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Increasing agility in Big Data analytics through implementation of the BASE/X framework
a case study

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Increasing Agility in Big Data analytics through implementation of the BASE/X framework: A case study.

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Abstract
By shifting the focus from delivering assets to delivering services, a rising number of organizations is moving towards service-dominant business. By doing so, also a shift in organizational structure is needed to exploit the benefits of service-dominant business. But are organizations ready to do so, and do they know how? In this research, a framework for service-dominant business design (BASE/X) is applied to a Big Data analytics service provider. Since Big Data keeps growing in popularity and an increasing amount of Big Data analytics techniques becomes available, the ability to providing all these Big Data analytics service rapidly is desired. By focusing predominantly on the Big Data analytics activities itself, a service catalog is designed to structure these analytics techniques into modular building block services (BBSs). These BBSs provide structure and enable reusability to increase agility in performing Big Data analytics, provide different customers with a different experience. In addition, a prototype for the implementation of a service catalog is designed.
Preface

This research paper is the final result of my master thesis project, performed at the IT engineering office Itility. This thesis represents the final phase of my seven years period of being a student at the Eindhoven University of Technology and more specifically, the final phase of my master studies Operations Management & Logistics.

With the completion of this project, I’m looking back on the last seven years feeling lucky to have experienced such a personal and professional growth. Not only caused by the well-organized education, but also by being a board member of study association Interactie, being a leader in the European student network ESTIEM, and by being an office manager at Tech United Eindhoven.

I performed this master thesis project from February to August 2016. Most of this time was spend at the headquarters of Itility in Eindhoven, where a lot of valuable insights for the progress of this project were provided. Therefore, I would like to thank all the employees and especially the analytics team, with the support I received in getting to know Itility, gathering data, and experiencing what the afterlife of a student looks like.

Also, special thanks go out to my supervisors from both the university and Itility: Paul Grefen, Remco Dijkman, and Marianne Faro. I truly admire their professional attitude, management skills, knowledge, and friendly attitude, by which they supported me in conducting this master thesis.

Finally, I would also like to thank my parents and my girlfriend for always being there for me and to support me wherever possible.

I had a great time writing this thesis which demonstrates a part of the knowledge that I’ve gained over the past seven years, hopefully you will have a great time reading it as well.

Olaf Klooster
Eindhoven, August 2016
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Part I – Introduction & Problem Description

1. Introduction
This report is the result of a 6 months master thesis project conducted at Itility, located in Eindhoven. As a Big Data service provider, Itility aims to delivering their solutions in an agile fashion as fast as possible towards their customers, while maintaining quality standards. In this research project the impact of a service catalog on increasing the delivery speed of the Big Data solutions provided by Itility is investigated.

This report is divided into five parts, starting with a company description and methodology of this research project including the problem formulation in Chapters 2 and 3. In the second phase, represented by Chapter 4, a literature summary is provided in which the main concepts for this research project Big Data, agility, and service catalog are explained. The third phase provides an analysis of the current situation and determines the impact of introducing a service catalog at Itility. Subsequently, a service catalog is designed for Itility in the fourth phase. The fifth and final phase includes an elaboration on the implementation of a service catalog a Itility. In addition, the results are summarized and recommendations are given, after which the report is concluded with the references and appendix.
2. Company Description

Itility is an IT engineering office based in Eindhoven employing about 120 employees. At the company, IT professionals work together to solve complex IT issues for Enterprises by designing, implementing and running end-to-end digital solutions. Itility assists their customers in changing from a traditional delivery cycle towards a resilient and cost effective digital “supply chain” management model. The focus lies on the application of new technology and innovative ideas, which was acknowledged by winning the Timmy Award 2014 for Most Innovative Leader.

Itility believes that the time of large-scale investments in IT is over as the focus shifts to menus with IT building blocks, plug-and-play, and pay per use. Therefore Itility addresses these building blocks, assembles them through configuration and continuously delivers value based on analytics-steering information. The main identified needs from IT customers, high-quality IT services, flexibility, and transparent invoicing, are incorporated in the strategy of Itility: the implementation of IT as a “utility-based service”, see Figure 1.

2.1 Services

Itility has employees with a variety of IT related expertise, such as IT Engineers, IT Infrastructure Architects, Data Engineers and Data Scientists. Because of this range of expertise and the ability to form multi-disciplinary teams, Itility is able to offer all-round IT solutions. Since this research is purely focused on Big Data analytics, see Figure 2, only the services that are offered in this domain will be described in this research, in particular the Itility Managed Analytics Platform (IMAP) and deep-dives. With Big Data analytics, Itility aims to find the “aha” moment from the data and to translate this into added business value.
2.2 Customers

At the moment, the target customers of Itility high tech enterprises of at least medium-size with their main office in the Netherlands. ASML and KPN are examples of current customers within this target group. Occasionally, customers from outside this scope are served.

Itility has a strong focus on maintaining a long-term relationship with their customers and is not a traditional one-time volume player. The company has a focus to plan, transition, control, run and continuously optimize business processes. Itility supports their customers with a variety of IT services, which start with Big Data analytics. The company aims at starting to perform analytics fast and in small chunks, in order to show the value of Big Data analytics rapidly. In addition to these short term results, Itility is aware that for achieving the best results on the long-term, it is necessary to have a close collaboration with their customers to add additional insights through advanced analytics. Therefore the company aims for a long-term relationship to support their customers to grow gradually in Big Data analytics performance.
3. Research Project
This section will describe and define the problem that forms the impetus for this research project. The problem is based on capabilities that Itility would like to obtain or improve. After defining the problem, the research questions and deliverables will be described.

3.1 Problem Introduction
As mentioned before in this research proposal, the focus will be on Big Data analytics at Itility. Until this moment, Itility has already successfully implemented a variety of Big Data analytics solutions at multiple customers. One indicator that Itility is delivering value as promised could be the current long-term relations that Itility has with its strategic customers, implicating that these customers are satisfied with the business value delivered by Itility. Since the quality of the offered solutions is sufficient, Itility wants to investigate if there are possibilities to deliver the corresponding business value faster by increasing their agility in Big Data analytics. After all, Itility also recognizes agility is an important factor for delivering Big Data solutions, meaning that you just have to start doing it in small steps which will lead to the business value.

In general, Itility already has some capabilities that enables them to operate in an agile way. A good example for this, is that Itility has a prefab catalog with standardized components to deliver an IT infrastructure with a customized combination of functionalities, compliance, and pricing. This enables Itility to think in terms of assembling instead of building a new solution. In addition, standard models are used to integrate the knowledge and experience from Itility and teams with multiple competences can be quickly formed to deliver business value within a short period of time.

Currently, the formation of a team with multiple competences, the usage of some standard models, and nuggets stimulate agility in Big Data analytics. A nugget contains a set of various combinations of data connectors, predefined dashboards, and automation practices that can reveal domain related business value for the customer driven from analytics perspective. But would it be possible to also have standardized methods to fast extract customer specific value from its data? Would it be possible to design a similar type of catalog used for assembling IT infrastructures, to assemble Big Data analytics solutions with predefined services? Potentially, the usage of such a service catalog with standardized service components can increase the agility in extracting value out of Big Data and the amount of business value for the customers of Itility.
3.2 Problem Formulation
As mentioned in section 3.1, Itility believes that agility is an important factor for Big Data analytics. Since a service catalog can potentially increase agility in their Big Data analytics, the following research question is investigated:

*What is the effect of the usage of a service catalog with standardized service components on the agility in Big Data analytics and how can such a catalog be implemented at Itility?*

The defined problem consists of two separate parts. Firstly, the research focusses on investigating which effect the usage of a service catalog can have on the agility in Big Data analytics compared to the current working methods. In addition, a method to implement such a catalog at Itility is investigated to find out if a positive effect on agility can be detected.

3.3 Research Questions
To answer the formulated problem, several research questions have to be answered. The answers to these questions can provide insights in the relevance of using a service catalog for Big Data analytics, what should be included in the service catalog, and how such a catalog can be implemented at Itility. These research questions are described in more detail in this section:

**Research question 1: What effect does the usage of a service catalog have on agility in Big Data analytics?**
Firstly, it is necessary to research the effect of using a catalog on agility in general and in Big Data analytics. Literature will support in finding and describing the benefits and challenges that may arise when using such a catalog.

