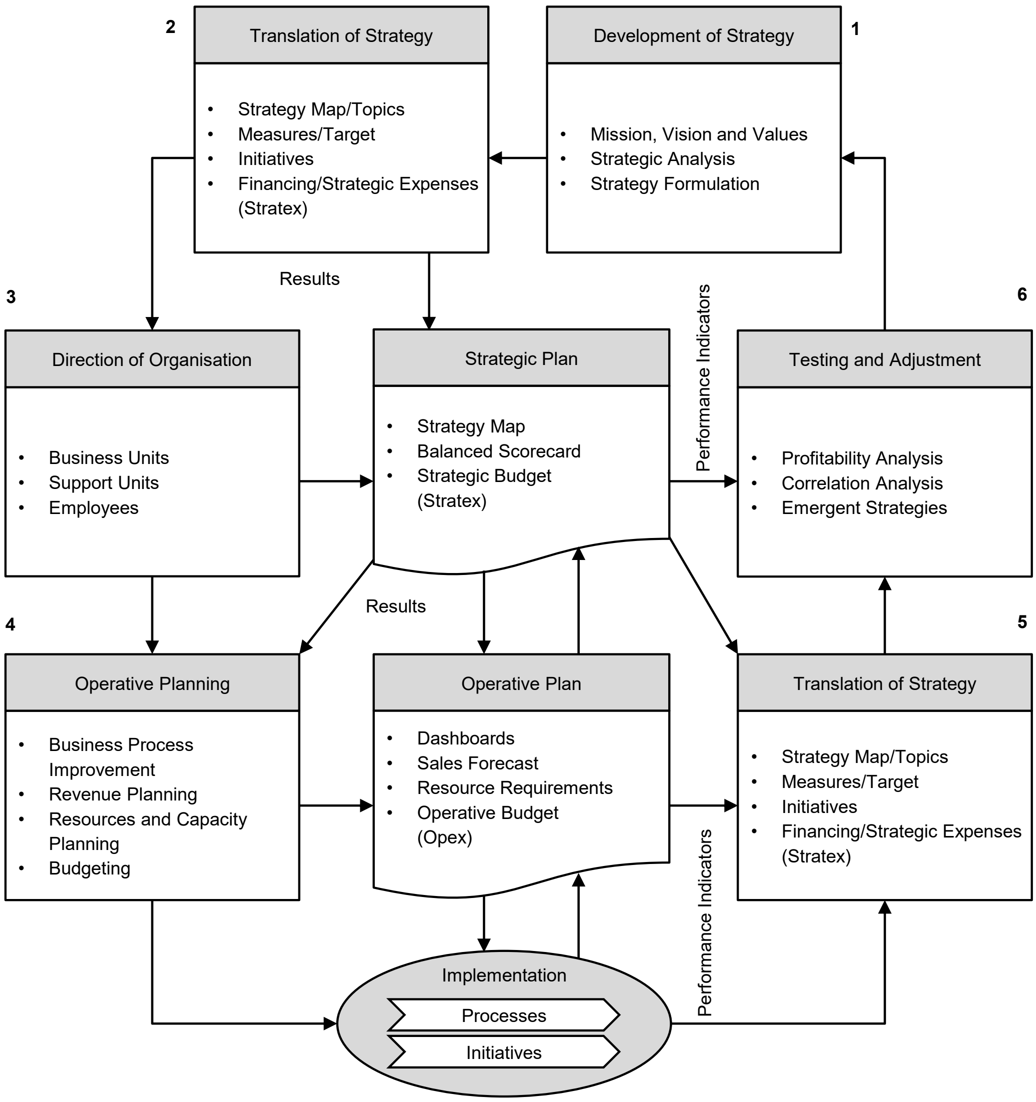


Figure 11-14: The effective strategy process (Kaplan and Norton, 2009, p. 52)

Process model of Kerth et al. (2015)

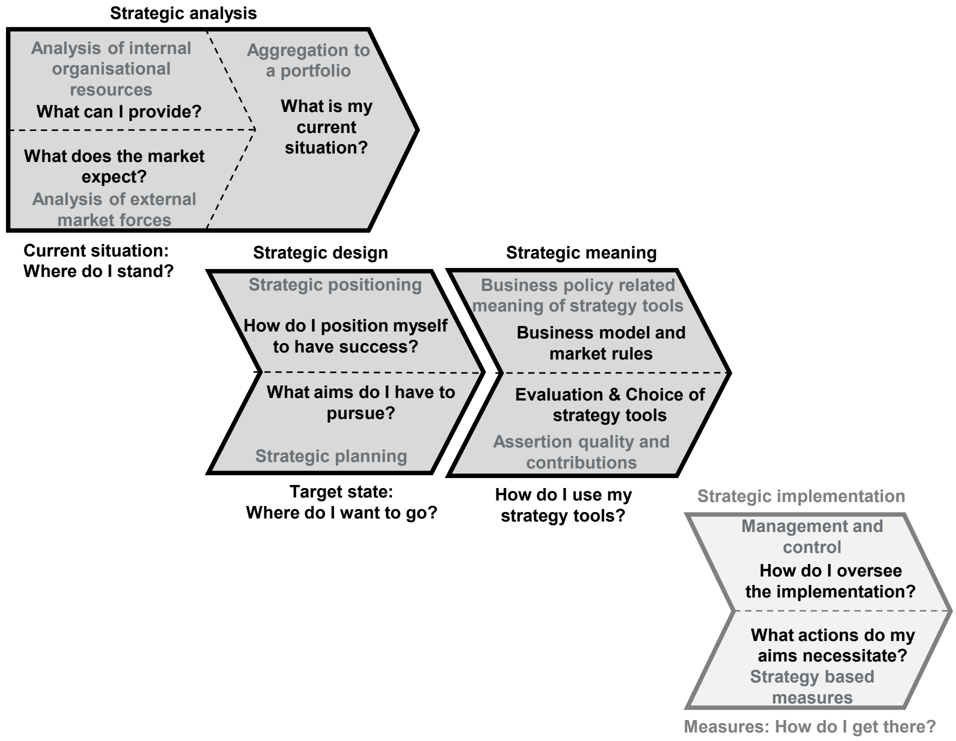


Figure 11-15: Strategy process (Kerth et al., 2015, p. IX)

Process model of Probst and Wiedemann (2013)

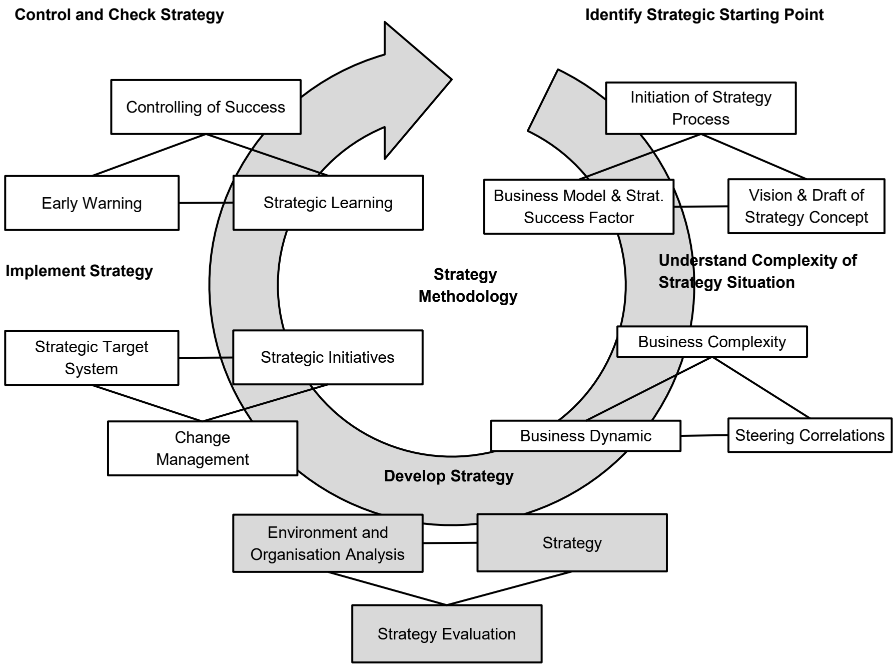


Figure 11-16: Strategy methodology (Probst and Wiedemann, 2013, p. 47)

Process model of Lombriser and Abplanalp (2012)

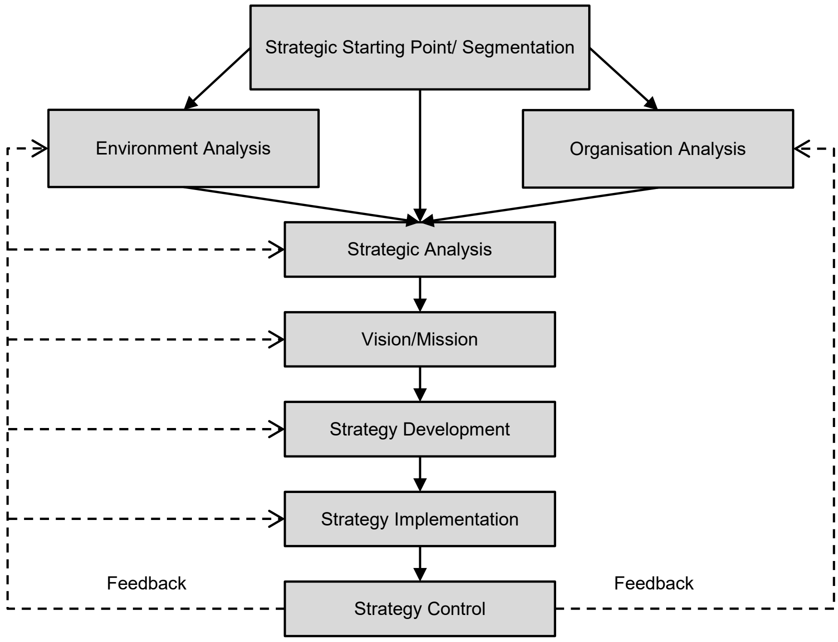


Figure 11-17: Model of strategic management (Lombriser and Abplanalp, 2012, p. 50)

Process model of Tschandl et al. (2014)

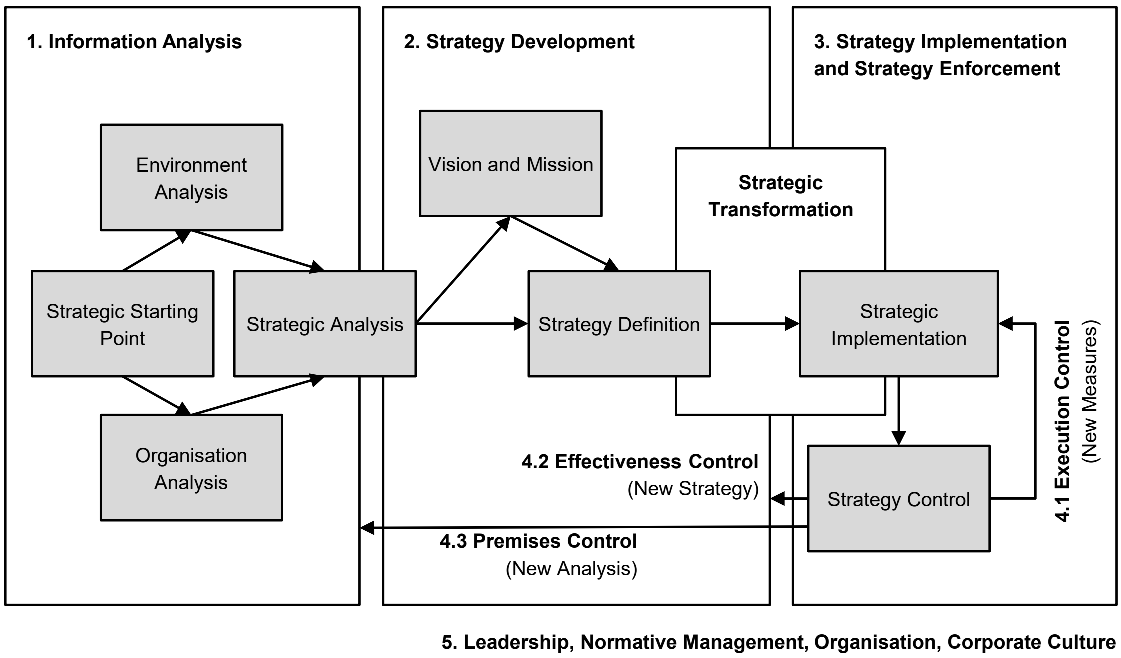


Figure 11-18: Process model of strategic controlling (Tschandl et al., 2014, p. 68)

Process model of Sternad (2015)

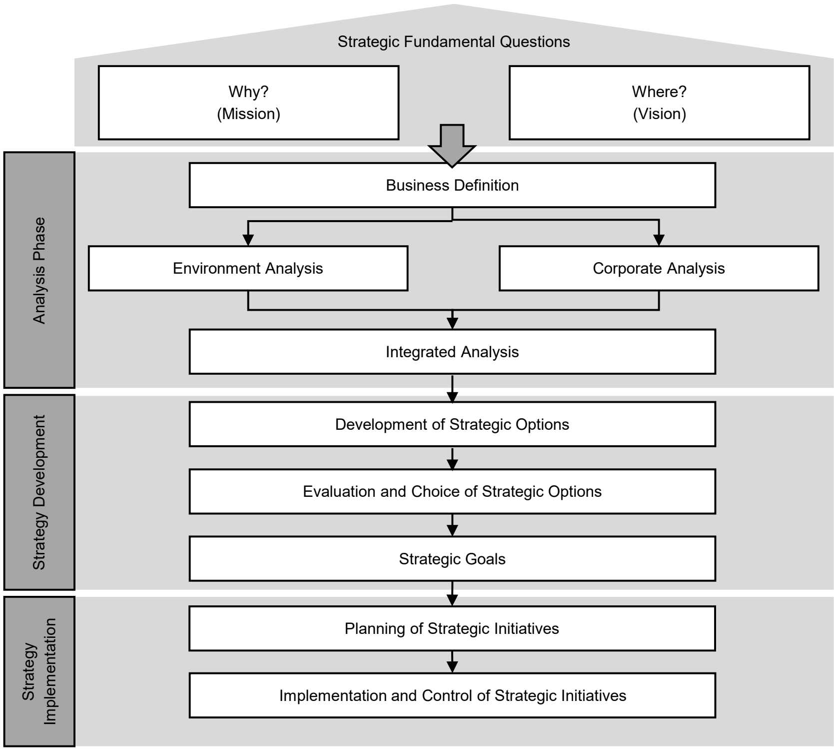


Figure 11-19: Overall strategy development process (Sternad, 2015, p. 5)

Process model of Bradley et al. (2013)

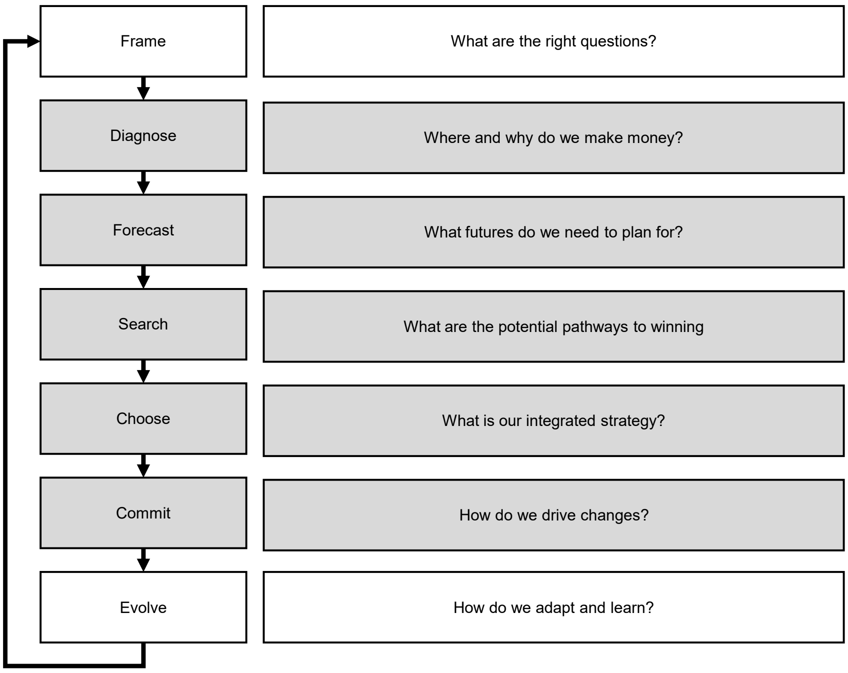


Figure 11-20: Building blocks of strategy (Bradley et al., 2013, p. 38)

Process model of Mussnig and Granig (2013)

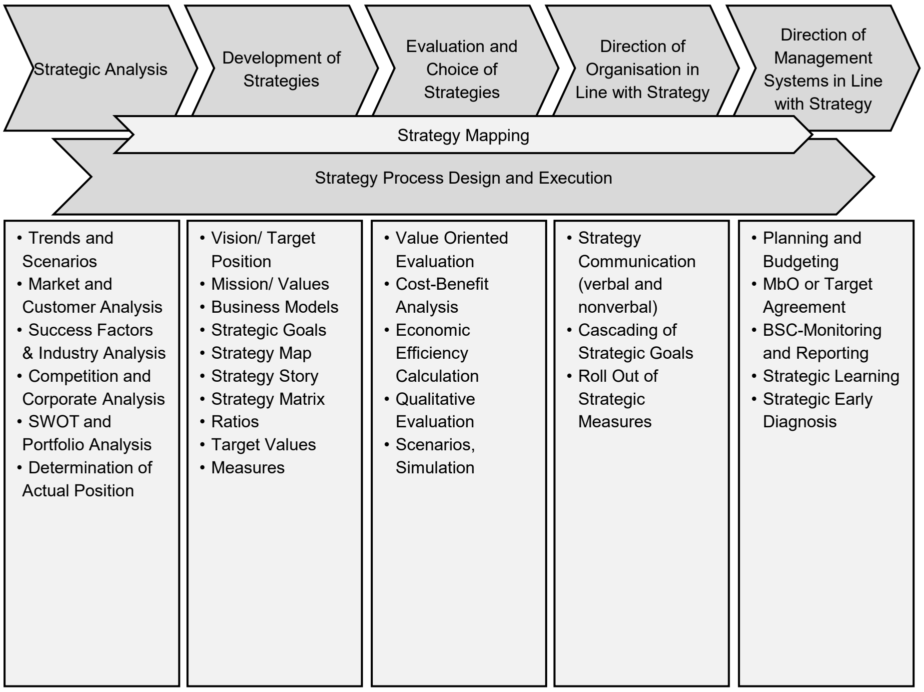


Figure 11-21: Process model for strategy development (Mussnig and Granig, 2013, p. 139)

Process model of Hungenberg (2014)

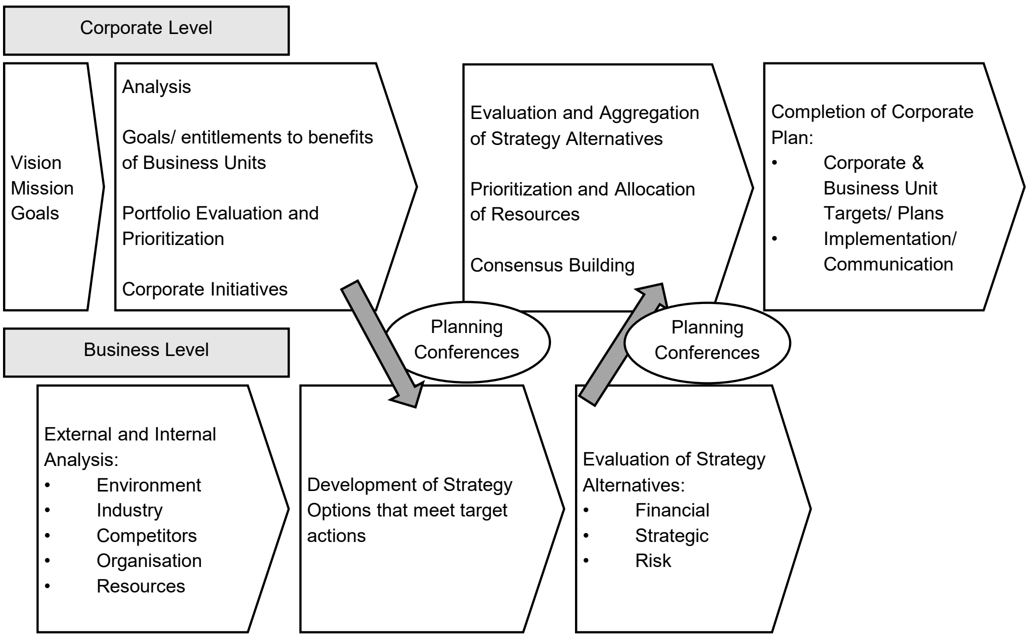


Figure 11-22: Process for strategic planning on a corporate and business level (Hungenberg, 2014, p. 535)

A5 English manual for the developed process model

The first version of the manual was developed in German based on the conceptual design of the process model during a student project (Fahrmeier, 2017).

A5.1 Overview of the process model

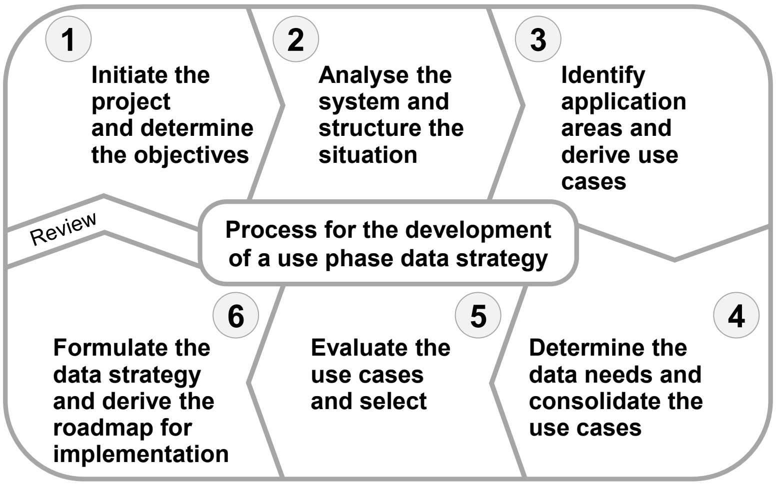
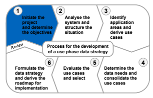


Figure 11-23: Depiction of the overall process model

A5.2 Step 1 – Initiate the project and determine the objectives

1 Step

Initiate the project and determine the objectives



Procedure

Initiate the project:

- **Initiate and place project within the company**
- **Define roles and responsibilities**
- **Compose an interdisciplinary team**
- **Create space for the team to work on the project**

Determine the objectives:

- **Analyse the framing company strategy and vision**
- **Identify other relevant projects within the company**
- **Define the objectives of the project**
- **Announce the project and make it visible**

Please note:

- **Composition of the team**
  - Interdisciplinary team with key persons from different departments
  - Inclusion of staff from the management level
- **Content of the objectives**
  - Timeframe for an implementation, timeframe for the project, purpose of the strategy, resources, beneficiaries, product group/class, and costs

Results

- Team for strategy development
- Catalogue with objectives for the use of data
  - Framework for the strategy development
  - Framework for the use cases
  - Boundary conditions for the project

Supporting methods

Initiate the project

- Overview of roles within a project

Determine the objectives

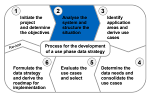
- SMART-method (specific, measurable, accepted, realistic, time bound)
- Domain and beneficiary matrix

Figure 11-24: Excerpt of the manual describing Step 1 of the process model

A5.3 Step 2 – Analyse the system and structure the situation

2 Step

Analyse the system and structure the situation



Procedure

Analyse the system:

- **Analyse the environment**
  - Examine the influencing factors of the macro environment (e.g., trends or legislation)
  - Perform a competitor analysis (e.g., competition, use cases, competencies, and sales concepts)
  - Conduct a customer and market analysis
  - Analyse the use phase data strategy of competitors
- **Analyse the company**
  - Analyse the product and service portfolio
  - Assess processes (e.g., product lifecycle or PDP)
  - Conduct a stakeholder analysis (internal and external)
  - Analyse IoT infrastructure and competencies
  - Reflect the current business model, the corporate strategy, and the use phase data strategy
  - Evaluate use phase data maturity level

Structure the situation:

- **Derive an overview of available (use phase) data**
- **Assess the current value proposition**
- **Merging of the company and environment analysis**
- **Review of the objectives**

Results

- Overviews of opportunities and risks for the development of a use phase data strategy
- Information about products and services, about data structure and about existing use phase data in the company
- Assessment of the use phase data maturity level of the company
- Adapted objectives

Supporting methods

Analyse the environment
- PESTEL analysis
- Market and customer analysis
- Porter's Five Forces

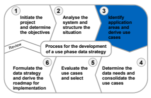
Analyse the company
- Stakeholder analysis
- Customer profiles
- Data journey

Structure the system
- SWOT analysis
- Strength-weakness analysis
- Data map

Figure 11-25: Excerpt of the manual describing Step 2 of the process model

A5.4 Step 3 – Identify application areas and derive use cases

3 Step



Identify application areas and derive use cases

Procedure

Identify application areas:

- **Search for application areas of use phase data**
  - Assess the product and corporate design
  - Analyse the stakeholder needs and interests (internal and external)
  - Examine competitors (within and outside the company's own business domain)
- **Consolidate the ideas for application areas**

Derive use cases:

- **Plan the search for use cases (e.g., review available material and select ideation methods)**
- **Identify suitable use cases**
  - Integrate internal and external stakeholders
  - Analyse use cases of other companies
- **Select suitable use cases and ensure compatibility with the objectives**
- **Document relevant use cases in a uniform way (e.g., indented value or required stakeholders)**

Please note:

- **No examination of the feasibility during ideation (technical, resource related)**

Results

- Overviews of possible application areas for the integration of use phase data
- Collection and documentation of possible use cases in a uniform format
- Understanding of the benefits intended by the use cases

Supporting methods

Identify application areas

- Product lifecycle
- Customer integration methods
- Stakeholder analysis
- Data map

Derive use cases

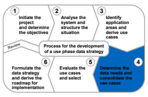
- Use case one-pager
- Use case catalogue
- Creativity methods

Figure 11-26: Excerpt of the manual describing Step 3 of the process model

A5.5 Step 4 – Determine the data needs and consolidate the use cases

4 Step

Determine the data needs and consolidate the use cases



Procedure

Determine the data needs:

- **Appoint an interdisciplinary team for the process**
- **Define a structured documentation format**
- **Detail the remaining use cases**
- **Determine data needs and reveal data delta**
- **Assess the available and required data quality**
- **Identify required analytics approaches and IT infrastructure**

Consolidate the use cases:

- **Derive interdependencies between use cases and stakeholders**
- **Identify relations and connections among the use cases**
- **Assess the dependencies between use cases and data needs**
- **Form benefit or use case clusters**
- **Check accordance of the use cases with objectives**
- **Define use case clusters and consecutive use cases**

Results

- Documentation of the use cases including the data needs
- Awareness about interdependence of the use cases
- Selection of use cases with a degree of detail for further comparison and evaluation

Supporting methods

Determine the data needs

- Use case template
- Service blueprint or data blueprint
- Data map
- Data quality template

Consolidate the use cases

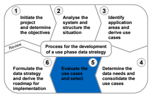
- Structural complexity management
- Evaluation methods

Figure 11-27: Excerpt of the manual describing Step 4 of the process model

A5.6 Step 5 – Evaluate the use cases and select

5 Step

Evaluate the use cases and select



Procedure

Evaluate use cases:

- **Select evaluation criteria (feasibility and attractiveness)**
- **Prepare assessment (e.g., stakeholder involvement and prototypical implementation)**
- **Conduct the evaluation of the use cases**
  - Feasibility-attractiveness analysis (qualitative)
  - Cost-benefit analysis (quantitative)
  - Risk assessment
- **Check evaluation results and document them**

Select use cases:

- **Comparison of the criteria, if applicable with a holistic assessment scheme for all criteria**
- **Visualize and summarize the evaluation results**
- **Review the underlying strategic motivation and objectives**
- **Conduct the final use case selection**
- **Document final selection of use cases**

Results

- Detailed evaluation results for the use cases
- Understanding of the use case related risks
- Selection of use cases for the use phase data strategy

Supporting methods

Evaluate use cases

- Scoring methods
- Pairwise comparison
- Approach for a cost-benefit analysis of use cases
- Use case template

Select use cases

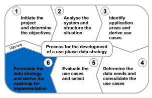
- Visualization approaches (e.g., portfolio matrices)

Figure 11-28: Excerpt of the manual describing Step 5 of the process model

A5.7 Step 6 – Formulate the data strategy and derive the roadmap for implementation

6 Step

Formulate the data strategy and derive the roadmap



Procedure

Formulate the data strategy:

- **Draft the use phase data strategy**
  - Outline the overall financial and non-financial goals
  - Formulate expected competitive advantages
  - Define the scope of the strategy (product and market)
- **Check the strategy for consistency and feasibility**
- **Ensure fit with the strategic context at the company**
- **Document and communicate the strategy**
- **Implement a monitoring system with reviews**

Derive the roadmap for implementation:

- **Analyse the current product roadmap**
- **Outline activities for the implementation**
  - Adaption of the products/services
  - Changes to the IT and IoT infrastructure
  - Adjustments on an organisational level (e.g., process)
  - Selection tools for data analytics
- **Derive an overall roadmap for all use cases and a use case specific roadmap**
- **Define the responsibilities for the implementation**

Results

- Use phase data strategy and its visualization
- Underlying objectives of the strategy
- Roadmap for the implementation concept

Supporting methods

Formulate the data strategy

- SWOT analysis
- Strategy map
- Balanced Scorecard
- Product profile

Derive the roadmap

- Organisation chart
- Template for an implementation roadmap

Figure 11-29: Excerpt of the manual describing Step 6 of the process model

A6 Method Box

A6.1 Linkage of the methods and the process model

The following sections describe all 15 developed methods in a structured way providing the following information for each method: purpose, situation, effect, and application process. In relevant cases, supporting methods are also mentioned as well as additional hints for the application of the method. The description of the methods follows the structure that is suggested by Lindemann (2009, pp. 61–62). Furthermore, Table 11-1 depicts which method is useful for which process step when developing a use phase data strategy. The allocation represents a suggestion based on the experience during the case studies. Therefore, the user of the process model can decide independently if and when to apply a method.

Table 11-1: Allocation of the developed methods to the method box

Process step	**Suggested methods from the method box**
Step 1	None
Step 2	• Fit-map • Product-market matrix • Strength-weakness analysis • Data journey template
Step 3	• Use case catalogue • Data journey template • Fit-map • Use case one-pager • Use case template
Step 4	• Use case template • Data quality assessment template • Effort-value portfolio • Matrix for the identification of use case clusters • Data blueprint
Step 5	• Portfolio for use case evaluation • Approach for a cost–benefit analysis of use cases
Step 6	• Strategy map for a use phase data strategy • Template for an implementation roadmap of a use phase data strategy

A6.2 Fit-map

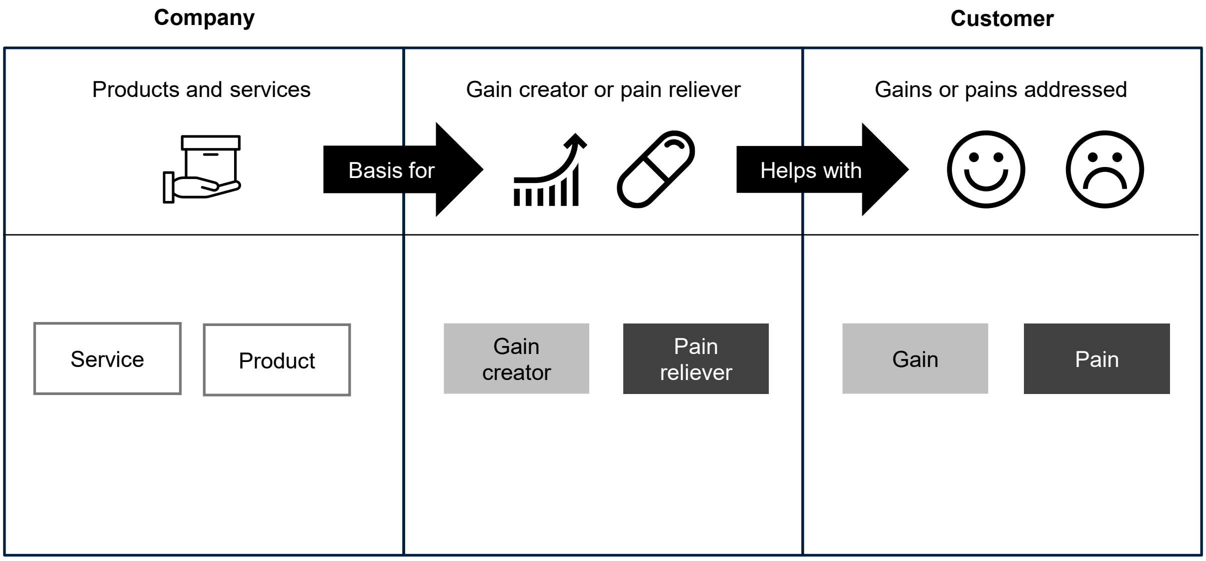


Figure 11-30: Depiction of the template for a fit-map

Purpose:

- Assessment of the value provided for customers by the existing products and services
- Identification of unaddressed gains and pains of the customer
- Generation of new use cases to offer additional value to customers which create gains or minimize pains for customers

Situation:

- Analysis of currently offered products and services (Step 2)
- Creation of new ideas for data-driven use cases (Step 3)

Effect:

- Systematic combination of offered products and services to address gains and pains of customers via the gain creators and pain relievers
- Highlighting unaddressed pains and gains in a systematic approach
- Structured approach to compare value of existing products and services
- Structured approach to identify use cases that address new pains and gains

Application Process:

Situation 1: Analysis of currently offered products and services

- Insert product and/or service
- Identify gain creators and pain relievers based on product or service
- Identify gains and pains addressed by these gain creators and pain relievers
- Check remaining and entered gains, pains, gain creators and pain relievers for fit to the product or service

Situation 2: Creation of new use cases

- Identify gains and pains that use cases should address
- Identify gain creators and pain relievers that would address these gains and pains
- Ideate new use cases that could offer these gain creators and pain relievers

Tools:

- Customer Profile and Value Proposition (Osterwalder et al., 2014)

Source:

- Rosenberger (2017)

A6.3 Product-market matrix

		Market 1		Market 2		Market 3		...
		Data usage	X %	Data usage	X %	Data usage	X %	
Product 1								...
Data generation	X %							
Data transmission	X %							
Data usage	X %							
Product 2								
Data generation	X %							
Data transmission	X %							
Data usage	X %							
Product 3								
Data generation	X %							
Data transmission	X %							
Data usage	X %							
...		...						