**Research question 2: How can Itility use a service catalog to increase agility in Big Data analytics?**
After determining the benefits and challenges found for using a catalog in Big Data analytics, the applicability of such a catalog at Itility will be investigated. How the potential benefits can be exploited and how to overcome the challenges are examples of questions that need to be answered. For doing so, the results of the previous research questions have to be integrated into the current working methods of Itility. This integration which will be done according to the guidelines of the BASE/X framework by Grefen et al. (2013), which will be explained in more detail in section 7.2.
Research question 3: How can a service catalog be implemented at Itility?
After describing how Itility can increase their agility in Big Data analytics, a method for implementation of such a catalog at Itility will be designed according to the guidelines of the BASE/X framework.

3.4 Scope
Since a master thesis research project runs for approximately six months, it is necessary to determine a scope to make sure that it feasible to complete the project within this given time period. Several decisions have been made to adjust the magnitude of this research project. An overview of these decisions is given in this section.

Analytics
As already stated in the company introduction in Chapter 2, Itility solves a wide variety of complex IT issues for enterprises by designing, implementing and running end-to-end digital solutions. For this master thesis project, the focus will be narrowed down to the Big Data analytics that Itility performs for their (potential) customers, since an increase of agility is especially desired in this department of Itility.

Phases of the Big Data analytics value chain
The analytics that Itility performs for their customers have been divided into five phases in the Itility Big Data value chain, which will be explained in more detail in section 5.1.3. The focus will be on the first two phases, which are the Explore and Pre-analytics phase, since in these two phases agility is most important to identify potential business value for customers. The consecutive three phases focus more on the quality and completeness of the solution. For this reason, the focus will be on achieving agility in the Explore and Pre-analytics phases.

BASE/X framework
For the creation of a service catalog to increase the agility in the first two stages of the Big Data value chain, the BASE/X framework will be used for the operationalization of agile service dominant business models by creating the ability to combine standardized components in a flexible way (Grefen et al., 2013). The reason for choosing this framework is fourfold. Firstly, the goal of both this research and the framework is to increase agility. Secondly, the service dominant framework fits Itility due to the fact that Itility is a Big Data analytics service provider. Thirdly, BASE/X is an holistic and ready to use framework, which makes it suitable for this project with a limited time scope. Fourthly and finally, a lot of knowledge about the BASE/X framework is
available at the Information Systems department at the Eindhoven University of Technology to provide critical insights in the integration of this framework at Itility. Many arguments support the usage of the BASE/X framework, but since it is a relatively new framework it is possible that best practices from different frameworks will be added to fill in any gaps if needed.

3.5 Research design

Now that the research questions have been described and the scope has been determined, this section will provide an overview of the research design for this project, which adheres to Action Design Research (ADR) principles. ADR combines the benefits of Design Research and Action Research, which are respectively innovation through solution designs based on theory and theory generation while solving an organizational problem. Thus, a dual mission can be pursued through ADR by assisting in solving problems of practitioners and making theoretical contributions (Sein et al., 2011). Both of these goal can be achieved by designing solutions based on theory and improving this design by executing multiple iterations in practice to improve the design with the theory generated during these iterations. The stages and principles of ADR are depicted in Figure 3.

In the problem formulations stage, an actual problem is described which forms the impetus for the whole research project. This problem formulation is already stated previously in this chapter. As a second step in the problem formulation, an overview of literature that can support the design of a solution is provided, since “a researcher cannot perform significant research without first understanding the literature in the field” (Boote & Beile, 2005). This literature overview will be a relevant summary of the literature review executed prior to this research project (Klooster, 2016).

The second stage of ADR uses the problem definition, supportive literature, and the previously introduced BASE/X framework to design a solution in the shape of an IT artifact. This IT artifact is further shaped during an iterative process, in which feedback and information from Itility is used to define the AS-IS situation and to improve the design. This information is collected using two different methods. Firstly, semi-structured interviews have been conducted with all members of the analytics team to provide insights in the current way of working. Secondly, a workshop is organized
to define the strategy of Itility’s analytics team in order to assure that the designed solution fits within their operations.

The Reflection and Learning stage of ADR, which is executed parallel to the first two stages from Figure 3, focusses on learning to apply the designed solution to a wider variety of problems. The stage recognizes that ADR involves more than simply solving a problem and asks for a reflection on for example design choices and used frameworks to ensure the contribution of knowledge.

During the final phase of ADR, the gained insights from this research project will be formalized into results and into a recommendation for Itility. In addition, a recommendation on how the designed solution could be used to solve problems in other field will be given.

3.6 Deliverables
The execution of this research project will be divided in multiple deliverables. In this section a description of these deliverables is given.

Deliverable 1: Analysis of the current way of performing Big Data analytics at Itility.
Before being able to finish a research project and provide a useful recommendation for Itility, it is important to start with the basics and get familiar with their current way of working in Big Data analytics.

Deliverable 2: Analysis of the potential increase in agility by using a service catalog for Big Data analytics.
After analyzing the current working methods from Itility to extract value out of data, it becomes possible to analyze the pros and cons of implementing a catalog to increase agility in these methods.

Deliverable 3: Applied BASE/X framework on Itility
If the previous analysis shows that the usage of a catalog has a positive impact on the agility in Big Data analytics, the BASE/X framework (Grefen et al., 2013) will be applied to Itility.

Deliverable 4: The Big Data analytics catalog tool
After applying the BASE/X framework to Itility, a concept tool which demonstrates the functionality of the Big Data analytics catalog will be created.
Part II – Theoretical background

4. Literature summary
In this section, the key concepts for this research are explained by summarizing the headlines from the literature review that was conducted during this research project (Klooster, 2016). In line with the objective of this research, this literature summary first describes the concepts of Big Data and agility, to continue with the relevance of increasing agility in Big Data. Subsequently, this literature summary describes best practices for increasing agility in Big Data. Finally, one chapter has been added to the literature summary, describing the benefits and challenges for using a service catalog.

4.1 What is Big Data?
In the last decade, the term Big Data has been growing in popularity under both academia and industry (Khan et al., 2014; Chen & Zhang, 2014) and became a ubiquitous term under practitioners in a wide variety of fields (De Mauro et al., 2015). Practitioners realized that the usage of Big Data can be extremely valuable and are aware that Big Data might play a key role in future competition (Chen & Zhang, 2014) and is able to reform existing management models (Fu et al., 2014). Big Data can lead to the adoption of a new decision making culture, basing decisions on the recognition of correlations between events instead of logical reasoning (De Mauro et al., 2015).

According to Nikulainen (2013), the ongoing ICT revolution created an ecosystem where it becomes easier to produce, collect and store a growing amount of data. Every day, more than 2.5 quintillion bytes of data are generated, which is so much that 90% of all data in the world has been created in the last two years (Chavan & Phursule, 2014; Sharma & Mangat, 2015). According to Rao & Ali (2015), data explosion is an inevitable trend as the world is becoming more connected, digitalization, decreasing costs for both storage and processing (Nikulainen, 2013; Geczy, 2014), and because of upcoming technologies such as cloud computing and the Internet of Things (IoT) (Chen et al., 2014; De Mauro et al., 2015; Rao & Ali., 2015; Acharjya & Ahmed, 2016).

Definition of Big Data
Despite the hype around Big Data, there is not one widely used definition available. Most of them state that Big Data is too big to be handled with traditional IT (Chen et al., 2014; Chavan & Phursule, 2014; Arun & Jabasheel, 2014), but vary in the remaining part. De Mauro et al. (2015)
identified this issue and surveyed multiple definitions posed in literature to finally derive the following comprehensive definition:

“Big Data represents the Information assets characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value.”

In the remainder of this literature summary, the loose elements (underlined) from this definition, will be described in more detail.

4.1.1 Big Data characteristics

Similar to the definition of Big Data, different methods exist among researchers to describe the characteristics of Big Data. In this section, the most common method is described in a more detail.