Figure 11-31: Template for a product-market matrix

Purpose:

- Analysis of the connectivity (data generation, transmission, and usage) of various products in different markets
- Comparison of connected products and market segments regarding the generation, transmission and usage of data

Situation:

- Analysis of the current situation
- Segmentation of market and product segments

Effect:

- Transparency about more/less developed (connected) products and identification of potential for improvement

- Clarity about the relevance of use phase data for the different market segments
- Knowledge about market specific requirements and potential for more connected products

Application Process:

- Identify relevant market segments and assess the relevance of use phase data for these market segments
- Identify product groups and assess the current data generation, data transmission, and data usage
- Identify differences as well as similarities among the markets and product groups
- Formulate requirements for each market
- Identify potential for products to enhance data usage

Source:

- Fetscher (2017)

A6.4 Strength-weakness analysis

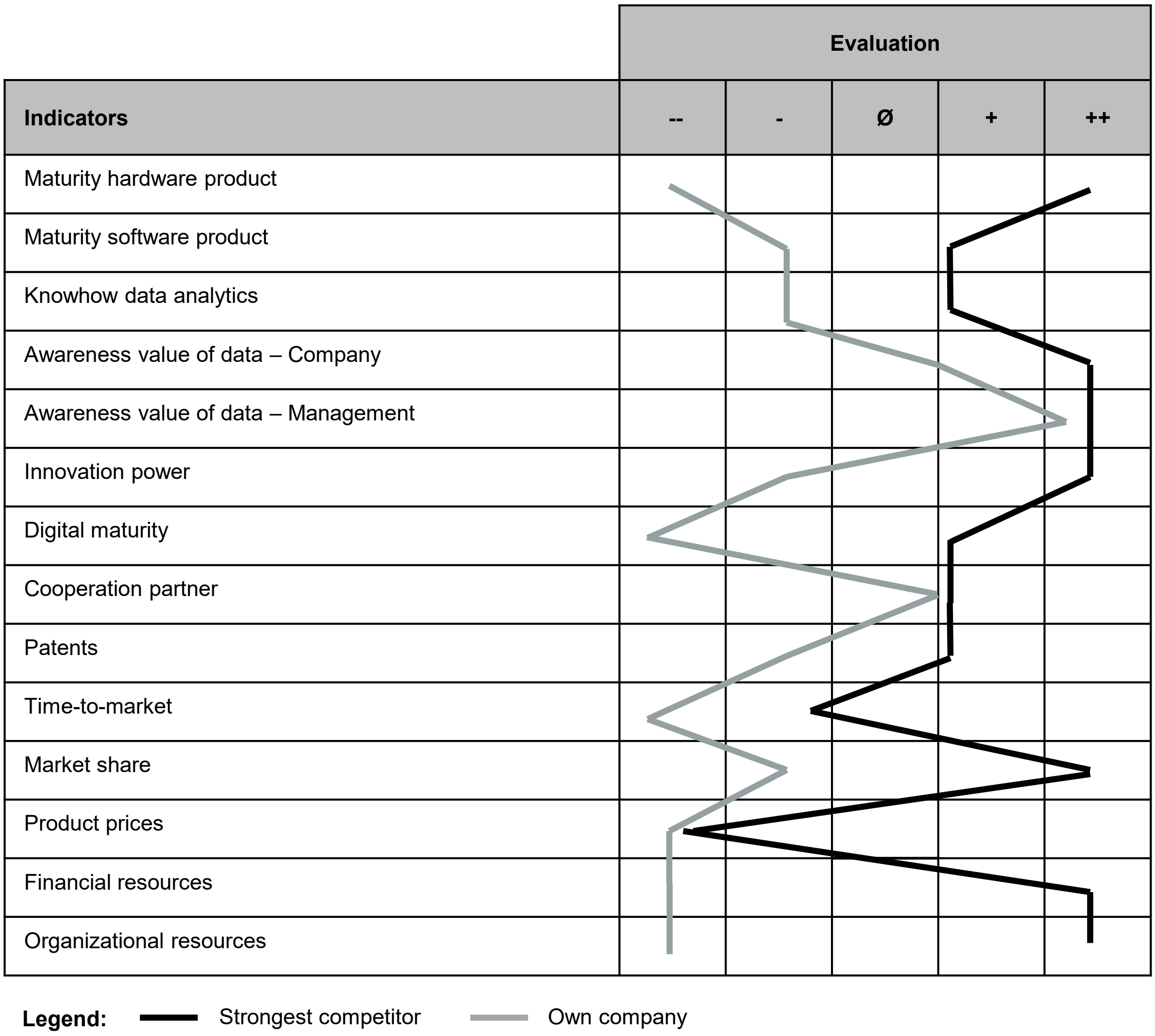


Figure 11-32: Depiction of an exemplary strength-weakness analysis

Purpose:

- Obtain transparency about own capabilities and resources regarding the implementation of a use phase data strategy
- Assessment of one's own strengths and weaknesses that are relevant regarding the implementation of a use phase data strategy in comparison with the strongest competitor

Situation:

- Strategy planning phase
- System analysis

Effect:

- Discovery of current and future competitive advantages as well as potential for optimisation in comparison with the strongest competitor

- Reveals the need for additional actions to address weaknesses

Application Process:

- Select the most relevant indicators for the analysis
- Identify the important competitors
- Select the most relevant competitor (e.g., market leader, technology leader)
- Assess the indicators regarding one's own capabilities
- Assess the indicators regarding the capabilities of the strongest competitor
- Compare one's own capabilities with those of the competitor
- Identify strengths and weaknesses and create methods to profit from strengths and to work on weaknesses

Sources:

- Kollmann (2009, pp. 371–373)
- Herrmann and Huber (2013, p. 72)
- Fetscher (2017)

A6.5 Data journey template

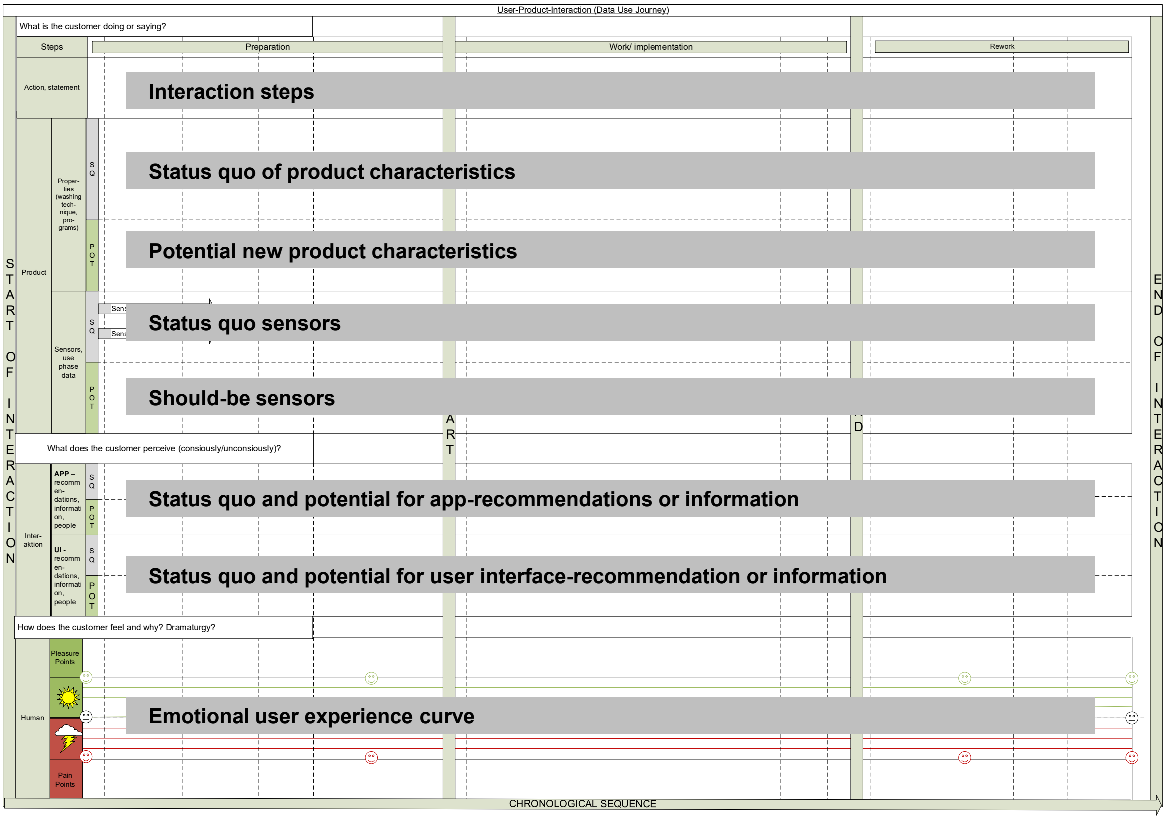


Figure 11-33: Overview concerning the structure of the data journey

A detailed depiction of the data journey can be found on page 288.

Purpose:

- Analysing and designing the user experience of connected products
- Identification of opportunities to better address needs through the exploitation of existing use phase data (additional product functionalities or services)

Situation:

- Analysis of current product offering as well as current interaction between the user and the product service
- Identification of novel use cases improving the user experience

Effect:

- Display of different perspectives on the needs of customers and users
- Structured and comprehensive description of the current interaction between the user and the product or service
- Identification of pain points during the use phase and at certain interaction steps
- Identification of use cases that improve user experience based on the connectivity of products and services

Application process:

- Define the level of detail for the analysis of interaction and define dimensions that the user journey should contain
- Define the starting point and endpoint for analysing the interaction between customer and product
- Fill in the available use phase data available as well as the emotional curve of the user during usage (status quo)
- Answer the following questions to detail the data journey:
    - What does, says, and expects the user during the product's usage?
    - What happens inside the product during its usage?
    - What do user or product sense during usage (consciously or unconsciously)?
    - How does the user feel during the interaction und why?
- Identify potential to solve pain points and create new use case ideas
- Insert the use case ideas into the data journey
- Adjust the user journey to highlight the impact that the use cases have on the data journey
- Derive recommendation for an implementation of the use cases

Source:

- Curraj (2018)
- Dorynek (2018)

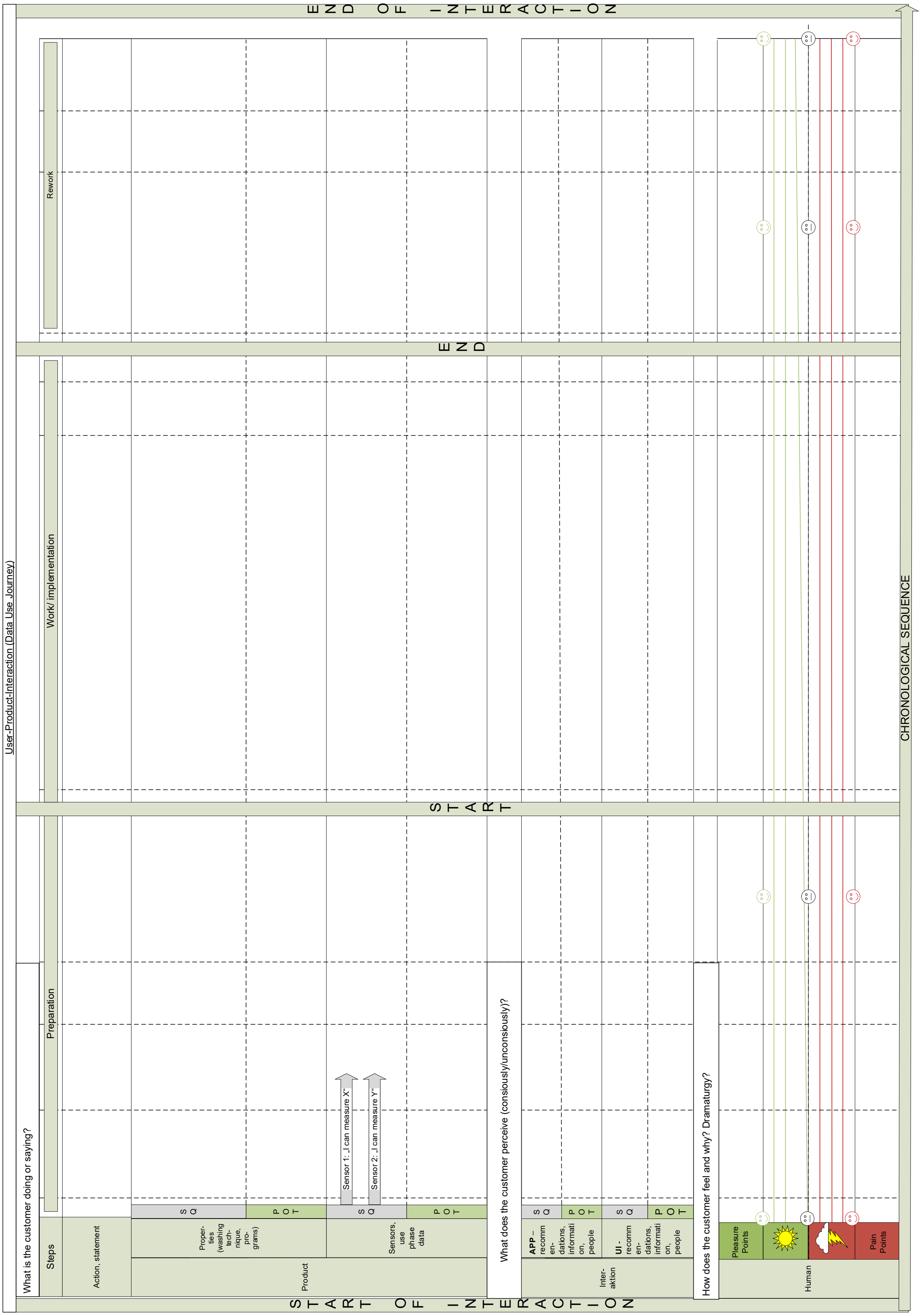


Figure 11-34: Detailed depiction of the template for the data journey

A6.6 Use case catalogue

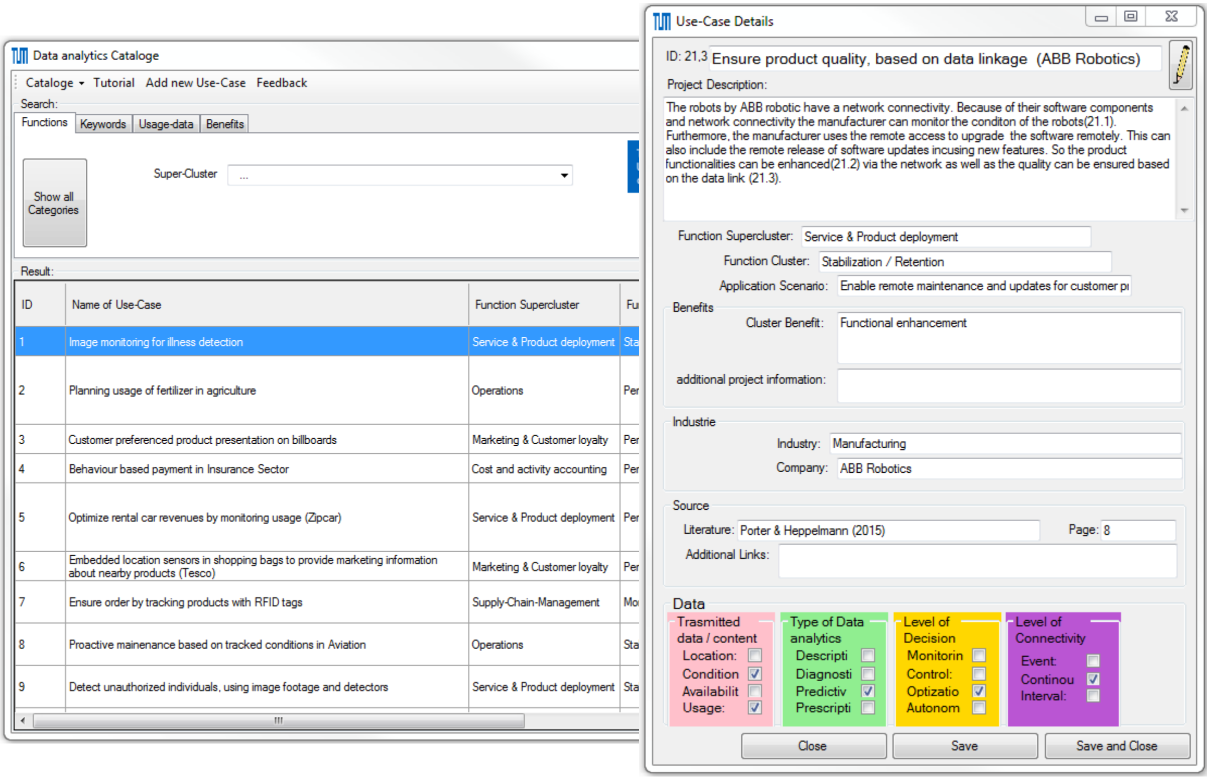


Figure 11-35: Software prototype of the use case catalogue. Left picture is showing the list of use cases. Right picture is showing the detailed description of an individual use cases (Wilberg et al., 2018c)

Further details on the methods are provided after the general description of the method!

Purpose:

- Identification of new application areas and use cases by creating analogies from best practice

Situation:

- After the first ideation or during the search for novel use cases

Effect:

- Use cases implemented by other companies or industries help to overcome one's own thinking barriers and trigger novel ideas for use cases
- Analogy building supports the search for new use cases
- Identification of unexpected application areas and use cases

Application Process:

- Determine core problems or benefits that the use cases should address
- Explore the use case catalogue and identify concrete use cases (source problem) that match the abstracted problem or benefit description (target problem)

- Select relevant use cases that suit one's own business and tailor the use cases to the individual context

Advice:

The use case catalogue can be explored by a single person individually, but it is also possible to integrate the catalogue into an ideation workshop. Therefore, enough time must be provided for the users of the catalogue to understand the structure and identify novel use cases.

Source:

- Nützel (2017)
- Wilberg et al. (2018c)

Detailed description of the use case catalogue

The software prototype of the use case catalogue is based on C# using the .net Framework. The prototype was developed as part of a student project (Nützel, 2017). Appendix A7 provides a brief overview of the use cases that the catalogue contains.

Figure 11-36 shows the home page of the use case catalogue. The software prototype offers four options to search for use cases:

1. Department in which the use case is applied (e.g., product development)
2. Use cases titles or keywords
3. Use phase data required for a use cases (e.g., location data)
4. Benefit that is provided by the use case for internal and external stakeholders (e.g., downtime reduction)

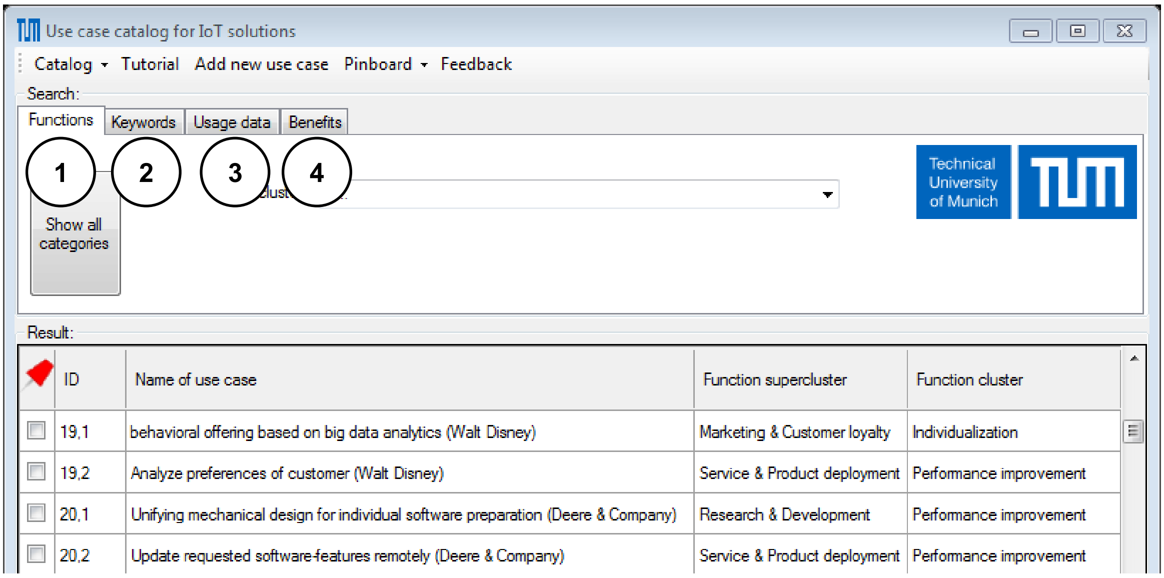


Figure 11-36: Home page of the use case catalogue

After the user selects a certain use case, the catalogue provides detailed information for each use cases. Figure 11-37 depicts detailed description of an exemplary use case. For each use case, the following information is provided:

1. Use case name and ID - Short name given to each use case
2. Project description - A few sentences describing the use case
3. Classification - Assignment to the three levels of clusters
4. Cluster benefit - Short description of the value provided
5. Applying company - Company and industry background for each use case
6. Source of the use case - Reference to paper or additional documents
7. Data type: location, condition, availability, or usage
8. Data analytics approach: descriptive, diagnostics, predictive, or prescriptive
9. IoT functionality: monitoring, control, optimization, or autonomy
10. Trigger for data transfer: event, interval, or continuous

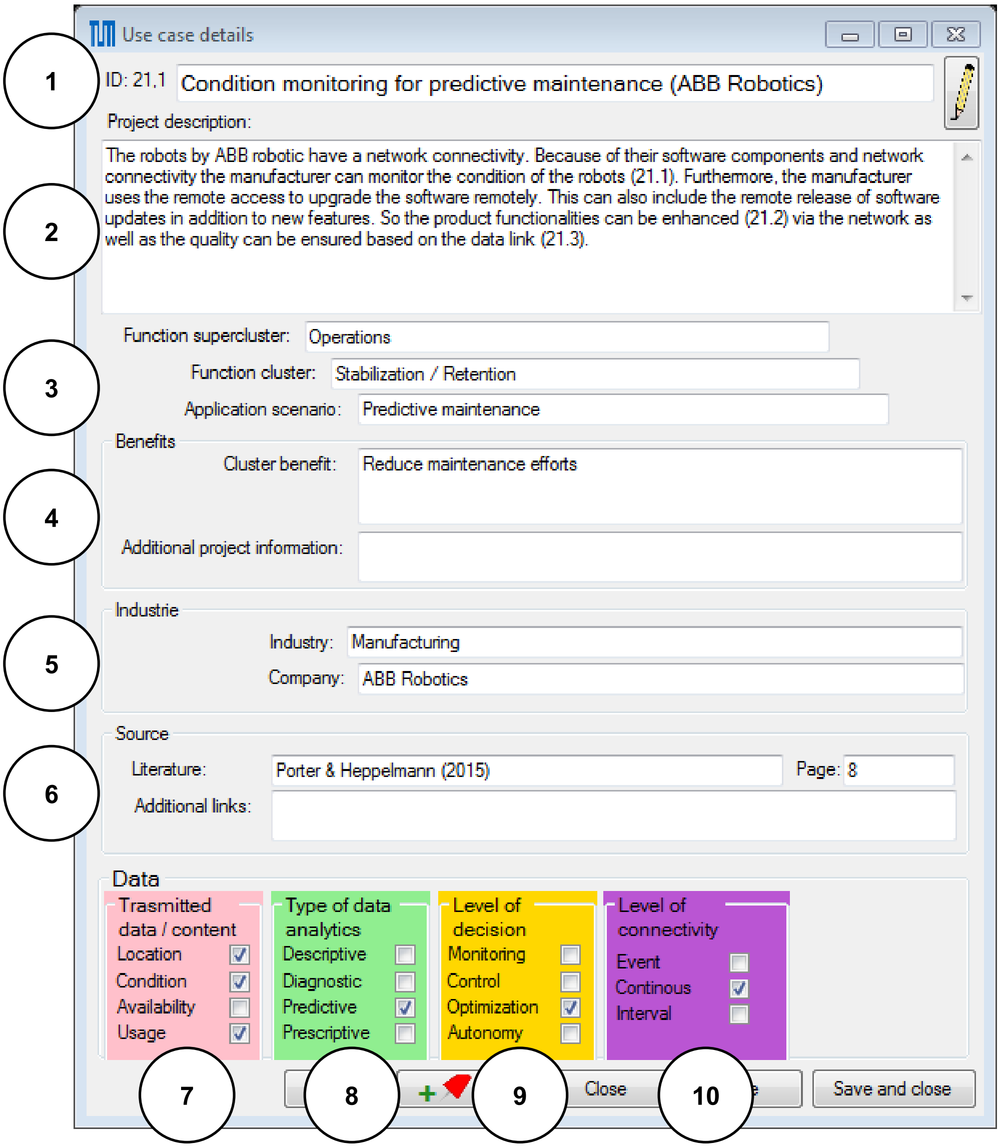


Figure 11-37: Details provided for each use case by the catalogue

A6.7 Use case one-pager

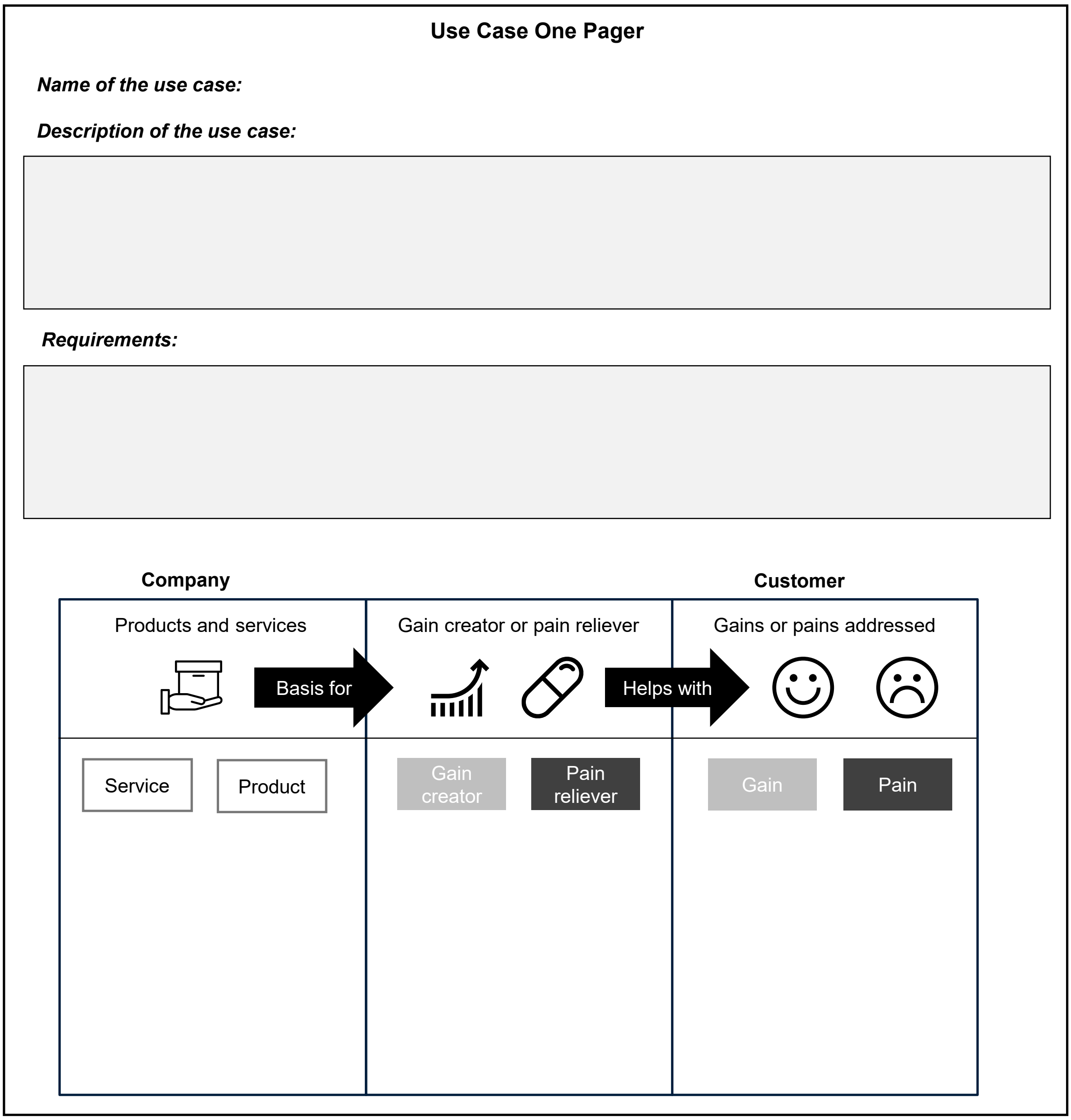


Figure 11-38: Template for the use case one-pager

Purpose:

- Initial description of (ideas for) use cases
- Provision of a brief overview concerning possible use cases
- Storage of ideas for use cases in a consistent way

Situation:

- After the first ideation or during the search for use cases
- Documentation of interview or workshop results

Effect:

- Comparison of use cases possible
- Structured description of ideas for use cases
- Identification of information that needs to be specified
- First basis for the discussion and assessment of use cases

Application Process:

- Think of relevant use cases that are valuable to implement within the company and its strategy
- Adjust the template to one's own needs
- Specify the use case by describing it and defining requirements
- Fill one pager with relevant information
- Think about the pains and gains addressed by use case and fill in the fit-map

Tools:

- Fit-map

Source:

- Rosenberger (2017)

A6.8 Use case template

Use case <name>	Use case <number of UC>
Context: <Short description of content>	**Status**: <Status Use Case>
Contact person: <Name>	**Last change:** <Date>

Description		
Stakeholder & interests	**Stakeholder**	**Interest**
	<Stakeholder name>	<Stakeholder interest>
	< … >	< … >
Data need	<Needed data points or sensors>	
Preconditions	<Describes the current state exclusive relevant IT-systems >	
Preconditions IT-systems	<Describes the current state exclusive relevant IT-systems, e.g. use phase data or data analysis.>	

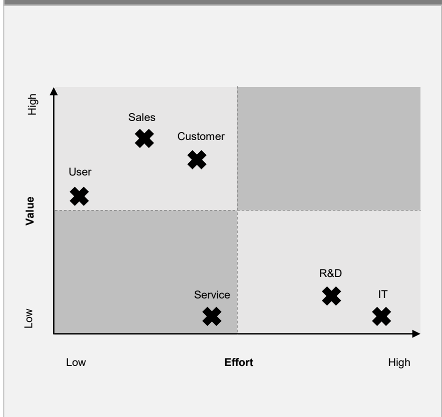
Use case procedure		
Trigger	<Action that makes use case start>	
Procedure of use case	**Step**	**Action**
	1.	<Trigger of steps, goal, Transfer of possible und stop after step>
	2.	< … >
Exceptions of use cases	**Step**	**Action**
	2a.	<State that leads to exception > : <Action of sub-use case>
End condition of use case	<Describes the state after end of use case>	

Evaluation			
Value	Very low ☐ ☐ ☐ ☑ ☐ Very high	**Complexity**	Very low ☑ ☐ ☐ ☐ ☐ Very high
Innovation	Very low ☐ ☑ ☐ ☐ ☐ Very high	**Costs**	Very low ☑ ☐ ☐ ☐ ☐ Very high

IT-effort estimation
<First or detailed assessment of efforts for the implementation of use cases and corresponding systems>

Additional information
<Notes, Connection to other use cases>

Effort-Value-Matrix



EXTERNAL	Custom-er	Effort	
		Value	
	User	Effort	
		Value	
INTERNAL	Sales	Effort	
		Value	
	Service	Effort	
		Value	
	Product-ion	Effort	
		Value	
	Develop-ment	Effort	
		Value	
	IT	Effort	
		Value	

List of open points		
Desxcription	**Responsibility**	**Due date**
<Task, action, activity>	<Name>	<Date>

Figure 11-39: Use case template

Purpose:

- Documentation and specification of use cases
- Identification of missing essential information regarding the implementation of the use phase data strategy

Situation:

- Use cases available
- Preparation of the evaluation of use cases
- Final documentation of selected use cases

Effect:

- Structured description of use cases
- Possibility to compare use cases
- Use cases are accessible to other stakeholders
- Reduced risk that use cases and related information are forgotten

Application Process:

- Identify relevant sections for the description of a use case
- Remove irrelevant and add relevant sections to the template
- Select use cases that should be detailed
- Create and fill out a template for each use case
- Add available information for each use case by integrating stakeholders' expertise

Tools:

- Effort-value portfolio

Advice:

- The template is only a suggestion and needs to be adjusted to the application context
- During the application of the process model, the information required for the template is generated in each step. Therefore, new information must be added in an iterative manner. Data scientists as well as relevant stakeholders should be integrated to get a comprehensive understanding of the use case.
- The single steps during the description of the use case must be logical and relevant in respect to the application area.

Source:

- Fetscher (2017)

A6.9 Data quality assessment template

Use case <NAME>				Nr. < Number of use case>				
Short description:								
	Nr.:	Data quality dimensions	Relevance	Degree of fulfilment				Need for improvement
				Current status	Target	Range of values	Weighted deviations	
Obligatory dimensions	1	Amount of data				{0;1;2;3;4;5}	0	
	2	Representational conciseness				{0;1;2;3;4;5}	0	
	3	Representational consistency				{0;1;2;3;4;5}	0	
	4	Precision				{0;1;2;3;4;5}	0	
	5	Consistency				{0;1;2;3;4;5}	0	
	6	Accuracy				{0;1;2;3;4;5}	0	
	7	Objectivity				{0;1;2;3;4;5}	0	
	8	Relevancy				{0;1;2;3;4;5}	0	
	9	Reputation				{0;1;2;3;4;5}	0	
	10	Understandability				{0;1;2;3;4;5}	0	
	11	Completeness				{0;1;2;3;4;5}	0	
	12	Value-Added				{0;1;2;3;4;5}	0	
	13	Timeliness				{0;1;2;3;4;5}	0	
	14	Availability				{0;1;2;3;4;5}	0	
	15	Security				{0;1;2;3;4;5}	0	
Optional dimensions	16	Currency				{0;1;2;3;4;5}	0	
	17	Believability				{0;1;2;3;4;5}	0	
	18	Interpretability				{0;1;2;3;4;5}	0	
	19	Performance				{0;1;2;3;4;5}	0	
	20	Auditability				{0;1;2;3;4;5}	0	
	21	Conciseness				{0;1;2;3;4;5}	0	
	22	Structure				{0;1;2;3;4;5}	0	
	23	Portability				{0;1;2;3;4;5}	0	
	24	Volatility				{0;1;2;3;4;5}	0	
	25	Recoverability				{0;1;2;3;4;5}	0	
	26	Reliability				{0;1;2;3;4;5}	0	

Figure 11-40: Depiction of the template to assess data quality

Purpose:

- Evaluation of the data quality of available use phase data
- Determination of the required data quality of a use case

Situation:

- Analysis of available use phase data
- Analysis and assessment of use cases

Effect:

- Comprehensive assessment of data quality
- Knowledge about the current data quality level
- Transparency of the required data quality
- Identification of required data quality improvements

Application Process:

- Fill in the header of the template
- Rate the relevance of the data quality dimensions (possibly complete list for use case)
- Determine the target and actual values for the data quality dimensions
- Evaluate the degree of fulfilment and derive need for quality improvement

Tools (integrated into the template):

- Weighted score
- Checklist

Advice:

- The template is by no means a fixed construct, because it should be adjusted for each application

Source:

- Möller (2017)