The V’s of Big Data

The V’s method to characterize Big Data has been developed by Laney (2001) and is widely adopted by other researchers (Nikulainen, 2013; Chen & Zhang, 2014; Duncan, 2014). In this V’s method, Big Data is characterized in terms of Volume, Velocity, and Variety. These three elements, also used by De Mauro et al. (2015) in their definition of Big Data, will be explained below:

- Volume: the growing amount of generated and collected data is increasing the scale of data that needs to be handled.
- Velocity: the timeliness of data, representing the need for faster data collection and data analysis.
- Variety: indicating the diversity of different types of structured, semi-structured and/or unstructured data.

During the last years, the three V’s method from Laney (2001) has been extended with two additional widely adopted V’s, consisting out of Value (Chen et al. 2014; Fu et al., 2014; Siddiqui & Gupta, 2014) and Veracity (Acharija & Ahmet, 2016; Arun & Jabasheel, 2014; Chebbi et al., 2016). In addition to these five V’s, Complexity is often added to further specify the characteristics of Big Data, even though it does not start with a V (Khan et al., 2014; Gani et al., 2015).

- Value: describing how the huge amount of data provides insights and benefits, and how it can support organizations to take decisions.
- Veracity: indicating to what extend the data can be trusted and thus providing insights on how accurate the decisions will be.
4.1.2 Benefits and challenges of Big Data

The hype around Big Data wouldn’t continue if benefits were not realized. But what exactly are the benefits that practitioners are gaining and what challenges do they need to face before experiencing these benefits? In this section, an overview of these benefits and challenges is given.

Benefits

Generally speaking, Big Data can unlock significant value for many different kinds of organizations in various ways (Yin & Kaynak, 2015). Chen & Zhang (2014) found out what benefits practitioners are looking for in Big Data, of which an overview is given in Figure 4.

![Figure 4: Big Data Opportunities, expected benefits (Chen & Zhang, 2014)](image)

Big Data has the potential to improve overall productivity, establish a significant competitive advantage, and to create benefits for consumers (Rouhani, 2015; Chen et al., 2014). Rouhani (2015), separates the benefits from Big Data into two categories, Decision Support benefits and Organizational benefits. The Decision Support benefits are directly derived from the value extraction process of Big Data and include better knowledge processing, reduced decision time, and reduced decision cost. The Organizational benefits stated by Rouhani (2015) are examples of indirect benefits that are caused by the ability of improved decision making and include effective decision making as it happens faster and based on more knowledge, competitive advantage as decisions can be made faster against less costs, and stakeholder satisfaction also due to less costs.

Challenges

While extracting the benefits from Big Data, practitioners will face a variety of challenges (Geczy, 2014). Intel (2012) provided an overview of the hardest challenges, which is shown in Figure 5. These challenges seem to be linked quite closely to the five V’s of Big Data including Complexity (Khan et al., 2014; Gani et al., 2015), as can be seen in Table 1. A summary of the most common Big Data challenges is given below.
Storage and transformation issues: The increasing needs in terms of Volume, Variety and Velocity of Big Data (Jagadish et al., 2014), require the design of storage systems able to cope with these characteristics (Acharjya & Ahmet, 2016; Anagnostopoulos et al., 2016).

Privacy & Security: Guaranteed privacy and security of Big Data is crucial to ensure that valuable data does not get out of the company’s border and to prevent reputational damage (Bhardwaj & Johari, 2015). Jagadish et al. (2014) point out the well-known example of the sensitivity of private electronic health records, on which strict laws apply (Chebbi et al., 2015). Security can be improved by implementation of for example authentication, fraud detection, and encryption techniques (Acharjya & Ahmet, 2016).

Data Quality: Schroeder (2016) states that practitioners usually work with data of low quality, which could be caused by a combination of factors proposed by Gao et al. (2016), see Figure 6. Data quality assurance is a process that supports practitioners to verify the quality of these factors to identify how the overall quality of the data could be improved (Clarke, 2016; Gao et al., 2016).
**Data Visualization:** The best analysis has only limited value if the results are not presented in an easy to understand visualization (Acharjya & Ahmed, 2016). Tools can help transforming complex data into intuitive pictures in a specific domain at the right level of detail (Jagadish., 2014), supporting practitioners to understand the results at a glance.

**Big Data talent gap:** By 2018, there will be a shortage of nearly 200,000 people with analytical skills and 1.5 million managers in the Big Data domain in the U.S. only (Manyika et al., 2011). To prevent a delayed time for value creation, organizations must adopt their human resources strategy accordingly (Kaur, 2016).

### 4.2 Big Data value extraction

Until now, the term Big Data is explained including its characteristics, benefits and challenges. In this section, methods on how value is actually extracted from Big Data are described.

#### 4.2.1 Big Data Value Chain

Porter (1998) introduced the value chain concept as a series of activities that can lead to the creation of value. Inspired by Porter, Miller & Mork (2013) applied this concept to Big Data and created a value chain for Big Data. The Big Data value chain consists of the steps data discovery, data integration, and data exploitation, which are shown in Figure 7.

![Figure 7: The Big Data value chain (Miller & Mork, 2013)](image)

**Data discovery**

Before getting to the actual value of Big Data, it is important to prepare the data accordingly. Staring with ‘collect and annotate’, a data inventory of available data sources including metadata is created after which the data is ‘prepared’ by enabling access to the previously inventoried data sources. Finally, during ‘organize’, data sources have to be described in terms of syntax, structure and semantics. Often, practitioners skip these step while they are only looking to extract their desired value, while doing so would enable a seamless data integration with other stakeholders.
Data integration
In the ‘integrate’ step, the data from all different data sources are merged into a common representation. By doing so, new and undiscovered information could arise as data from different sources might correlate with each other.

Data exploitation
During the ‘analyze’ step, various analytical techniques can be used to extract valuable information from the data. The step ‘visualize’ involves presenting the information in an easy to understand visualization (Acharjya & Ahmed, 2016). Finally, practitioners are enables to ‘make decisions’. The impact of these decisions determine the value that is created by traversing this value chain.

4.2.2 Most commonly used Big Data techniques?
With a wide Variety of data and goals to extract Value by analyzing data, also a wide variety of Big Data analytical techniques is needed to fulfill the ‘analyze’ step of the Big Data value chain by Miller & Mork (2013). In this section, examples of the most popular techniques for the four different types of capabilities of Big Data analytics by Kart et al. (2015) will be given. These capabilities are descriptive, diagnostic, predictive and prescriptive as shown in Figure 8.

Descriptive: relatively simple techniques, mostly used for simple statistical operations, trying to explain the what, where, when and who questions (Chen & Zhang, 2014; Chen et al., 2014), without diving deeper into the data (Patidar & Sharma, 2015).

Diagnostic: a bit more complex techniques, trying to find out why something happened, which will lead to more questions and insights to base decisions on. Correlation matrices can for example show the correlation between several variables and a specific event.

![Figure 8: The four different types of Big Data analytical capabilities (Kart et al., 2015)](image)
**Predictive**: these techniques, also known as Machine Learning (Chen & Zhang, 2014) focus on predicting what will happen based on what has already happened (Ali et al., 2016). Decision trees can for example classify events to enable organizations to create an action plan that will be suited for the future situation.

**Prescriptive**: at the moment the most advanced techniques, which can recognize what decisions need to be made and which actions have to be initiated. These capabilities can be obtained by for example adding business rules to predictive techniques.

In Appendix 1, an overview of more Big Data analytics techniques described in the relevant literature for this sub question can be found. The usage of more advanced big data analytics capabilities eases decision making as less (or no) human input is needed, see Figure 8. Organizations should take into account, that it is not possible to obtain prescriptive capabilities, without mastering the other three types of capabilities as for example descriptive capabilities can monitor if the prescriptive decisions turn out right and diagnostic capabilities can show the reason why expectations were (not) met (Kart et al., 2015).

4.3 The potential of agility in Big Data

Next to Big Data, agility is another concept that is gaining significant attention from academia and organizations. In this section an explanation of agility is given and consecutively, several methods to incorporate agility in Big Data will be provided.