A6.10 Effort-value portfolio

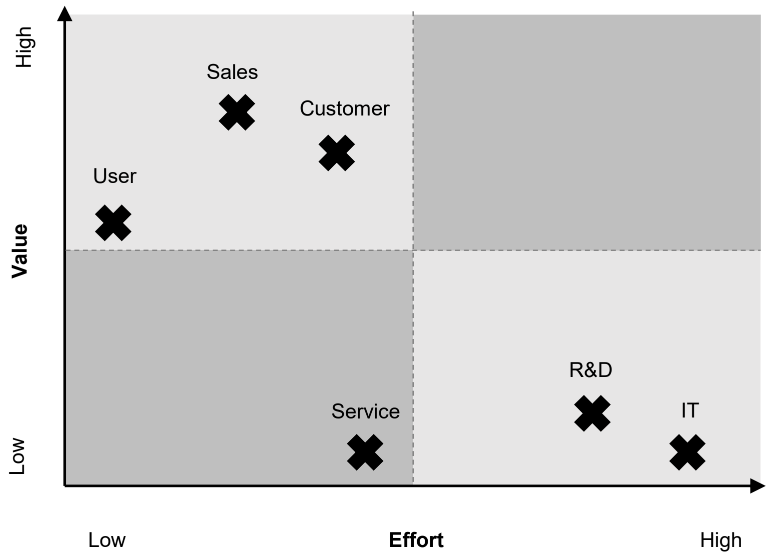


Figure 11-41: Exemplary effort-value portfolio

Purpose:

- Overview of the properties of the available use cases
- Communication of the use cases to internal stakeholders
- Assessment and identification of relevant use cases

Situation:

- Use cases have been identified
- Internal and externa stakeholders that are addressed by use cases are identified

Effect:

- Rapid overview of the consequences of the use cases for affected stakeholders
- Support of communication and collaboration concerning the implementation
- Transparency concerning the individual values and efforts

Application Process:

- Identify the stakeholders that are affected by the use cases and/or needed for the use case implementation
- Rate the value for affected and required stakeholders generated by the use case
- Rate the effort needed for the implementation of the use case for the affected and required stakeholders
- Select adequate scale for effort and value on the axes
- Place the stakeholders in the portfolio based on the rating of value and effort

Source:

- Fetscher (2017)

A6.11 Matrix-based approach for the identification of use case clusters

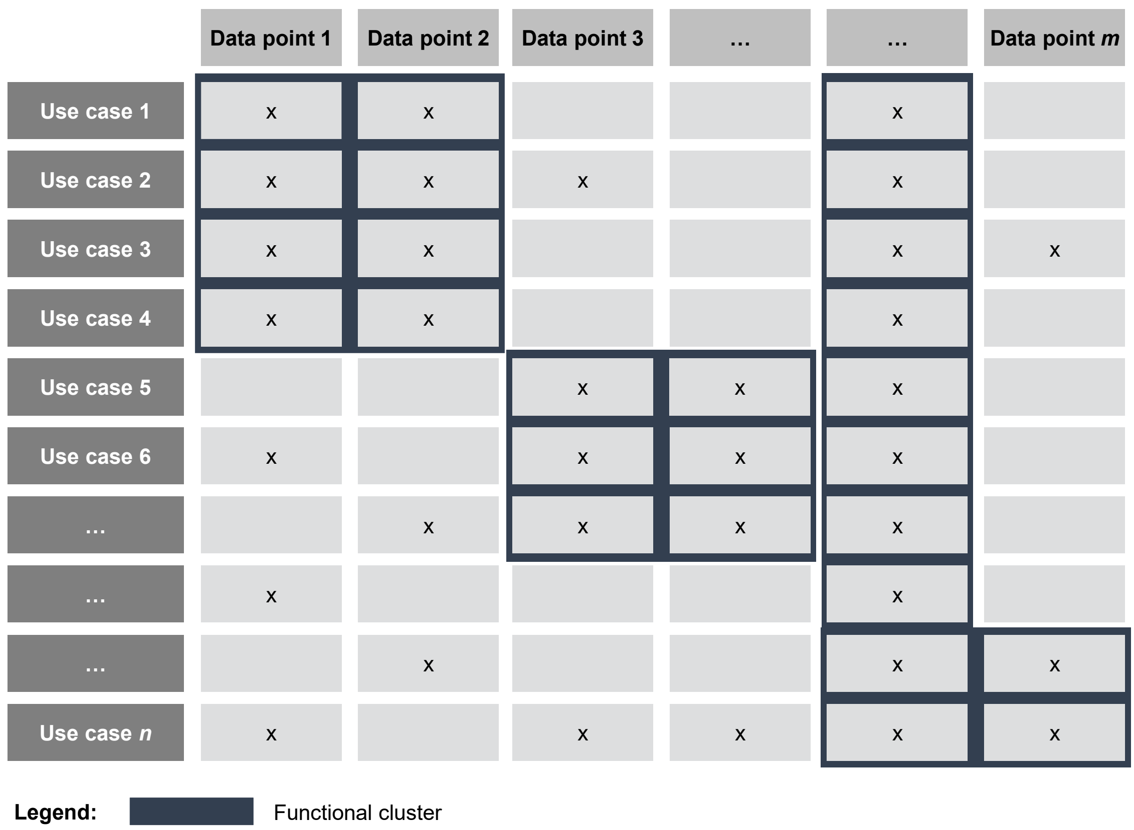


Figure 11-42: Matrix for the identification of use case clusters

Purpose:

- Classification of use cases into functional clusters
- Identification of required data points for each use case
- Identification of the need and relevance of the same data points for several or the same use cases

Situation:

- Existing overview of use cases
- Missing knowledge about dependencies among the use cases in terms of required data points

Effect:

- Visualisation of functional dependencies among use cases
- Identification of functional clusters of use cases
- Identification of important data points that enable many use cases

Application Process:

- Determine required data points for each use case
- Compare use cases and data requirements in the form of a matrix
- Assign data requirement per use case by marking with an "x"
- Sort the use cases based on the data points used, creating visual clusters based on the set markers
- If necessary, further classify identified clusters, for instance based the end users of the use cases

Tools:

- Spreadsheet program
- Clustering algorithm

Suggestions:

The classification of use cases gives a first indication of existing dependencies within functional groupings and should be used in combination with the selection procedures in Step 5 of the process model.

Source:

- Fetscher (2017)

A6.12 Data blueprint

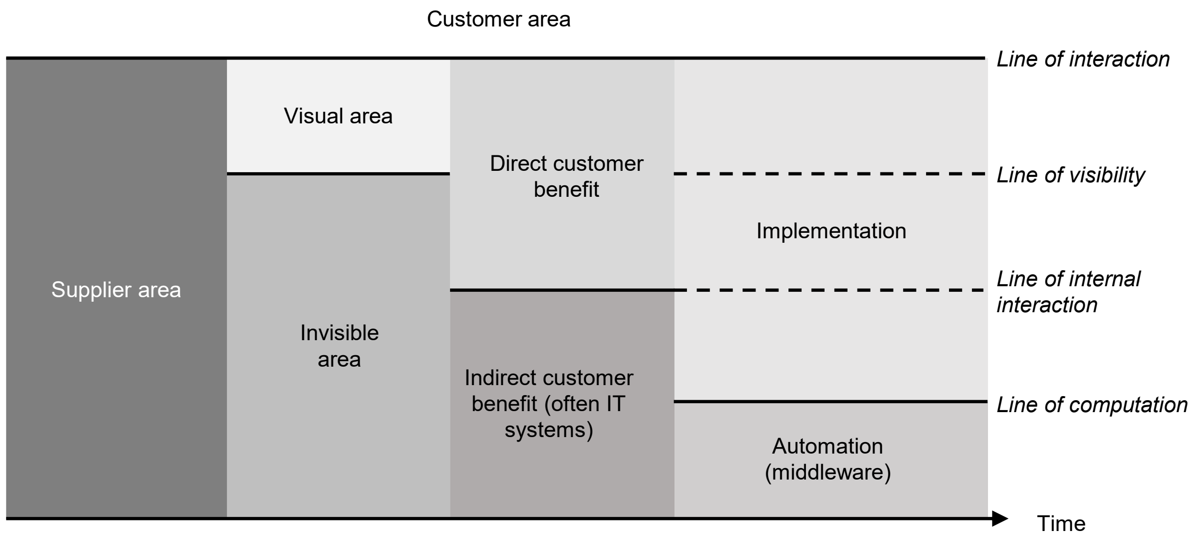


Figure 11-43: General layout of the data blueprint (derived from Wilberg et al. (2018b, p. 9))

Purpose:

- Description of the core process of a use case
- Input for a first cost-benefit-analysis

Situation:

- Transfer of responsibility for the implementation of a use case to the department

Effect:

- Documentation of the procedure linked to the use case
- Description of the interaction between the customer and the service provider

Application Process:

- Determine the sequential process of the use case, the individual activities and the necessary data requirements through the defined symbols
- Assign activities to the respective levels
- Depict the dependencies between the individual activities with arrows

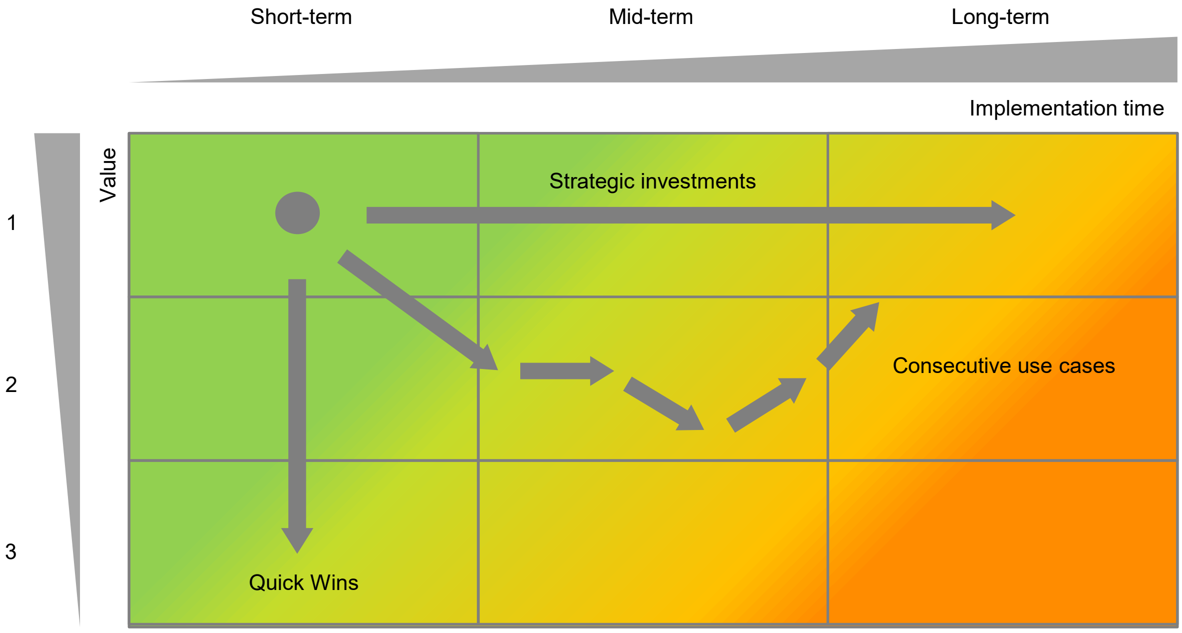
Tools:

- Use case template
- Service blueprinting
- Methodology and symbols of a flowchart

Advice:

The different levels can be adapted to the character of the service that has to be documented.

A6.13 Portfolio for use case evaluation



Legend:
Value: 1 = direct customer demand, 2 = improvement of customer experience, 3 = supporting
Implementation time: short-term = up to 6 months, mid-term = up to 2 years, long-term = 2 years and more

Figure 11-44: General structure of the portfolio for evaluating use cases

Purpose:

- Evaluation of use cases for selection of those that should be implemented

Situation:

- Classification of use cases based on data requirements is completed
- Final selection of the use cases to be implemented is pending

Effect:

- Identification of multi-level, consecutive use cases

Application Process:

- Determine the characteristics for the dimensions of the prioritisation and the time horizon for each use case
- Exclude use cases based on defined criteria (e.g., low prioritisation with simultaneous long-term horizon, missing technologies or competences)
- Identify enabler use cases within the functional groups
- Assign the remaining use cases per category to expansion stages based on the enablers

Source:

- Kalla (2017)

A6.14 Approach for a cost–benefit analysis of use cases

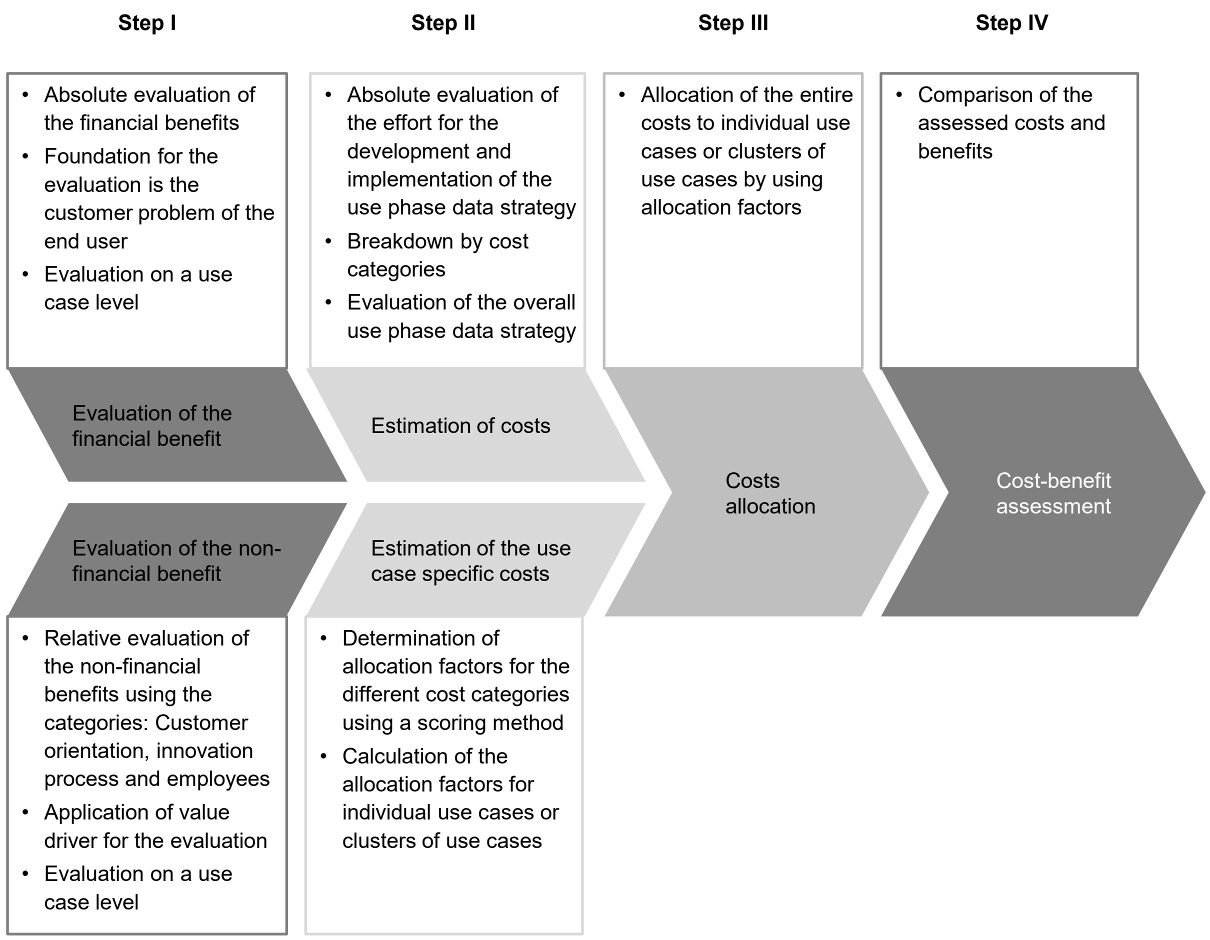


Figure 11-45: General process for the cost-benefit analysis

Purpose:

- Financial and non-financial cost-benefit analysis for identified use cases

Situation:

- Availability of different use cases on a detailed level
- Selection of a number of use cases with a suitable cost-benefit ratio

Effect:

- Transparency concerning the financial and non-financial benefits of use cases
- Knowledge of the use case related costs
- Reduced number of use cases

Application Process:

- Select the use cases for the analysis

- Evaluate the financial and non-financial benefits of the use cases
- Estimate the general costs and derive the use case specific costs
- Allocate the costs to the use cases or clusters of use cases
- Perform the cost-benefit analysis
- Select suitable use cases

Source:

- Straub (2018)

A6.15 Strategy map for a use phase data strategy

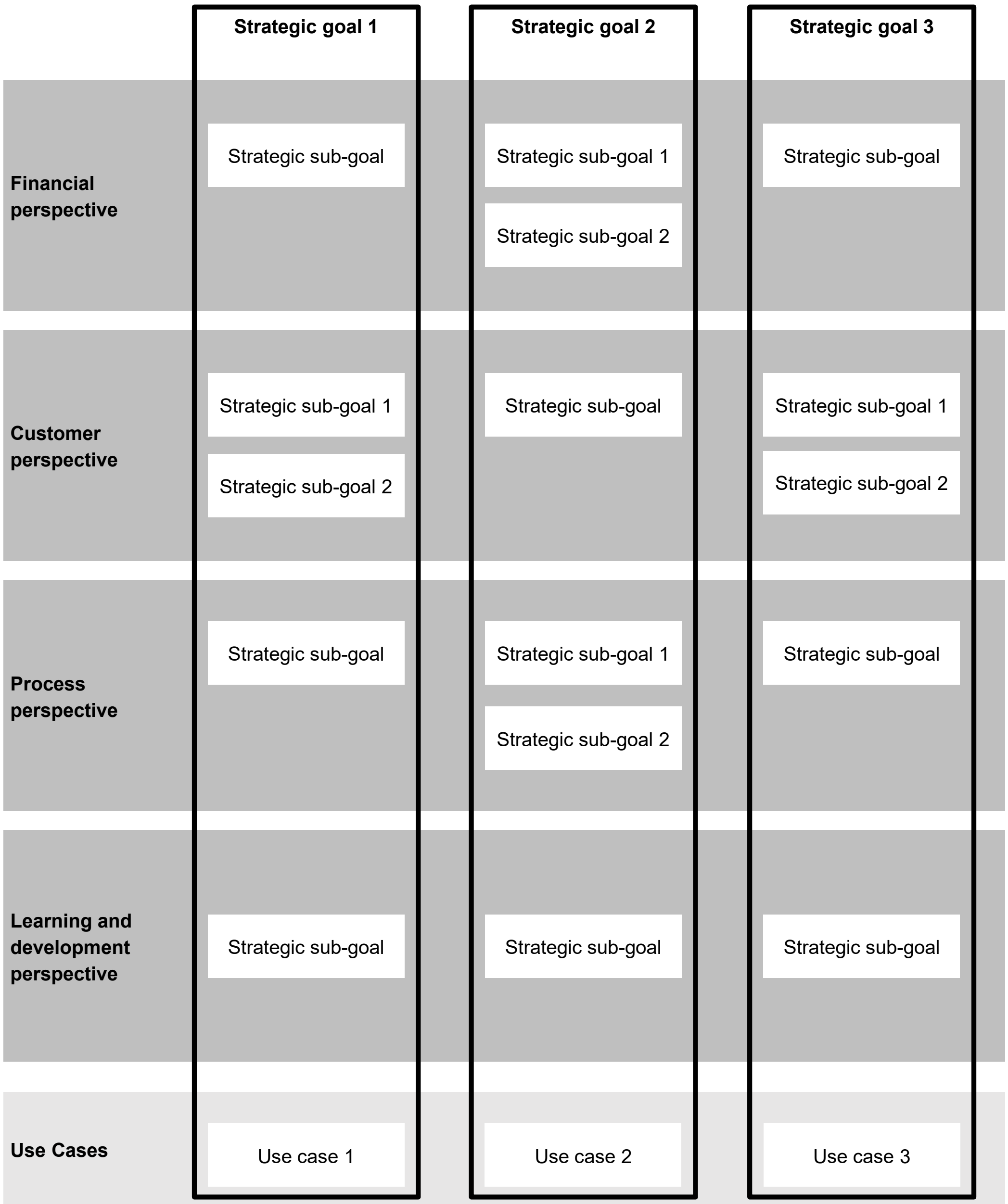


Figure 11-46: Template for a strategy map to visualise the use phase data strategy

Purpose:

- Documentation of the strategy
- Determination of indicators, target values and measures to steer the implementation of the strategy

Situation:

- The strategy development has been completed
- The strategy document is being created to conclude the strategy development

Effect:

- Quick overview of the strategy
- Goals and measures of the strategy are summarised in a transparent way

Application Process:

- Identify the major strategic goals and the use cases that should be implemented in the strategy
- Insert the use cases and assign them to the related strategic goal
- Examine each use case concerning the provided benefit for the financial-, customer-, process- and learning & development-perspective
  If necessary: Fill out a balanced scorecard for each individual use cases
- Insert the strategic sub-goal that each use case helps to address

Source:

- Kaplan and Norton (2009, p. 74)
- Koch (2018)

A6.16 Template for an implementation roadmap of a use phase data strategy

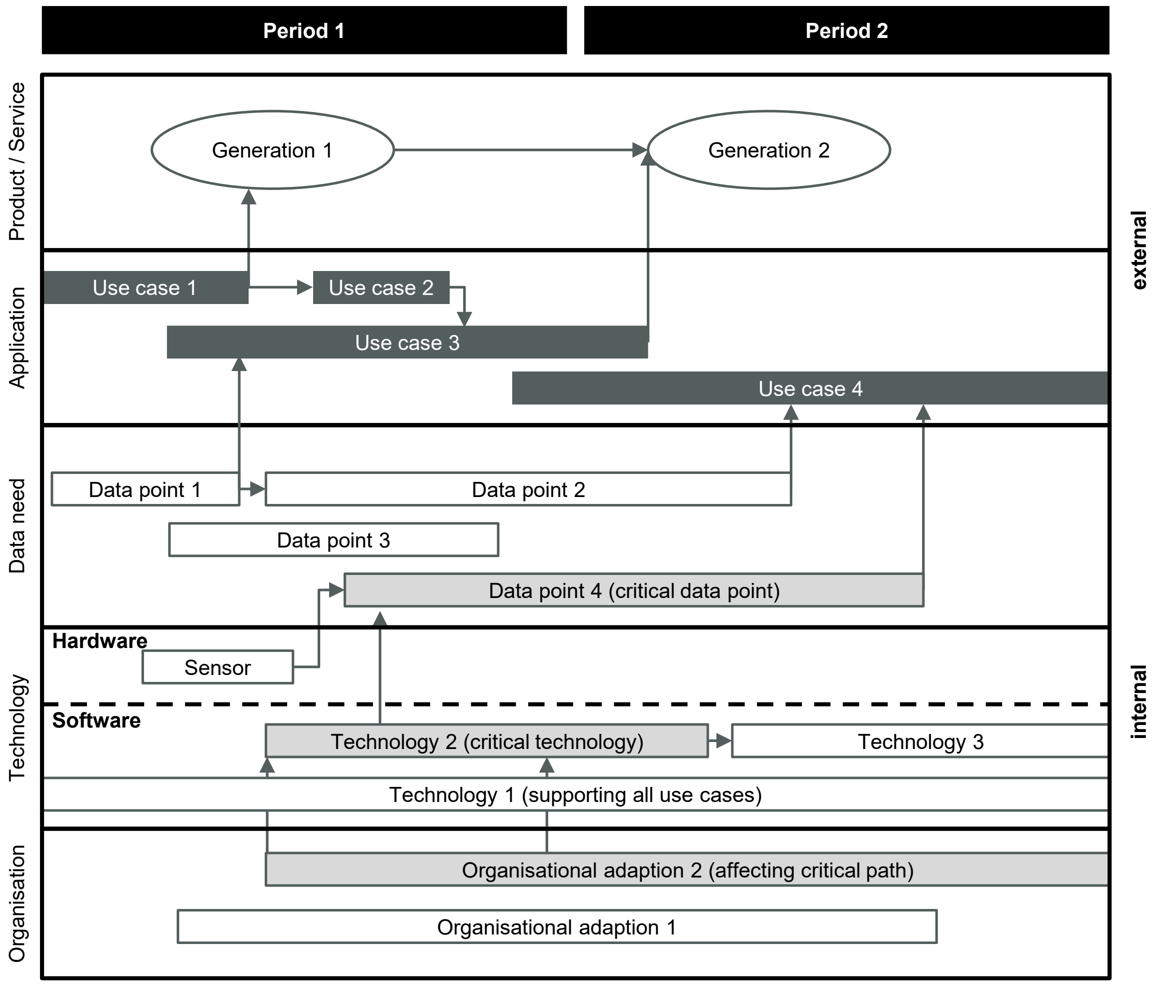


Figure 11-47: Suggested design for implementation roadmap (based on Wilberg et al. (2018b, p. 10))

Purpose:

- Support to plan the implementation of selected use cases

Situation:

- Detailed description of use cases available
- Knowledge about required data points

Effect:

- Harmonisation of use case implementation with the product roadmap
- Visualisation of the time planning for the implementation
- Clear understanding of the dependencies among tasks and use cases
- Understanding of the responsibilities and requirements linked to the stakeholders

Application Process:

- Creation of a Gantt chart according to the timing of use cases in the previous step
- Transfer of the temporal implementation of use cases into the roadmap
- Filling the remaining dimensions of the roadmap with tasks or preconditions according to their temporal occurrence
- Representation of dependencies with arrows
- If necessary, visualisation of bottlenecks by colour highlighting

Tools:

- Visualisation- or presentation tool
- Road mapping

A7 List of use cases provided by the use case catalogue

The use cases for the catalogue were derived during three student projects (Fetscher, 2017; Lau, 2017; Nützel, 2017).

UC ID	Name of use case	Cluster Benefit
1	Image monitoring for illness detection	Support health condition
2	Planning usage of fertilizer in agriculture	Optimize production planning
3	Customer referenced product presentation on billboards	Tailored marketing
4	Behaviour based payment in Insurance Sector	Behavioural / dynamic pricing
5	Optimize rental car revenues by monitoring usage (Zipcar)	Functional adjustment
6	Embedded location sensors in shopping bags to provide marketing information about nearby products (Tesco)	Behavioural offering
7	Ensure order by tracking products with RFID tags	Improve inventory/Stock management
8	Proactive maintenance based on tracked conditions in Aviation	Prevent downtimes
9	Detect unauthorized individuals, using image footage and detectors	Increase understanding
10	Routing adjustments based on weather und traffic patterns	Optimize routing
11	Providing information about location of gun fire	Increase understanding
12	Searching resources by analysing the condition of soil	Access to new resource possibilities
13	Detect shopping routes to optimize retail layout	Optimize POS
14	Monitoring and warning of patients	support health condition
15	Remotely chance position of objects in assembly line	Optimize asset allocation
16	Adjust process-temperature based on sensors (paper industry)	Increase process productivity
17	Smart metering (Pacific Gas and Electrics (PG&E))	Behavioural feedback
18	Predictive maintenance in Aviation (Etihad Airways)	Prevent downtimes
19,1	Behavioural offering based on big data analytics (Walt Disney)	Behavioural offering
19,2	Analyse preferences of customer (Walt Disney)	Support the product experience
20,1	Unifying mechanical design for individual software preparation (Deere & Company)	Simplify & unify the design
20,2	Update requested software-features remotely (Deere & Company)	Enhance variety & Individualization
21,1	Condition monitoring for predictive maintenance (ABB Robotics)	Reduce maintenance efforts
21,2	Enhance product functionalities via remote updates (ABB Robotics)	Enhance product life cycle
21,3	Ensure product quality, based on data linkage (ABB Robotics)	Functional enhancement
22,1	Enhance product functionalities via remote updates (Tesla Motors)	Functional enhancement
22,2	Usage centred design in Automotive (Tesla Motors)	Enhance variety & Individualization

23,1	Real Environment data for ongoing quality improvements (Tesla Motors)	Usage-based design improvement
23,2	Remote software updates for quality purpose (Tesla Motors)	Ensure product quality
24	Connected services as enabler for more precise product development	Usage-based design improvement
25,1	Unlocking rented bike by smartphone application (Smoove)	Convenient product access
25,2	Location tracking for optimized asset allocation (Smoove)	Optimize asset allocation
25,3	Pay-per-use via location tracking (Smoove)	Pay-per-use/ -go
26,1	Pay-per-copy using order tracking in office-printers (Xerox)	Pay-per-use/ -go
26,2	Remote maintenance and updates in office-printers (Xerox)	Ensure product quality
26,3	Predictive maintenance in office-printers (Xerox)	Prevent downtimes
26,4	Prevent running out of stock using monitoring (Xerox)	Ensure compliance
27,1	Connected ecosystems in smart home devices (Nest Lab)	Increase range
27,2	Self-learning product condition adjustment in smart home devices (NestLab)	Automated product condition adjustment
27,3	Remote product condition adjustment (NestLab)	Remote product condition adjustment
28	Remote door access via digital service (Kwikset)	Remote product condition adjustment
29,1	Analyse patterns in order to predict maintenance (GE)	Prevent downtimes
29,2	Real-time process-monitoring in Manufacturing (GE)	Real time visibility
30	Anomaly detection and warning in medical devices (Witlings)	support health condition
31	Process adjustments for last-minute feature ordering	Increase process flexibility
32,1	Route optimization for automated drones (Amazon)	Optimize routing
32,2	Planning and optimization of automated drones (Amazon)	Increase efficiency
33,1	Manufacturer sells hours the engine operated (Rolls-Royce)	X as a Service
33,2	Supervise engine by sensors to ensure warranty related behaviour (Rolls-Royce)	Ensure compliance
34	Connected ecosystem in consumer goods (SmartThings)	Increase range
35	Remote maintenance in healthcare (Sysmex Corporation)	Ensure product quality
36,1	Connected machines to avoid accident (Caterpillar Inc.)	Avoid loss and damage of asset
36,2	Using GPRS information to track machines (Caterpillar Inc.)	Optimize asset allocation
36,3	Optimize usage of different machines on building sides (Caterpillar Inc.)	Optimize resource allocation
37	Connected airplanes to predict maintenance	Reduce maintenance efforts
38,1	Design and optimize processes by user data	Functional enhancement
38,2	Remote maintenance of laundromats	Enhance product life cycle

38,3	Controlling device via reserving time slots by customer	Remote product condition adjustment
38,4	Ordering new cleaning material if running low	Individual services
39	Optimize resource allocation in healthcare	Optimize asset utilization
40,1	Optimize routing of cleaning machines	Optimize routing
40,2	Process optimization through optimizing of cleaning routes	Increase process efficiency
41,1	Business innovation in automotive (Uber)	X as a Service
41,2	Pay per use model for transportation (Uber)	Shared economy
42	Remote medical advices by connected medical devices	support health condition
43,1	Dynamic pricing for parking slots	Behavioural / dynamic pricing
43,2	Informing the user about available parking slots	Optimize asset utilization
44,1	Predictive maintenance in aviation (Taleris - Accenture & GE Aviation)	Prevent downtimes
44,2	Optimizing flight routes using real time information (Taleris - Accenture & GE Aviation)	Optimize routing
45,1	Monitor manufacturing processes (Saarstahl AG)	Real time visibility
45,2	Adjust process steps according condition information in steel production (Saarstahl AG)	Increase process efficiency
46	Predictive maintenance in transportation sector (DB Systel GmbH (in corporation with T-Systems))	Prevent downtimes
47	Predictive maintenance in Services (Thyssen Krupp AG (in corporation with Microsoft))	Prevent downtimes
48,1	Real time information to optimize the engine (Mercedes AMG)	Usage-based design improvement
48,2	Real time information to detect issues (Mercedes AMG)	Increase product quality
48,3	Embedded sensors in Cars help to improve quality management in R&D (Mercedes AMG)	Increase product quality
49	Predictive maintenance in Manufacturing (Rolls-Royce)	Prevent downtimes
50	Detecting medical equipment condition to predict replacements (Philips AG)	Optimize replenishment
51,1	Usage-based design improvement (Fanuc / Cisco)	Usage-based design improvement
51,2	Learning and optimizing actions executed by robots (Fanuc / Cisco)	Ensure operational process
52,1	Pay-per-copy using order tracking in office-printers (HP Inc.)	Pay-per-use/ -go
52,2	Predictive maintenance in office-printers (HP Inc.)	Prevent downtimes
53	Optimize resource allocation within operational process (IBM)	Optimize resource allocation within operational process
54,1	Enabling remote updates for functional enhancements (Cisco Systems Inc.)	Functional enhancement
54,2	Remote update to enhance feature in lifecycle (Cisco Systems Inc.)	Enhance product life cycle
55	Gathering energy data (Monitoring) to reduce the energy consumption (Cisco Systems Inc.)	Reduce energy consumption
56	Monitoring for reducing energy consumption (Enlighted)	Reduce energy consumption
57	Remotely access and control several light points in a city (Philips)	Reduce energy consumption

58,1	Optimize replenishment of City lightning elements (Philips)	Optimize replenishment
58,2	Real-time performance monitoring of light illumination in Cities (Philips)	Real time visibility
59,1	Automatically adjust temperature based on user-schedule (Tado)	Automated product condition adjustment
59,2	Developing features based on user data (Tado)	Remote product condition adjustment
60,1	Change light-state based on environmental factors (Philips)	Reduce energy consumption
60,2	Replace individual components based on usage time (Philips)	Enhance security
61	Use data to enable a compared monitoring (OPower)	behavioural feedback
62	Publishing energy consumption to enable compared monitoring (E.On)	Behavioural feedback
63,1	Monitoring wind turbines to prevent damages (General Electric Inc.)	Prevent damages
63,2	Monitor effectiveness of wind turbines (General Electric Inc.)	Insight into real condition
63,3	Automated wind turbine adjustment based on environment condition (General Electric Inc.)	Automated product condition adjustment
64	Monitor condition of solar panels to detect faults (BBOXX Ltd. and ProductHealth)	Issue/Fault detection
65	Monitoring user condition via smart wearables	support health condition
66	User-data related subscription of medicine	support health condition
67	Predict maintenance by medical devices (Varian Medical Systems)	Reduce maintenance efforts
68	Monitoring tires to predict maintenance (Pirelli)	Enhance lifetime
69	Adapt car design based on user preferences (Ford Motor Company)	Revealing underlying pattern
70	Using image footage by cameras to predict evacuation routes (Boston police department)	Increase understanding
71,1	Selecting music based on consumer preferences (Bose)	Behavioural offering
71,2	Designing of the Audio-speaker based on Usage data (Bose)	Functional adjustment
71,3	Enhance the product family of audio speakers' which suits environment situations of users (Bose)	Support the product experience
72	Predict the demand patters of elevators based on usage data (Schindler)	Behavioural adjustment
73	Situational based recommendations during elevator breakdown (Schindler)	Behavioural adjustment
74	Monitoring utilities to prevent damages (ABB)	Prevent damages
75	Change drive of ceiling fan based on environment conditions (Big Ass Solutions)	Automated product performance adjustment
76	Sensors und patient skin to inform patient in tenuous situations (Medtronic)	Increase awareness
77,1	Monitor mining equipment across countries for benchmarking (Joy Global (Komatsu Mining))	Insight into real condition
77,2	Monitor conditions of mining machines to predict maintenance (Joy Global (Komatsu Mining))	Prevent downtimes