4.3.1 What is Agility?

In today’s world, with high market volatility, economic uncertainty, customer expectations and products with a shorter life cycle, organizations are pushed to become agile (Bharadwaj et al., 2016; Couto et al., 2015). The latter even states that in order to survive in today’s world, organizations must be agile. According to Oosterhout et al. (2007), business agility can be defined as:

“The ability to sense highly uncertain external and internal changes, and respond to them reactively or proactively, based on innovation of the internal operational processes, involving the customer in exploration and exploitation activities, while leveraging the capabilities of partners in the business network.”

As can be derived from the definition, the first important factor to achieve agility is the ability to sense internal and external uncertainty. This includes sensing whether a change will happen, its
corresponding impact and the uncertainty of the appropriate response. The second important derived factor is response. According to (Canter, 2000), organizations can respond either reactively to changes, or proactively by leading initiatives to prepare for potential changes.

According to Lee (2012), one of the most important enablers of agility is IT, for example through Service Oriented Architecture (SOA) (Bharadwaj et al., 2016). By enabling loose coupling, the complexity of adding or removing components is significantly reduced and SOA also enables the reusability of services (Brown, 2008). These are characteristics that directly contribute to an increased response speed.

Couto et al. (2015) discovered that governance could lead to higher agility since organizational procedures, monitoring, and control could be implemented to support identifying upcoming challenges and how to handle them. On the down side, the implementation of such rules could lead to less freedom to act on unexpected situations and thereby even reduce agility or performance.

Looking further than just the organization itself, Bharadwaj et al. (2016) state that organizational agility involves agility throughout all activities in the value chain including activities with partner organisations. Organizations that reach a high level of organizational agility possess the ability to design and create innovative products (Swafford et al., 2006).

4.3.2 Current integration of agility in Big Data?
In the previous section, the importance of agility in the current turbulent world is explained as it enables an organization to sense and respond quickly on the changing environment. But how can agility be integrated in the earlier described key concept of Big Data? Would it be possible to traverse the Big Data value chain quicker and thus provide valuable information faster to decision makers? Are there possibilities to create synergy between these concepts? In this section current applications of agility in Big Data and opportunities to incorporate them are discussed.

The main benefit of Big Data is enabling organizations to make better informed decisions (Rouhani, 2015; De Mauro et al., 2015). To achieve strategic advantage in today’s turbulent world, organizations need to make decisions fast to cope with the changing circumstances (Stodder, 2013). Since most of the decisions today are based on Big Data, it becomes obvious that achieving agility in Big Data can contribute to gaining this strategic advantage (Knabke & Olbrich, 2013). Zimmer et al. (2012) defined agility in Big Data as:
“the ability to develop or alter a business intelligence solution in a given timeframe even when unforeseen and/or volatile requirements arise.”

Incorporating agility into Big Data can lead to the development of complex and dynamic organizational environments (Krawatzeck et al., 2015; Larson & Change, 2016; Earley, 2014). To cope with this issue, various frameworks and methodologies have been developed, two of which will be discussed below.

Knabke & Olbrich (2013) recognized that in order to enhance agility in Big Data, it is first key to gain understanding of the criteria that influence agility in Big Data. Therefore, an overview of these criteria has been established and visualized in the framework shown in Figure 9.

![Figure 9: Framework for understanding Big Data agility (Knabke & Olbrich, 2013)](image)

The column on the right including the environment that is surrounding the whole framework depicts the eight key dimensions that practitioners should take into account when striving to achieve agility in Big Data. These key dimensions are further divided into sub dimensions (left columns) in which Big Data practitioners can assess themselves to get insights in how higher agility could be reached.

Another overview of actions to improve agility in Big Data is given by Krawatzeck & Dinter (2015). The latter divided these actions in four different categories including principles, methods, techniques, and technology and in three importance segments, stating if the action is a potential solution, validated solution by theory, or proven in practice. In Appendix 2, a visualization of this actions catalog is depicted. Additional to this catalog, Krawatzeck & Dinter (2015) described what aspects of Big Data agility correspond to which actions. Before doing so, 12 different Big Data agility aspects were identified, by combinations of three types of agility and four phases of Big Data value extraction. Firstly content agility, meaning the reaction time and efforts to apply
changes to data repositories. Secondly, functional agility, implying the reaction time and efforts to apply changes in the functionality. Thirdly, scale agility, meaning the reaction to scale a project to handle bigger volumes or higher processing capacity needs (Baars & Zimmer, 2013). The four phases of extracting value out of Big Data are quite similar to the (sub)steps from the Big Data value chain from Miller & Mork (2013). The overview of which Big Data agility actions correspond to which aspect of Big Data agility is depicted in Appendix 2.

### 4.4 Benefits and challenges for usage of a service catalog

In this section, an overview of the benefits and challenges related to using a service catalog with standardized components for Big Data analytics are described. As no specific literature has been found on the usage of such a catalog in the domain of Big Data analytics, the general benefits and challenges of using a service catalog have been described using the key concepts of SOA, one of the enablers of agility as stated in section 4.1.3 (Bharadwaj et al., 2016).

According to the key concepts of SOA, a service catalog supports the communication between three different entities, being the service provider, the service consumer, and the service catalog itself, see Figure 10. In the catalog, service providers can publish their standardized pre-defined service offerings and based on the descriptions, service consumers can select the best fitting services to fulfill their own business processes. After the desired service is selected, this service can be invoked through the service catalog, which connects the service consumer to the service provider (Sarno & Herdiyanti, 2016). According to Janssen & Feenstra (2016), a service catalog can also be used as a roadmap for the future by indicating which services are needed, which services need to be developed, and who will deliver these services.

![Figure 10: The Key concepts of the SOA service catalog (Banerjee & Aziz, 2007)](image-url)
4.4.1 Benefits
There are several ways in which a service catalog can be beneficial, not limited to increasing agility. Also, these benefits are not only valid for the service consumer, but indirectly also for their respective customers. These main benefits, divided over three categories, are given below (Janssen & Feenstra, 2016).

**Agility:** First of all the agility could be increased through the incorporated characteristics of SOA, which enable loose coupling, reusability of services, extensibility, interoperability, and integration (Sarna & Herdiyanti, 2016). Janssen & Feenstra (2016) add that a catalog provides a systematic overview of all possible actions including costs and duration to enable fast decision making. Further, the acknowledgement of dependencies across these actions provide the opportunity to create executable chains to create customer value.

**Efficiency:** Utilizing a catalog provides increased insights in costs and other performance criteria to be used to further improve the service offerings towards customers. As the process of extracting an executable chain of services is very structured, it is efficient and thus a limited amount of time is required (Janssen & Feenstra, 2016).

**Governance:** Ranking the performance of different services will increase support for decision making and can lead to higher value creation for the customer. In addition, a focus on composition design leads to increase cooperation and by working on a service portfolio, partners in a business network can be involved and clear tasks can be assigned (Janssen & Feenstra, 2016).

The benefits described above will together lead to the creation of a higher value for the customer by delivering solutions faster due to the increased agility and efficiency. In addition, they will lead to solutions of higher quality because governance over the service catalog will support in choosing the best services.

4.4.2 Challenges
Similar as to Big Data, challenges have to be overcome before being able to benefit from a service catalog. An overview of the main challenges are given below.

**Alignment:** In order to benefit from some of the characteristics of a service catalog such as interoperability and reusability, all stakeholders need to handle this service catalog according to standardized procedures. Mendes & da Silva (2010) state that service definition is one of the top risks for a successful catalog implementation. Therefore, a new service should be defined according
to specific standards before including it in the catalog to enable fellow team members to invoke all the services from the catalog.

**Creation:** In order to benefit from for example the acknowledgement of dependencies between services and the creation of executable service chains, a wide variety of services needs to be included in the catalog. The creation of such a catalog can be very time consuming. Additionally, service catalog management is needed to keep the catalog up to date by for example adding innovative services and removing outdated services (Kohlborn et al., 2009).
Part III – AS-IS situation

5. Current way of working at Itility
In this section an analysis of the current way of working with Big Data analytics is given. This analysis includes the methods and tools that Itility uses for Big Data analytics, their customer experience journey and organizational maturity. Throughout this section, the literature summary is integrated in the current way of working to answer the question whether using a service catalog for Big Data analytics would be beneficial for Itility.

5.1 The “ABC” method
For value extraction from Big Data, Itility needs to find the right questions to “ask” to the data from the customer, the right questions to find the answers which can be translated into business value. Itility states that Big Data analytics is not mainly about technology (tools or platforms) but about agility, meaning that you just have to do it starting with small steps instead of already taking a lot of time choosing the tools that you need. Therefore, Itility is using an “ABC” method, including the formation of a team, grow as you go, and always keeping the end goal in mind. An overview of the steps of this “ABC” method is given below.

5.1.1 Team Up
The first step of the “ABC” method from Itility is to form a team which has the ability to extract value from the data. This small team with the right mix is depicted in Figure 11 and consists of a data scientist, a data engineer, and a domain expert.

The data engineer represents the team member that proves his value mostly by using scripting & analytics modelling language skills to gain access to the needed data sources for analysis. In addition, the data engineer can use his programming skills to develop algorithms to extract value from the data.

![Figure 11: Team Formation at Itility](image)
The data scientist represents the team member that is mainly responsible for pulling valuable insights from the data by performing for example several techniques in statistics, machine learning, and predictions on the data. In addition, the data scientist is responsible for visualizing the results/hypotheses to help the customer to understand them.

The domain expert is a person with a strong knowledge of the domain in which the customer is operating and the operations of the company itself. Usually, this person is an employee of the customer. This domain expert can provide valuable directions to gain business value and set hypotheses which might expose this value. Subsequently, Itility can gather the needed data to validate or reject the hypotheses. The hypotheses with an unexpected answer usually contain most business value, as they provide new insights in the current operations of the customer. The domain expert can validate if the results of the validation indeed contain business value.

5.1.2 Grow as you go
The second step of the “ABC” method represents the growth that Itility aims to establish at their customers. For the offered analytics services, Itility uses a maturity level model, see Figure 12, which is similar to the earlier described maturity model by Kart et al. (2015) from Figure 8. In line with the statements of the latter, Itility always needs to start supporting their customers at the descriptive level, which has the lowest maturity and is least valuable. By supporting their customers to grow gradually into higher maturity levels by measuring the models, automating and steering on the end-to-end solutions, Itility aims to increase their value creation and to establish a close and long-term collaboration.

5.1.3 Keep the end goal in mind
The third step of the “ABC” method represents the goal of Itility to always keep the end goal in mind, which is providing the customer with business value through analytics & automation. Before
being able to deliver this business value, the Itility Big Data analytics value chain, depicted in Figure 13, has to be traversed. The value chain of Itility differs from the previously described Big Data value chain by Miller and Mork (2013) by focusing more on the analytics itself and excluding the collection phase and by adding an analytics and automation step for the creation of more business value. Additionally, Itility provides insights if the focus should be on either agility or quality in each separate phase of the value chain.

During the explore and pre-analytics phase, the customer’s data is interpreted to determine what kind of intelligence Itility can deliver and a first set of hypotheses and dashboards with potential business value will be created. In these first two phases agility is important to identify potential business value as quickly as possible. Keeping the end goal in mind is essential here, since otherwise Itility could be stuck in these phases for too long, searching for more and more relatively small additional business value. In the model and Proof of Concept (PoC) phase, agility becomes less relevant because the quality and completeness of the model and the PoC become dominant as these phases will resemble the quality of the solution provided by Itility. Keeping an eye on the end goal is essential here as well, since Itility could keep on adding components to the models and PoC’s, but that would delay the moment when the customer receives value. Most of the effort will go to the analytics & automation phase where the solution is implemented, where more components can be added and more processes can be automated over a long-term relationship. It is important to notice that the domain expert is involved in the first four phases, since this plays a major role in the co-creation of the value for the customer. This is explained in more detail in section 7.3.1.

![Figure 13: The Itility Big Data Analytics Value Chain](image-url)
5.2 Big Data Toolset
Even though Itility states that Big Data analytics is mainly about agility and not about technology (tools or platforms), the company possesses an extensive Big Data toolset to ingest, store and traverse their Big Data analytics value chain (Figure 13). By having the capabilities to work with this wide variety of tools, Itility is able to choose the optimal tools for value creation at their customers. An overview of this diverse toolset is given in Appendix 3. As this research project focuses on increasing the agility in the explore and pre-analytics phase of their value chain, the tools that are used most in these phases are discussed below.

5.3 Services
By using the methods and tools described above, Itility is able to deliver services that provide their customers with business value. An overview of the two main analytical services which Itility delivers is given below, including how Itility manages to overcome the Big Data challenges which are described in the literature summary for their customers.

*Itility Managed Analytics Platform (IMAP)*
IMAP is a Big Data Software as a Service (SaaS) solution, providing a fully managed, elastic, and secure analytics environment and managed services. This service is built in Splunk Enterprise, one of the tools from the Itility Big Data toolset, in combination with the programming language R. The big advantage of Splunk is that it’s able to index all data types to turn it into powerful operational intelligence. The combination with R enables Itility to integrated customized algorithms. In addition IMAP is delivered in the cloud which provides customers benefits such as a short delivery lead time, ease to start and stop contract, security, and scalability. In addition, customers have the opportunity to access the delivered value from anywhere. Itility can also guarantee the security of IMAP, as it has recently been ISAE 3402 certified, meaning that Itility has demonstrated to have effectively designed control objectives and activities for the security of this platform. On top of IMAP, the analytical nuggets are offered to specific business domains. For the IMAP service, Itility aims at maintaining a long term relationship with their customers, supporting them to reach a higher Big Data maturity according to the model of Figure 12.

*Data deep-dive*
A data deep-dive is a service that Itility provides in order to show their (potential) customers how their data could be transformed into business value. Instead of just explaining how to extract this business value, Itility asks the (potential) customer for a data dump and a time period of about 1-2
weeks. During this time period, the analytics team of Itility performs a wide variety of analytical techniques to find relevant and customer specific examples on how this customer could directly use his data to optimize its business. By offering this service, Itility aims at showing their ability to extract business value from the (potential) customers’ data, and at becoming the partner that will implement this business value, for example through IMAP.

Data science on-site
The third analytics service offered by Itility is data science on-site, which implies that one of the analytics team members works at an office of the customer. Basically, the customer is hereby insourcing data science capabilities from the specialists of Itility to improve its internal operations. The team member that delivers this service on-site gains more company specific knowledge and is therefore able to identify more opportunities to improve the customers operations through data analysis. In addition, this team member often needs to work with the tools that are used at the customers’ site.

Overcome the Big Data challenges
With the two services described above, Itility aims at extracting the benefits as discussed in the literature summary from Big Data for their customers. In order to do this successfully, the challenges that have been described in the same section need to be faced. How does Itility overcome these challenges and extract business value for their customers?

First of all, it is important to take a step back and to notice that in the case of Itility, the company that will exploit the benefits and the company that has to face the challenges are not the same. As a part of the delivered services, Itility is responsible for taking care of these challenges for their customers. Below, an overview of the described challenges from the literature summary is given in Table 2 including how Itility handles them.

<table>
<thead>
<tr>
<th>Challenge</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Storage &amp; Transformation</td>
<td>With a subscription to an IaaS provider to store data, and a license for Splunk Enterprise to index data, Itility is able to store data for transformation. Since both tools are cloud-based, Itility can easily scale up and down. In addition, Splunk is known for its ability to index and structure a great variety of data types, enabling Itility to perform analytics on all these data types.</td>
</tr>
</tbody>
</table>
| Privacy & Security         | Security is of utmost importance, and every employee is made aware of that from the first day on. Verifying the integrity of employees, using several authentication methods, signing Non-Disclosure Agreements, and the ISAE }
certification for IMAP are examples of measures that Itility takes to protect their customers from security breaches and thus from reputational damage.