78	Adjust light levels using environment conditions (Philips)	Automated product performance adjustment
79	Remote access to door lock (Doorbot)	Remote product condition adjustment
80,1	Increase range via connected ecosystems and digital service (Ring)	Increase range
80,2	Remote access to door lock (Ring)	Remote product condition adjustment
81	Remote repair of connected ATM machines (Diebold Nixdorf)	Enhance service quality
82,1	Robots lean form user patterns (iRobot AG)	Automated product performance adjustment
82,2	Update product design based on room layouts (iRobot AG)	Enhance variety & Individualization
83	Autonomous longwall mining system (Joy Global (Komatsu Mining))	Increase efficiency
84,1	Monitoring engine based on actual performance-measurements (General Electric Inc. (GE Aviation))	Insight into real condition
84,2	Optimizing flight procedures by data analysis (General Electric Inc. (GE Aviation))	X as A Service
85,1	Behavioural feedback in tennis racket (Babolat)	Behavioural feedback
85,2	Improving players gaming techniques by monitoring behaviour (Babolat)	Improvement suggestions
86	Informing about hazardous environment by sensors (Thermal Fisher Scientific Inc.)	Increase level of security
87	Remote monitoring of patient condition in healthcare (Biotronik)	support health condition
88	Tracking livestock to detect unusual behaviour (Litams)	Improve inventory/Stock management
89,1	Information based on data, collected from fields in agriculture (Jasper (Cisco) & Semios)	Real time visibility
89,2	Adjust actions in precision agriculture (Jasper (Cisco) & Semios)	Increase process efficiency
90,1	Using driver-data to continuously develop software features (Garmin & Jasper Cisco)	Support the product experience
90,2	Remote maintenance by service updates (Garmin & Jasper Cisco)	Ensure product quality
91	Planning of resource allocation for vending machines (Cantaloupe Systems & Jasper Cisco)	Optimize resource allocation within operational process
93	Predict maintenance at the device level of connected robots (ABB Robotics)	Enhance service quality
94,1	Condition monitoring of connected mining systems to detect faults (Goldcorp (& Cisco))	Issue/Fault detection
94,2	Real-time process-monitoring of mining systems (Goldcorp (& Cisco))	Real time visibility
94,3	Avoiding unnecessary abrasion of mining machines based on soil-data (Goldcorp (& Cisco))	Avoid unnecessary abrasion
95,1	Optimize routing for fleet management based on GPS data (GPSTrackIt)	Optimize resource allocation within operational process
95,2	Predictive Maintenance for fleet management (GPSTrackIt)	Enhance lifetime
96	Avoid loss and damage within car-fleet (GPSTrackIt)	Avoid loss and damage of asset

97,1	Monitoring engine performance in real-time (CTM)	Real time visibility
97,2	Using analysis to optimize diesel engines (CTM)	Ensure compliance
98	Personalized routing in airports (Miami International Airport)	Tailored marketing
99	Improving management decision by monitoring machines in manufacturing (ATI Specialty Materials)	Reduce respond time
100	Tracking blood sugar to detect risk level of pregnant women (AMC Health)	support health condition
101,1	Monitoring water conditions to detect anomalies in seafood production (Ward Aquafarms)	Prevent damages
101,2	Optimize routing in food supply chain (Ward Aquafarms)	Optimize routing
101,3	Tracking food condition to avoid spoiling (Ward Aquafarms)	Avoid loss and damage of asset
102,1	Matched mattresses to individual customers by body shape (Sheela Foam)	Behavioural offering
102,2	Learning algorithm to design better product composition (Sheela Foam)	Enhance variety & Individualization
103,1	Reserve access to on-demand fleet by mobile app (Daimler)	Convenient product access
103,2	Connected ecosystem in Transportation (Daimler)	Increase range
103,3	Dynamic pricing by booking behaviour, destination and car usage (Daimler)	Pay-per-use/ -go
103,4	Improve asset allocation by determine usage-areas for on-demand fleet (Daimler)	Usage-based design improvement
104,1	Managing supply and demand of parts to feed (Daimler)	Optimize production planning
104,2	Reduce downtimes in Production by low supplies (Daimler)	Increase process productivity
104,3	Reducing large inventories down to essential supplies (Daimler)	Improve inventory/Stock management
105,1	Product tracking by RFID (Daimler & Festo)	Ensure operational process
105,2	decentralized planning by RFID (Daimler & Festo)	Increase process flexibility
106,1	Improving the design of cars based on customers' daily needs (Daimler)	New design
106,2	Improving the design of cars based on customers' daily needs (Daimler)	Usage-based design improvement
107	Increasing transparency and flexibility in car manufacturing (Daimler)	Transparency of value creation
108,1	Detect issues in manufacturing process by condition monitoring (Daimler)	Issue/Fault detection
108,2	Increase flexibility in process adjustments based on flagged faults (Daimler)	Increase process flexibility
109,1	Enabling predictive maintenance in Transportation (Daimler) (Daimler)	Prevent downtimes
109,2	Track connected lorries for optimizing routing in transport (Daimler)	Optimize routing
110,1	Optimize utilization of car-sharing fleet (BMW)	Optimize asset utilization
110,2	Transmits data of car-usage and the user (BMW)	Optimize asset allocation
110,3	Analyse the driving behaviour and the usage behaviour of the car to optimize the car design (BMW)	Usage-based design improvement

111	Remote maintenance in vehicle software (Wind)	Ensure product quality
112	Climate change monitoring (University of Alberta)	Increase understanding
113	Inform user if parts are likely to fail in agricultural vehicles (Deere & Company)	Insight into real condition
114,1	Real-time Monitoring of Field conditions (Deere & Company)	Real time visibility
115	Initialize training phase	determine necessary support required by the operator
116	Product settings in User profiles	Create profiles from saved user-settings
117	Security relevant object recognition	identifying objects to prevent dangerous situations
118	Optimal use of machines and products	identifying optimal product parameter
119	Condition Monitoring	Show important information on a display
120	display movement in Real-time	Analyse efficiency of products
121	Display of POI	Show important information on a display
122	Preventive product-protection	Prevent damage of machines by stopping wrong use
123	Autonomous workspace assignment	Automatic assignment of work areas
124	Support connection to experts	Improve communication between users and experts
125	User Authentication	Stop unauthorized Persons from using the products
126	Documentation of energy consumption	Documentation of energy consumption
127	Benchmarking	Comparing consumption of resources
128	Product localization	Tracking location
129	Product-Sharing	Additional sharing strategies
130	Communication of optimal material requirements	Planning material supply based on consumption of machines
131	Theft protection	Protecting products with geofence technology
132	Calculation generation	Automatic billing
133	Data-based insurance contracts	Customer segmentation-based insurance policies
134	Income statement calculation	Usage based Income statement
135	Multi-project planning	Improving planning by using ERP systems
136	Project controlling	Identification of the need for action in project controlling
137	Connected project management	Distribute work contents by employee profiles
138	Optimization of distribution	Optimizing distribution
139	Tracking of products	Carry out value and cost streams in logistics

140	Monitoring of product quality	Identifying product improvements by sensor data
141	Parameter identification for simulation	Improve simulations by usage data
142	Reduction of over-engineering	Improving design by reducing over-engineering
143	Direct customer feedback	Fast customer feedback through an app
144	Optimization of product-tests	Optimize safety dimensioning
145	Strengthening customer loyalty	Strengthening customer loyalty by individual Service actions
146	Optimized stock-tracking	Proactive inventory generation
147	Data-based sales support	Support sales
148	Targeted marketing	Improving marketing activities
149	Monitoring social media platforms	Strengthening customer loyalty and reputation
150	Customer acquisition	Customer acquisition by machine information
151	Pattern recognition in customer complaints	Quality improvements
152	Pattern recognition from service-reports	Service und product improvements
153	Sales Forecast of spare parts	Forecasting maintenance
154	Simplification of the warranty process	Improved warranty process
155	Optimized routing of service staff	Optimized routing
156	Tracking products over product life cycle	Information about quality of safety-critical parts
157	Development of maintenance scenarios	Improve maintenance
158	Proactive maintenance	Improving service by automatic maintenance offers
159	Predictive maintenance	Usage recommendations based on usage data
160	Product-complementary service solutions	Improved product service
161	Remote maintenance	Access to maintenance relevant data
162	Optimized sales-planning	Production and Sales planning based on customer requirements
163	Optimized maintenance of production-machinery	Improved maintenance

A8 Evaluation

A8.1 Questionnaire used for the evaluation

Questionnaire for the evaluation of the research input and the case study results

Over the last months, the process model for the development of a use phase data strategy and different connected methods were applied at your company. The objective was to develop a sound use phase data strategy in a systematic and methodical way. Your feedback is very valuable to evaluate the research support that was developed by research and applied at the company. In case any tasks or statements are unclear please do not hesitate to ask for clarification!

The results of this evaluation will be used for the student thesis and the evaluation of Julian at the Technical University of Munich.

The questionnaire consists of the following four blocks:

Evaluation of the process model
Assessment of the usability, applicability, and usefulness
Evaluation of the case study process and the case study results
Evaluation of additional methods applied during the case study
Open questions

Instructions: Please indicate for each statement to which degree you agree with the statement by marking one of the five options with a cross (x)

Thank you very much for your valuable feedback!

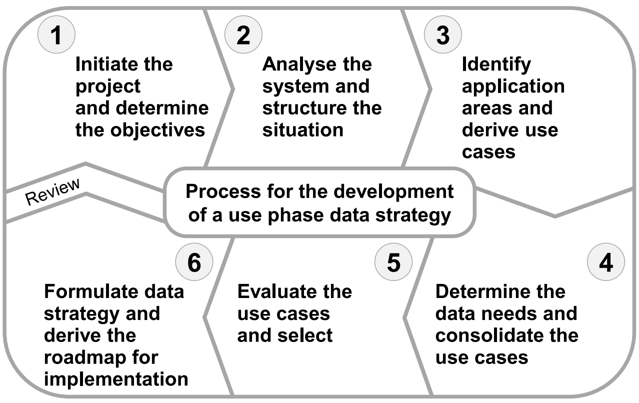
Information concerning the professional background

Position at the company: ____________________________________

Years of industry experience:________________________________

Experience with exploiting use phase data (Yes or No): ___________

Evaluation of the process model



Evaluation questionnaire Page 1

Usability

The objective of this section is to understand whether users are able to understand the developed process model and would be able to apply it independently.

Statements	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
The process model in combination with the manual enables users to develop a use phase data strategy in a structured way.					
The description of each process step (tasks, methods, and results) in the manual contains all the relevant information for users to conduct the relevant activities to develop a strategy.					
The process model and the manual are comprehensible to the user.					

Applicability

The objective of this section is to assess whether the developed process model can be applied in the intended environment.

Statements	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
The process model is suitable for the development of a use phase data strategy in engineering companies with connected products and services, as well as those that plan to develop them.					
The process model is flexible enough to be adjusted to different company specific application contexts (e.g., industry sector, company size, B2C vs. B2B).					
The process model provides means and methods to develop a use phase data strategy that addresses **internal stakeholders** (e.g., product development, service management, or marketing).					
The process model provides means and methods to develop a use phase data strategy that addresses **external stakeholders** (e.g., users, or customers).					
The process model supports a use phase data first (bottom-up) as well as a use case first (top-down) approach for the development of a use phase data strategy.					
The process model requires information and data input for the development of the use phase data strategy that is available in a company.					
The effort (time) required for the application of the process model matches the intended outcome of the process model.					

Usefulness

The objective of this section is to evaluate if the process model has the desired effects and helps to overcome challenges connected with the development of a use phase data strategy.

Statements	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
The comprehensive internal and external analysis improved the understanding of the context within which the development of the use phase data strategy was conducted.					
The application of the process model created transparency regarding available and required use phase data.					
The systematic approach of the process model helped to gain a comprehensive overview regarding possible use cases.					
The application of the process model generated new and feasible use cases that were unknown before.					
The analysis of the dependencies among the use cases helped to identify clusters of use cases that require similar use phase data.					
The comprehensive exploration of possible use cases prior to selecting individual ones leads to a coherent and technically feasible use phase data strategy.					
The structured consolidation and assessment of use cases by using a set of criteria ensured that informed decisions were made based on the related costs and benefits.					
The process model fostered the integration of relevant stakeholders with different perspectives during the development of the use phase data strategy.					
The application of the process model led to use cases that provide additional value (e.g., additional turnover, higher customer satisfaction, or reduction of over engineering) for internal as well as external stakeholders.					
The main output of the process model (use phase data strategy and implementation roadmap) provides a clear vision and highlights important implications for an implementation (technical and organisational).					

Evaluation of the case study process and the case study results

The objective of this section is to evaluate the underlying process of the case study and the overall results of the case study.

Statements	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
The tasks of each process step were useful for the development of the use phase data strategy.					
All relevant stakeholders were involved in the strategy development process during the case study.					
The value of the results (use phase data strategy) exceeds the time invested in the development of the data strategy.					
The developed strategy matches the objectives that were set at the beginning.					
The developed use phase data					
of the company.					
and service quality.					
Other benefits:					

How would you rate the overall results of the case study using school grades (1 very good 6 insufficient):

____

What are the main reasons for your rating of case study results?

____

____

Evaluation questionnaire Page 4

Evaluation of the supporting methods

The objective of this section is to assess the usability, applicably, and usefulness of methods that were applied to support the development of the use phase data strategy.

Statements	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Use Case Catalogue					
The software implementation of the use case catalogue enables users to search for suitable use cases from other companies.					
The use case catalogue can be applied during the search for use cases to find new ones that have already been implemented by other companies.					
The use case catalogue has a positive impact on the idea generation by triggering new ideas for use cases based on analogy building.					

Statements	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Cost-Benefit Template					
The structure of the template is clear.					
The template can be used to assess the cost-benefit ratio of use cases during the development of a use phase data strategy.					
The template leads to higher transparency concerning the use case related benefits and costs.					

Complementary open questions

What was the main contribution of the application of the process model?

What were the drawbacks of the application of the process model?

How could the process model be further improved?

What were the main learnings from the case study (benefits of the case study)?

Additional comments:

Thank you very much again for your input and feedback!

Evaluation questionnaire Page 6

A8.2 List of use cases derived during evaluation case 1

The following table provides an overview of the use case that were derived during the first evaluation case. For details on the case please consult Section 7.2. Due to confidentiality it is not possible to provide further details on the use cases.

UC #	UC name	Beneficiary	Source
1 (3.1)	Identify points of truth	Internal	Customer Operations
2 (2.2)	Customer support	Internal	Customer Operations
3	Customer management	Internal	Customer Operations
4	Customer insights	Internal	Technology Operations
5	Washing behaviour	Internal	Management
6 (3.4)	Customer segmentation	Internal	Technology Operations / Sales
7	Predict remaining time	Customer	Technology Operations
8	Assign favourite machine	Customer	Customer Operations / Management
9	Queue management	Customer	Management
10 (2.1)	Use balancing	Customer	Customer Operations
11	Setting suggestions	Customer	Management
12	Personal washing behaviour	Customer	Management
13	Guidance for washing	Customer	Management
14	Operations improvement	Internal	Data Operations
15 (3.6)	Predict need of machines	Internal	Data Operations
16	Washing room comparison	Internal	Data Operations
17	Sale of detergent	Internal	Management
18	Machine services	Internal	Management
19	Maintenance service	Internal	Management / Technology Operations
20	Pricing	Internal	Technology Operations
21	Price models	Internal	Management / Data Operations
22	Predict level	Customer	Data Operations
23	Customer steering	Customer	Management
24	Customer incentives	Customer	Data Operations / Management
25	Determine optimum timeouts	Internal	Technology Operations
26	Incident management	Internal	Customer Operations
27 (2.4)	Identify need for maintenance	Internal	Data Operations
28	Maintenance planning	Internal	Technology Operations
29	Cleaning plan	Internal	Customer Operations
30	Billing management	Internal	Management / Data Operations
31 (1.1)	Incident assessment	Internal	Data Operations
32	Incident patterns	Internal	Data Operations
33	Design improvements	Internal	Management / HW Dev
34 (1.3)	Incident monitoring	Internal	Technology Operations
35	Testing design	Internal	Technology Operations
36 (1.3)	Software version monitoring	Internal	Technology Operations

37 (3.3)	Predict profitability	Internal	Data Operations
38	Sales support	Internal	Sales / Data Operations
39	Customer acquisition	Internal	Sales / Management
40	Prioritisation of opportunities	Internal	Sales
41	Identification of up-selling potential	Internal	Sales / Data Operations
42 (3.5)	After sales support	Internal	Sales
43	Connectivity management	Internal	Management / Data Operations
44	Location monitoring	Internal	Technology Operations
45 (1.5)	Analysis of incidents	Internal	Data Operations
46	Commissioning support	Internal	Data Operations
47	Incident prevention	Internal	Technology Operations
48	Identify and report errors	Internal	Customer Operations
49	Categorisation of incidents	Internal	Customer Operations
50	Diagnosis for self service	Internal	Technology Operations
51 (2.5)	Claim management	Internal	Customer Operations
52	Staff planning	Internal	Management
53 (1.4)	Correlation of connection situation	Internal	Technology Operations
54 (2.3)	Customer understanding	Internal	Customer Operations
55 (1.2)	Context understanding for customer management	Internal	Customer Operations

A8.3 List of use cases derived during evaluation case 2

The following table provides an overview of the use case that were derived during the second evaluation case. For details on the case please consult Section 7.3. Due to confidentiality it is not possible to provide further details on the use cases.