**Data Quality**

Itility transforms and converts new data into processable data, for example by using regular expressions to extract new variables that will be indexed. After analysis and setting up hypotheses, this data can be validated together with the customer once more. In this stage, Itility is also able to provide the customer with advice on how to improve their data management to further increase the data quality.

**Data Visualization**

Splunk comes with a set of standard and custom visualizations that the analytics team uses. Often, multiple of these visualizations are combined into a dashboard to enable customers to understand the extracted business value at a glance. In addition, the standard visualizations of R and Rapidminer are used, predominantly at deep-dives.

**Big Data talent Gap**

By enabling customers to outsource operations on their data, Itility takes away the need of hiring employees with the right skills to perform these operations.

<table>
<thead>
<tr>
<th>Table 2: How does Itility face the Big Data challenges for their customers?</th>
</tr>
</thead>
</table>

5.4 Organizational maturity

To determine the current efficiency of the operations of the analytics team at Itility, the current way of working is mapped onto the Capability Maturity Model (CMM) from Humphreys (1988). This model aims at achieving a controlled and measured process as the scientific foundation for continuous improvement. The CMM consists of the five maturity stages that are depicted in Figure 14. Each of the maturity stages consists of a set of requirements, which a company should fulfill in order to rank itself into that maturity stage. This model can support organizations to improve their processes by gaining understanding of the current status of their operations, by developing a vision of the desired process, and by establishing a list of required process improvements to advance to a higher maturity stage.

---

**Figure 14: The maturity stages of the CMM (ECCI, 2015)**
Even though the analytics team of Itility seems to fulfill some of the requirements in the third, fourth and even the fifth stage of the CMM, the team is currently positioned in the second stage. The reason for this is that in order to reach a maturity stage, an organization needs to fulfill all the requirements of that stage (and the stages below), and Itility does not seem to fulfill one of the most crucial requirements of the third stage, which is the requirement of defined processes.

Surely, the analytics team has the majority of their processes defined, but not the main process within the scope of this research which might be the most crucial one to extract maximum value from their customers’ data. During semi-structured interviews with the analytics team members of Itility, it became clear that there is no defined process for extracting value from a newly received data set during a deep-dive, as all the team members were using different steps, analytical techniques, and tools, see Appendix 4. This means that for analyzing a similar data set, the amount of extracted value for the customer can differ significantly between the results of all team members, which might not even seem strange considering the wide variety of available analytical techniques (Appendix 1). Itility stated that not defining a process for the value extraction from data was done intentionally to provide team members with the freedom to extract value with their preferred techniques. This also means that multiple team members have to analyze the data to ensure that all the business value is extracted. In order to grow to the next maturity stage and to ensure a certain level of value extraction, this is an issue that needs to be tackled by Itility.

5.5 Agility
In the company introduction in Section 2, a part of the agile capabilities of Itility has already been described. By integrating the current way of working into the literature overview of agility in Big Data from Section 4.3, a more detailed analysis of the agile capabilities of the analytics team of Itility is created.

According to Lee (2012) and the dimensions “model and technology” from the framework of Knabke & Olbrich (2013) depicted in Figure 9, one of the most important enablers of agility is IT, which is also clearly the case for Itility. As described earlier, Splunk Enterprise and Microsoft Azure cloud storage enable Itility to easily index any kind of data and to easily scale up or down when needed, and the analytical tools of Appendix 3 are used to extract value from data. Other examples are represented by an online ticketing system to regulate internal and external support, an online tool that eases file sharing and team collaboration, and all employees are equipped with
the right computers and phones to make use of this IT. The ticketing system also supports Itility to increase agility throughout the value chain as suggested by Bharadwaj et al. (2016).

Couto et al. (2015) stated that governance can have a significant impact on agility through for example monitoring, procedures, and control. Monitoring has been identified as a strength of Itility, as the company installed alerting on their cloud environments, which enables the company to quickly sense when, where and why a problem occurred and to decide how to respond to it. Itility also maintains quite some procedures to manage the creation of their services and to prevent issues, of which the most important ones are maintained to ensure data security. Examples of other procedures are the version control through BitBucket, a checklist for determining the quality of a dashboard, and the procedures to push developed dashboards from the development environment in Splunk Enterprise to the production environment for the client. It is interesting to note that the majority of these procedures are maintained for a successful delivery of business value to the customer, and not for the creation of business value. Control is established at Itility every Monday during a team call discussing the planning for that week and every Friday discussing the results and issues of that week during a team meeting.

When looking at the agile characteristics of Itility as described above, it can be concluded that the company is performing a lot of actions that positively influence agility in Big Data analytics. By being able to proactively react to changes through monitoring and alerting, documenting all solutions to support tickets that Itility receives, and by optimizing customer processes, Itility also scores well on the most important Big Data analytics agile dimension from Knabke & Olbrich (2013): “Change behavior”. One might even think that Itility has an abundance of procedures that cause a reduction in agility (Couto et al., 2015), which could be explained by the dimension “perceived customer value” from the framework of Knabke & Olbrich (2013). In line with this dimension, it is crucial for Itility that the services delivered to customers do not include any flaws and are of desired quality in order to maintain or establish a long term relation. Therefore, there is little to no room to “play” with this threshold between performance and agility. Even though it is intentionally, procedures for value extraction from Big Data are lacking, indicating that Itility has an opportunity to grow in the “approach” dimension of Knabke & Olbrich (2013) towards a more agile business processes. The lack of structure in the value extraction process is also (partly) caused by the diversity of available Big Data analytical techniques and tools.
6. Impact of a service catalog at Itility
Now that the current way of working at Itility is analyzed, it is possible to integrate this analysis in the benefits and challenges for using a service catalog, as described in the literature summary. This chapter shows how the use of a service catalog would be beneficial for Itility, in particular to increase agility, and how the challenges for using such a catalog can be overcome.

6.1 Service Catalog Structure
First of all it is important again to take one step back to realize that the service catalog differs from the service catalog presented in Figure 10. Since the catalog will be for internal use, the service provider and service consumer will both be members of the analytics team of Itility. The collaboration between the three entities can in this case be depicted as in Figure 15. In this structure, all analytics team members publish their mastered Big Data analytics techniques in the Big Data analytics catalog. The team members that need to perform Big Data analytics can now search through the catalog to find techniques that can support them to extract business value. Due to the standardized way of publishing a service, the team members know exactly how to use this analytics technique himself and could ask the publisher for any help if needed. This whole process should be managed by a service catalog manager to ensure the quality and completeness of the catalog.

![Figure 15: The service catalog concept for Itility](image)

6.2 Benefits
First of all, the use of a service catalog can increase the agility in Big Data analytics. Predominantly, since a systematic overview of all possible Big Data analytics techniques will be provided including examples and information on how and when to use these techniques. Such an overview will decrease the amount of time that the analytics team members need to spend on finding and developing the required analytical techniques themselves. Knowledge management will be increased as best practices of all team members can be gathered in the catalog in order to stimulate the reusability of analytical techniques and the interoperability between the team members.
The opportunity to create executable chains of standardized analytical techniques will help Itility to climb to the third stage of the CMM depicted in Figure 14, indicating that a higher process efficiency has been reached. From the third maturity level on, Itility can use the CMM model to create a roadmap for further development of the efficiency of Big Data analytics.

The service catalog would allow Itility to rank the analytical techniques on costs and other performance criteria to improve decision making on which analytical techniques fit best in a specific situation. Indirectly, the improved decision making between a wider variety of analytical services will result in higher customer satisfaction due to a service delivery of higher quality.

6.3 Challenges
To ensure alignment in the use of the service catalog, a service catalog manager should be appointed to ensure the quality of the services in the catalog in order to make them usable for the whole analytics team.

The service catalog manager can also be responsible for the creation of the service catalog. As a wide variety of services is needed to create a complete service catalog, the manager should identify which services have the highest priority and steer the analytics team to create these standardized services. If managed correctly, the service catalog can grow stepwise by efforts of the whole analytics team. In addition, the manager should keep the service catalog up to date by removing/improving the included services.