UC #	UC name	Beneficiary	Source
1	Usage patterns	Customer	Workshops
2	Location based actions	Customer	Workshops
3	Monitoring of patterns	Customer	Workshops
4	Energy efficiency	Customer	Workshops
5	Energy saving competition	Customer	Workshops
6	Supply network assessment	Customer and external company	Workshops
7	Product suggestions	Customer	Workshops
8	Service provider suggestion	Customer and external company	Workshops
9	Usage statistics	Internal	Workshops
10	User insights	Other company	Workshops
11	Adaptive design	Customer	Workshops
12	New appliance recommender	Customer	Workshops
13	Display of consumption	Customer	Workshops
14	Detergent management	Customer and external company	Workshops
15	Dynamic adjustment	Customer	Workshops

16	Sustainable drying	Customer	Workshops
17	Status of the washing cycle	Customer	Workshops
18	Insights customer feedback	Customer	Workshops
19	Detergent recommendation	Customer and external company	Workshops
20	Monitor product usage	Customer	Workshops
21	Reduction of over-engineering	Internal	Workshops
22	Textile management	Customer and external company	Workshops
23	Washing program suggestion	Customer and external company	Workshops
24	Monitoring of washing cycles	Customer and external company	Workshops
25	Suggestion of washing cycles	Customer	Workshops
26	Detection of clothes	Customer	Workshops
27	Consumer insights for marketing	Internal	Workshops
28	Usage monitoring	Customer	Internal source
29	Usage tips	Customer	Internal source
30	Feature insights	Customer	Internal source
31	Tips & tricks reminder	Customer	Internal source
32	Drying tips	Customer	Internal source
33	Suggestion of accessories	Internal	Internal source
34	Suggestions for cleaning	Customer	Internal source
35	Suggestion of partner products	Customer and external company	Internal source
36	Installation guide	Customer	Internal source
37	Setting optimisation	Customer	Internal source
38	Tuning of the settings	Customer	Internal source
39	Program reminder	Customer	Internal source
40	Cleaning suggestion	Customer	Internal source
41	Usage passed suggestion	Customer	Internal source
42	Program reminder	Customer	Internal source
43	Shirts program	Customer	Internal source
44	Improvement of the washing result	Customer	Internal source
45	Adjusted laundry program	Customer	UC catalogue
46	Energy system monitoring	Customer	UC catalogue
47	Condition based laundry program	Customer	UC catalogue
48	Washing schedule	Customer	UC catalogue
49	Data usage	Internal	UC catalogue
50	Water analysis	Other company	UC catalogue
51	Preventive maintenance	Customer	Internal source

A8.4 List of use cases derived during evaluation case 3

The following table provides an overview of the use case that were derived during the third evaluation case. For details on the case please consult Section 7.4. Due to confidentiality it is not possible to provide further details on the use cases.

UC #	UC name	Beneficiary	Source
1	Adaptive pricing	Internal	Workshop 2, Innovation Day
2	Program information	Customer	Workshop 2
3	Adjustment of settings for the drying	Customer	Workshop 1
4	Location based operation	Customer	Workshop 2
5	Auto dosing	Customer	Internal, Workshop 1
6	Auto prepping for maintenance cars	Internal	Internal
7	Auto quiet	Customer	Internal
8	Auto replenishment	Customer	Internal
9	Auto dosing	Customer	Workshop 2
10	User specific functions	Customer	Internal, Innovation Day
11	Automatic reordering	Customer	Workshop 1
12	Door mechanism	Customer	Workshop 1, Internal
13	Program suggestions	Customer	Workshop 2, Innovation Day
14	Country specific functions	Internal	Workshop 1, Innovation Day, UC catalogue
15	Basket functions	Customer	Internal
16	Design improvements	Internal	Workshop 2, Innovation Day
17	Rewards system	Customer	Workshop 2
18	Location driven programs	Customer	Workshop 2
19	Pattern recognition	Internal	Workshop 1, UC catalogue
20	Feature assessment	Internal	Washing machine, Innovation Day
21	Consumption monitoring	Customer	Internal, UC catalogue
22	Customer insights	Customer	Internal
23	Error tracking	Internal	Workshop 1
24	Customer clustering	Internal	Internal
25	Database	Internal	Workshop 1
26	Digital user manual	Customer	Internal
27	Dirt recognition	Customer	Internal, Innovation Day
28	Dynamic dosing	Customer	Workshop 1
29	Error recognition	Internal	Workshop 1, Innovation Day, UC catalogue
30	Dynamic end	Customer	Workshop 2
31	Easy start	Customer	Internal, Innovation Day
32	Program selection	Customer	Workshop 2, UC catalogue
33	Eco prognosis	Customer	Internal
34	Education dishwasher	Customer	Internal
35	Customisation	Customer	Internal

36	User experience	Internal	Workshop 1
37	Testing support	Internal	Internal
38	Error tracking	Internal	Workshop 1, UC catalogue
39	Design adjustments	Internal	Workshop 2
40	Failure patterns	Internal	Internal, Innovation Day
41	Performance monitoring	Internal	Workshop 1
42	Flexible start	Customer	Internal, UC catalogue
43	Dynamic program length	Customer	Workshop 1, Innovation Day, UC catalogue
44	Gamification	Customer	Internal
45	Warranty	Customer	Internal
46	Sustainability	Internal	Workshop 1
47	Environment monitoring	Customer	Workshop 1
48	Environment analysis	Customer	Workshop 2
49	Recognition	Customer	Workshop 2
50	Cycle monitoring	Customer	Workshop 2
51	Content monitoring	Customer	Workshop 2
52	Loading suggestions	Customer	Workshop 1
53	Device protection	Customer	Internal, Innovation Day
54	Status updates	Customer	Workshop 1
55	Water analysis	Internal	Workshop 1
56	Context understanding	Internal	Workshop 1
57	Health recommendation	Customer	Internal
58	Hints and Tricks	Customer	Internal
59	Holiday option	Customer	Internal
60	Software	Internal	Internal, Innovation Day, UC catalogue
61	Hygiene support	Customer	Internal
62	User support	Customer	Internal
63	Usage monitoring	Customer	Workshop 1, Innovation Day
64	Marketing support	Internal	Workshop 2
65	Installation support	Customer	Workshop 1
66	Program options	Customer	Workshop 1
67	Component monitoring	Internal	Workshop 1
68	Compatibility	Customer	Internal, Innovation Day
69	Location analysis	Customer	Internal
70	Customer understanding	Internal	Workshop 1
71	Program adjustments	Customer	Workshop 1, UC catalogue
72	Customer empowering	Customer	Workshop 1
73	Country specific options	Customer	Workshop 1
74	Loading support	Customer	Workshop 2
75	Noise control	Customer	Workshop 1
76	Setting adjustments	Customer	Internal
77	Setting optimisation	Customer	Workshop 1

78	Condition monitoring	Internal	Workshop 2
79	Load assessment	Customer	Internal, Innovation Day
80	Load support	Customer	Internal
81	Care support	Customer	Internal
82	Marketing fun facts	Internal	Washing machine
83	Noise check	Customer	Internal
84	Customer patterns	Internal	Workshop 2, Internal, Workshop 1
85	Preference understanding	Internal	Workshop 1
86	Experience analysis	Customer	Internal, Workshop 2
87	Online shop	Customer	Internal
88	Sales support	Internal	Workshop 2
89	Preventive maintenance	Customer	Internal, Innovation Day, UC catalogue
90	Dynamic washing cycle	Customer	Workshop 1, UC catalogue
91	Customer guidance	Internal	Workshop 1
92	Quality control	Internal	Workshop 1, Innovation Day
93	Check program selection	Customer	Workshop 1
94	Regional usage/environment analytics	Internal	Internal, UC catalogue
95	Remote control	Customer	Internal
96	Remote diagnostics	Internal	Internal
97	Remote monitoring	Customer	Internal
98	Dishwasher management	Customer	Workshop 2
99	Rack mechanism	Customer	Workshop 2
100	Unloading support	Customer	Workshop 2
101	Collaboration	Internal	Internal, UC catalogue
102	Smart home	Internal	Internal, Innovation Day
103	Load management	Customer	Workshop 1
104	Smart kitchen	Customer	Internal, Innovation Day, UC catalogue
105	Smart start	Customer	Internal, Innovation Day
106	Statistics	Customer	Internal
107	Tab management	Customer	Internal
108	Testing design	Internal	Workshop 2, Internal
109	Additional services	Customer	Internal, UC catalogue
110	Mistake monitoring	Customer	Internal, Innovation Day
111	Turbidity	Internal	Workshop 1, UC catalogue
112	Door operation	Customer	Workshop 2
113	Door monitoring	Customer	Workshop 1
114	Condition adaption	Customer	Workshop 2, Innovation Day
115	Customer specific services	Customer	Internal
116	Business model	Customer	Internal, Innovation Day, UC catalogue
117	Product improvements	Internal	Internal, Innovation Day

118	User Behaviour recognition	Customer	Internal, UC catalogue
119	User feedback	Internal	Internal
120	Customer characteristics	Internal	Internal
121	Control options	Customer	Internal, Innovation Day
122	Voltage analysis	External company	Internal
123	Program length	Customer	Workshop 1
124	Door notification	Customer	Workshop 1
125	Result monitoring	Internal	Workshop 1
126	Cycle monitoring	Internal	Workshop 1
127	Water quality	Internal	Workshop 1
128	Load analysis	Customer	Internal
129	Dynamic loading	Customer	Workshop 2, Innovation Day

A8.5 Questions for the interview-based evaluation

The interview-based evaluation was conducted in German. Therefore, an English translation is provided for each question.

1. War die Vorstellung des Vorgehensmodells und der Anwendung verständlich?
   Was the presentation of the process model and its application understandable?

2. Verfügt das Unternehmen über eine Nutzungsdatenstrategie?
   Does the company have a use phase data strategy?

3. Haben die Schritte des Vorgehensmodells eine logische Reihenfolge?
   Do the steps of the process model have a logical order?

4. Beschreibt das Vorgehensmodell alle wichtigen Schritte zur Entwicklung einer Nutzungsdatenstrategie?
   Does the process model describe all important steps for developing a use phase data strategy?

5. Ist das Handbuch für das Vorgehensmodell verständlich?
   Is the manual of the process model understandable?

6. Wäre das Vorgehensmodell beim Unternehmen anwendbar falls eine Nutzungsdatenstrategie entwickelt werden soll?
   Would the process model be applicable at the company for the development of a use phase data strategy?

7. Welchen Mehrwert hat das Vorgehensmodell bei der Verwertung von Nutzungsdaten?
   What benefits does the process model provide for the exploitation of use phase data?

8. Welche Herausforderungen bei der Verwertung von Nutzungsdaten können durch das Vorgehensmodell adressiert werden?
   Which challenges linked to the exploitation of use phase data can the process model address?

9. Welche möglichen Schwächen hat das Vorgehensmodell?
   What possible weaknesses does the procedure model have?

10. Welche Herausforderungen bei der Verwertung von Nutzungsdaten werden nicht adressiert werden?
    Which challenges related to the exploitation of use phase data are not addressed?

11. Welche Verbesserungspotenziale bestehen beim Vorgehensmodell?
    Which potential for improvement exists for the process model?

A8.6 Radar charts for the evaluation results of the first three evaluation cases

The following four diagrams summarize the results of the evaluation. Each of the three evaluation cases is described in Chapter 7. The order of the evaluation cases is identical to the one from Chapter 7. In order to derive an overall conclusion, the answers from the questionnaire (see Appendix A8.1) were converted into numerical values (-2 = strongly disagree and +2 = strongly agree). Afterwards, the mean value for each question was derived for each evaluation case. The results are illustrated in the following radar charts.

Number	Statement
S1	The process model in combination with the manual enables users to develop a use phase data strategy in a structured way.
S2	The description of each process step (tasks, methods, and results) in the manual contains all the relevant information for users to conduct the relevant activities to develop a strategy.
S3	The process model and the manual are comprehensible to the user.

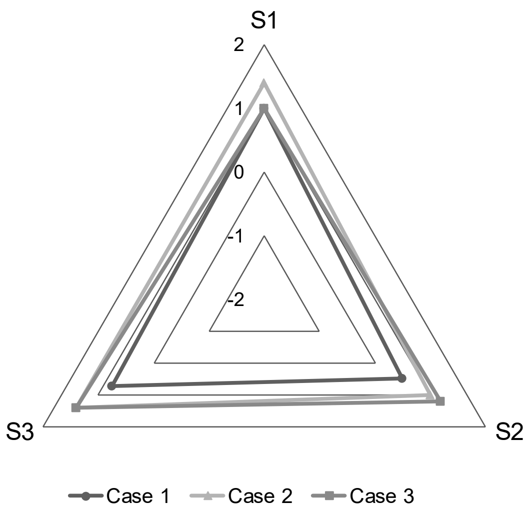


Figure 11-48: Summary of the evaluation results concerning the usability of the process model

Number	Statement
S1	The process model is suitable for the development of a use phase data strategy in engineering companies with connected products and services, as well as those that plan to develop them.
S2	The process model is flexible enough to be adjusted to different company specific application contexts (e.g., industry sector, company size, B2C vs. B2B).
S3	The process model provides means and methods to develop a use phase data strategy that addresses internal stakeholders (e.g., product development, service management, or marketing).
S4	The process model provides means and methods to develop a use phase data strategy that addresses external stakeholders (e.g., users, or customers).
S5	The process model supports a use phase data first (bottom-up) as well as a use case first (top-down) approach for the development of a use phase data strategy.
S6	The process model requires information and data input for the development of the use phase data strategy that is available in a company.
S7	The effort (time) required for the application of the process model matches the intended outcome of the process model.

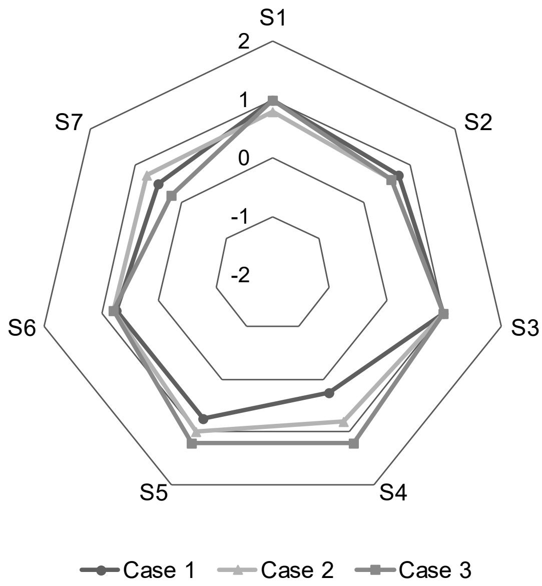


Figure 11-49: Summary of the evaluation results concerning the applicability of the process model

Number	Statement
S1	The comprehensive internal and external analysis improved the understanding of the context within which the development of the use phase data strategy was conducted.
S2	The application of the process model created transparency regarding available and required use phase data.
S3	The systematic approach of the process model helped to gain a comprehensive overview regarding possible use cases.
S4	The application of the process model generated new and feasible use cases that were unknown before.
S5	The analysis of the dependencies among the use cases helped to identify clusters of use cases that require similar use phase data.
S6	The comprehensive exploration of possible use cases prior to selecting individual ones leads to a coherent and technically feasible use phase data strategy.
S7	The structured consolidation and assessment of use cases by using a set of criteria ensured that informed decisions were made based on the related costs and benefits.
S8	The process model fostered the integration of relevant stakeholders with different perspectives during the development of the use phase data strategy.
S9	The application of the process model led to use cases that provide additional value (e.g., additional turnover, higher customer satisfaction, or reduction of over engineering) for internal as well as external stakeholders.
S10	The main output of the process model (use phase data strategy and implementation roadmap) provides a clear vision and highlights important implications for an implementation (technical and organisational).

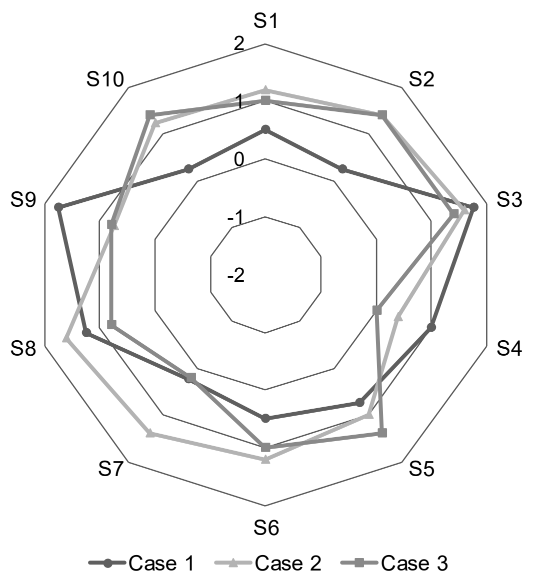


Figure 11-50: Summary of the evaluation results concerning the usefulness of the process model

Number	Statement
S1	The tasks of each process step were useful for the development of the use phase data strategy.
S2	All relevant stakeholders were involved in the strategy development process during the case study.
S3	The value of the results (use phase data strategy) exceeds the time invested in the development of the data strategy.
S4	The developed strategy matches the objectives that were set at the beginning.
	The developed use phase data strategy will …
S5	…help to increase the turnover of the company.
S6	…improve the product and service quality.
S7	…lead to a higher customer satisfaction.
S8	…provide insights into the actual usage of the product.

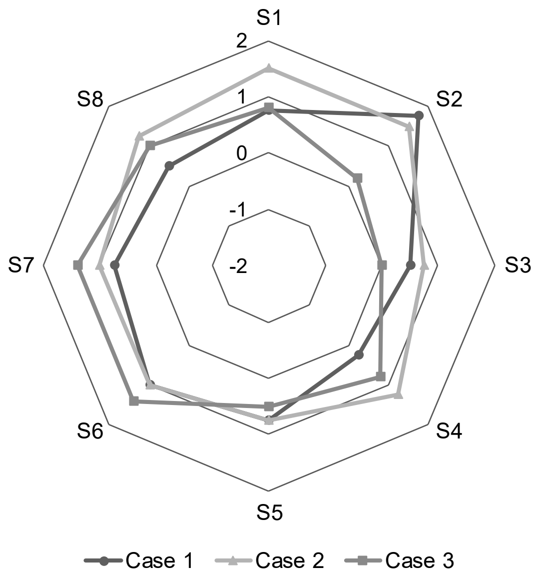


Figure 11-51 Summary of the evaluation results concerning the results of the case study

List of dissertations

Lehrstuhl für Produktentwicklung
Technische Universität München, Boltzmannstraße 15, 85748 Garching
Dissertations under supervision of:

- Prof. Dr.-Ing. W. Rodenacker,
- Prof. Dr.-Ing. K. Ehrlenspiel and
- Prof. Dr.-Ing. U. Lindemann

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