6.4 Conclusion
Overall, it can be concluded that Itility can increase their agility in Big Data analytics mainly through the reusability of the included Big Data analytics techniques. Also, additional benefits such as increasing the quality of their service offerings towards customers, which is crucial for Itility, can be improved. Note that this is only possible if the service catalog is managed correctly.
Part IV – Solution design

7. BASE/X framework
Now that the potential increase in agility along with the additional benefits of using a service catalog is supported by literature, the next step is to design a service catalog that can be implemented at Itility. In this chapter, such a service catalog will be designed using the BASE/X framework for service-dominant business engineering from Grefen et al. (2013). First, an introduction about service dominant business is given to understand the background of the BASE/X framework. After that introduction of the framework itself is provided after which the framework is applied to Itility.

7.1 Service-dominant business
Vandermerwe and Rada (1988) identified that a rising number of companies from different industries started to focus more on services rather than assets. They termed this phenomenon “servitization” which according to Baines et al. (2009) implies “the innovation of an organization’s capabilities and process shift from selling products to selling integrated products and services that deliver value-in-use”. During the last decades, the phenomenon servitization has continued and the service economy keeps on rising. In 2013 for example, the European Commission showed that services are more interrelated and integrated to all economic activities, institutions and society organizations. Ehret and Wirtz (2010) add that services constitute the highest share of GDP, are the central factor of economic growth within developing economies, and that services are the major contributors to growth within today’s economy. With the change of focus from assets towards services, many companies of which Itility is one, are acting in a service-dominant business setting.

Services differ from assets (or products) and can be characterized by the IHIP characteristics, which are “intangibility, “heterogeneity”, “inseparability of production and consumption”, and “ perishability” (Oliveira & Roth, 2012). In addition, a service involves interaction with customers or property in their possession which makes the value creation unique and which does not result in a transfer of ownership (Ehret & Wirtz, 2010). By performing deep-dives or providing customers with value through IMAP, Itility indeed meets all of the mentioned characteristics of this paragraph.

Vargo and Lusch (2004) pointed out the key differences between traditional goods-dominant business and service-dominant business. According to service dominant logic (SDL), knowledge
and skills are the core competences of an organization, unlike operand resources such as machines and money. For Itility, these core competences include the knowledge and skills on how to use a variety of data mining techniques to extract value from Big Data. Instead of selling goods as the end product, goods are transmitters of the core competences according to SDL and not important to the customer. In the case of Itility the used infrastructure and analytics tooling help the analytics team to deliver their services, but if Itility could deliver the same value using other assets, that would not be a problem for the customer. The third key difference is represented by the role of the customer. According to SDL the customer is a co-producer of the service, thereby contributing to the value creation, and not just buying a product. For Itility, the customer gets involved throughout each of the steps of the Itility Big Data value chain (Figure 13) as domain expert, to indicate what kind of value could be extracted and to validate the hypotheses and proof of concepts from the analytics team of Itility. Since Itility seems to operate according to the SDL principles, it can be concluded that Itility acts in a service-dominant business setting.

7.2 Introduction BASE/X
Since BASE/X is a framework to increase agility in a service-dominant business setting, it is perfectly suited to be applied at Itility for this research project. For reaching an increase in agility, BASE/X provides a holistic view which covers the entire business spectrum including everything from defining business strategy to designing the infrastructure needed to execute this strategy. To stay in scope of this research project, the focus remains on the mapping of the operations of Itility on the business aspects and on designing a business service catalog.

Key ingredients
According to BASE/X there are three basic ingredients of service-dominant business thinking including their relationships which need to be taken into account when designing new service-dominant business structures. The concept of the BASE/X framework is designed around these principles which are depicted in Figure 16 (Grefen et al., 2013).

- The value-in-use fulfills the customers’ requirements.
- Business networks deal with the complexity of solutions providing the value-in-use.
- Business agility deals with the fluidity of customer requirements, market circumstances and technology developments.
The overall structure of the BASE/X framework consists of three different pyramids, which are the business pyramid, information system pyramid, and the platform pyramid. The business pyramid is applied to Itility in the solution design phase, where the other layers are applies in the implementation phase.

The business pyramid consists of the following four layers, depicted in Figure 17: strategy (S), business models (BM), service composition (SC), and business services (BS). These layers support the service-dominant business design by making a distinction between the business goals in the two top layers (the “business what”) and the business operations in the two bottom layers (the “business how”). In addition, a distinction is made between the stable essence of an organization (S and BS) and the agile essence (BM and SC), which forms the basis for the creation of agile market offerings as depicted in Figure 17 (Grefen et al., 2013).

The Business Strategy (S) layer describes the overall strategy of a service-dominant organization. It describes the identity of an organization in a business market and is relatively stable. The business strategy is designed to exist in a market with other players, but it is not formulated in concrete relationships with these players (Grefen et al., 2013)
The Business Model (BM) layer describes the market offerings in terms of customer-oriented solutions with a value-in-use and associated costs and benefits. Business models are agile, they are established and discharged when market circumstances change. In contrast to the service layer, the business models are formulated in terms of concrete business relationships with other players (Grefen et al., 2013).

The business service (BS) layer describes the business services of an organization in modular capabilities. These business services are relatively stable as they evolve over time and completely encapsulate business resources since they are not directly relevant to the customer. These business services can also include modular capabilities offered by collaborating organizations in a network (Grefen et al., 2013).

The service composition (SC) layer describes how business services are composed to fulfill the value-in-use of a business model. The service composition determines the realization of the customer journey. Services may belong to the organization or may be offered by collaborating organizations in a network. Service compositions are agile; they are created and dismissed along with business models (Grefen et al., 2013).

**Alignment between pyramid layers**

To deal with the disadvantages of designing top-down, which is too time consuming, or bottom-up which can become too chaotic, the BASE/X layers are tightly integrated with each other in order to manage service complexity. This integration between the layers is depicted in Figure 18.

Business Engineering with BASE/X takes place in two design loops. The strategic design loop runs in the stable layers and periodically verifies if the business strategy is represented by all offered customer facing capabilities of an organization. By having such a set of capabilities, the complexity of service offerings is broken down into small, reusable, functional modules (Grefen et al., 2013).
In the tactical design loop, business models are mapped to a service composition to create the needed set of services to execute a business model. If the stable layers are designed well, this loop enables business agility as it is mainly about combining the right services in the right way to fulfill the goal of the business model (Grefen et al., 2013).

The confrontation of goals represents the alignment between the identity of an organization and its market offerings. Finally, the confrontation of means, represents the alignment between the required and available capabilities or an organization (Grefen et al., 2013).

7.3 Application to Itility

In this section, the BASE/X framework will be applied to the analytics team of Itility. The applications start with the stable layers by first defining the strategy (S) of the team after which its modular capabilities are discussed (BS). Subsequently, the business model (BM) and the service composition (SC) will be applied.

7.3.1 Strategy

For defining the business strategy for Itility Analytics, it is important to keep in mind that this strategy should not be defined based on current market structures, but should be made with a long-term focus. To get a clear overview of the strategy from the analytics team, it is defined with a wider scope, including all of their operations. In a later stage, the application of the BASE/X framework is limited to the scope again. According to the BASE/X framework, a business strategy contains three main elements.

Firstly, the value-in-use represents the general added value that a customer perceives through the service delivery. This value-in-use is expressed in terms of an experience that is brought to the customer, rather than in terms of assets. As the customer is a co-creator of the value-in-use, the interactions with them are specified as well. Secondly, the service eco-system, specifying what is strategically required to create the value-in-use, needs to be specified. This eco-system consists of the focal organization, which is the owner of the strategy, and the core (must-have) service and enriching (nice-to-have) service providers, who can provide essential or enriching modular capabilities to fulfill the value-in-use. Thirdly, collaboration management specifies how the focal organization manages its collaborations with the partners within the service eco-system.
To define the service-dominant strategy for Itility, the service-dominant strategy canvas tool proposed by the BASE/X framework will be used (Grefen et al., 2013). This tool elaborates on the three main elements described above by answering specific questions, as depicted in Figure 19.

![Figure 19: The service-dominant strategy canvas (Grefen et al., 2013)](image)

For determining the service-dominant strategy, a workshop has been given at Itility to gather information to answer the questions in the canvas of Figure 19. The results of the workshop are presented in Appendix 5 and are incorporated in the strategy design process. For this process, first the focal organization is identified after which the value-in-use is defined. Subsequently the service eco-system is worked out after which the preferred collaboration management of Itility is given.

**The Focal Organization**

As Itility is the orchestrator of the business network and the service provider that aims to deliver the value-in-use to its customer, Itility is the focal organization. More specifically, the analytics team of Itility is the focal organization as the focus of this research is on Big Data analytics.

**Value in use**

The added value that the Itility analytics team aims to deliver is specified in terms of (potential) customers, experience of the customer, and the interactions needed to co-create this experience.

**Customer**

A customer of the analytics team of Itility can in fact be any high tech company that is knowingly gathering data as the team has the ability to extract value from all types of data. Since the pricing corresponds to the high quality of delivered services, the focus is on medium and large enterprises.
Experience
By delivering its service, the analytics team aims at creating a seamless optimization of business operations experience, by performing data analysis. Thinking in terms of an experience is essential for service-dominant business engineering, as it is not important for the customer how this experience is created as long as the customer is able to enjoy the benefits.

Interactions
The experience is not only established during the final service delivery, but during every contact moment between Itility and the customer. Therefore, it is important to understand the customers’ journey (Berry et al., 2002). To understand this journey, a customer experience eco-cycle has been created to provide an overview of all the interactions between Itility and the customer in Figure 20.
In line with the definition of a service, the interactions with between the analytics team and the customer are needed for the co-creation of the experience.

The customer experience eco-cycle starts with getting in contact with Itility. In this phase, Itility already starts creating the experience by explaining what business value the analytics team can potentially deliver. In the following two stages, the analytics team shows customized value creation opportunities, by performing a deep-dive on the customers’ data. When satisfied with the outcomes, the collaboration with Itility is initiated and the customers’ data can be connected.
During the next two interactions, the domain expert sets up hypotheses with potential business value which are validated by Itility through data analysis. Subsequently, the customer has to validate the Proof of Concept (PoC) that delivers the business value extracted from the hypotheses. During these stages, also business rules can be obtained from the customer to be incorporated in the final service delivery. Finally, the customer should be able to seamlessly improve their business operations using the services from Itility. These services are delivered through online apps such as dashboards including business rules, machine learning algorithms, or alerts. Support is also included in the seamless business optimization as it minimizes the effort of the customer to handle
issues and questions. As Itility aims at supporting to help the customer grow to the highest Big Data maturity level of Figure 12, the analytics team continuously investigates if there are more opportunities to improve the customers’ operations to repeat the process. The interactions described in the customer experience eco-cycle, are mapped onto the interactions element of the service-dominant strategy canvas. Note that the interactions between the customer and other departments of Itility are not included in the strategy canvas since they are out of scope for this research project.

Service eco-system
In addition to the focal organization, the core and enriching services that are required to create the value-in-use are defined including the partners that are required to deliver these services.

Core services
Core services represent services that must be executed to reach the value-in-use for the customer. These core services have been determined as follows: profiling of the customer, providing Infrastructure as a Service (IaaS) for data storage and access to IMAP, data (pre-) processing, and dashboarding and alerting. Support is added as a core service as well since it directly contributes to the seamless experience as any issues are solved quickly by the analytics team.

Enriching services
Enriching services represent the services that are not essential, but would be nice to have to increase the value-in-use for the customer. These enriching services have been determined as follows: desired state management, data science on-site, data science training, and a sandbox environment, which is a customer specific environment on IMAP where the customer can “play around” with its own data.

Core partners
Not all core services are executed by the analytics team. The IaaS has to be provided by an IaaS provider and for the data processing an analytics toolset provider is needed. In addition, a customer services software provider is required to ensure smooth support towards customers, and finally a domain expert is needed who is able to provide domain specific business optimization. Note that this domain expert can be an employee of the customer, which is currently often the case.

Enriching partners
No enriching partners have been identified as the analytics team of Itility is able to deliver all of the enriching services by itself.
Collaboration management
As final element of the service-dominant strategy canvas, the collaboration management specifies the preferred relations between the analytics team and its core and enriching partners.

Core relationships
The relationships with the core partners are preferably short-term. Since their services are commodity services, it enables Itility to switch to another service provider when beneficial. In addition, a variable rate is desired to be able to scale up or down the service capacity. In case the domain expert is employed by the customer, this relationship is preferably trusted and long-term, which is in line with the relationship that Itility wants to establish with their customers.

Enriching relationships
No enriching partners have been identified as the analytics team of Itility is able to deliver all of the enriching services by itself.

After answering all the questions about defining the service-dominant strategy for the analytics team of Itility, the result is presented in Figure 21. Even though security also plays a key role in the experience of the customer, it is not separately included in the strategy canvas as it is encapsulated in all the actions of the analytics team.

Figure 21: The service-dominant strategy canvas applied to the Itility Analytics team
7.3.2 Business Services

Now that the service-dominant strategy for the analytics team is provided, the second stable layer of the BASE/X framework is defined. According to the BASE/X framework, business services are defined by the following three criteria. Firstly, business services must have a clear functionality that describes what the business service does. Secondly, this functionality must be customer-facing, implying that it impacts the value-in-use as perceived by the customer. Thirdly, it is essential that the business services are designed modularly and in the right granularity. This enables Itility to combine multiple business services into a service composition and it also enables the reuse of the business service for multiple customers and business models.

All the services offered by Itility and its partners are gathered and structured in a service catalog. A complete service catalog forms the basis for increasing agility, because it deals with service complexity by enabling the assembly of a solution from the available modular business services, represented by the confrontation of means in Figure 18. To make a structured service catalog, the included business services are grouped into service domains by their goal and functionality. According to the strategic design loop in Figure 18, Itility must be able to execute its strategy using the components in the service catalog. To ensure that all components of the service-dominant strategy canvas in Figure 21 are represented in the service catalog, a mapping between the Business Service and Strategy layer of the BASE/X model is created, see Appendix 6. Visualizing the business services from Appendix 6 resulted in the service catalog depicted in Figure 22.
The service catalog contains all services that the analytics team of Itility should be able to provide to create the value-in-use for their customers as it is directly mapped from the service-dominant strategy. Because of its completeness, the catalog forms the basis for structuring the capabilities into standardized processes throughout the customer experience eco-cycle (Figure 20). In line with the scope of this research project, an elaboration for the service “validate hypotheses” follows.

**Elaboration on “Validate Hypotheses”**

To verify if the business service “Validate hypotheses” fulfills the criteria of the BASE/X framework for a business service, it is assessed on the criteria in Table 3 as proposed by the BASE/X framework. In this assessment it becomes clear that the service is within the context of the strategy and transforms the perception of the value-in-use by the customer. Also, the size of the business service is defined in such a way that it can easily be included into a service composition and that it is not overlapping other business services. In addition, the performing role and beneficiary role are represented by respectively an analytics team member and the customer, and the clear start and end point of the business services are represented by respectively setting the hypotheses and the validation of the PoC with the customer.

<table>
<thead>
<tr>
<th>Class</th>
<th>Name</th>
<th>Criteria</th>
<th>Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Why</td>
<td>Right context</td>
<td>Does the service fit in the context of the defined business strategy?</td>
<td>Yes, it is linked with the core services: (pre-) processing and visualizing</td>
</tr>
<tr>
<td></td>
<td>Right goal</td>
<td>Does the service transform the state of the customer perception of the value-in-use?</td>
<td>Yes, after validating the hypotheses set by the domain expert, the validated hypotheses will be presented to the customer.</td>
</tr>
<tr>
<td>What</td>
<td>Right size</td>
<td>Can the service be easily combined into multiple service compositions?</td>
<td>Yes, as the services are defined on a high aggregation level. Within this business service a wide variety of data processing techniques are available.</td>
</tr>
<tr>
<td></td>
<td>Right scope</td>
<td>Is there any functional overlap with existing service(s)?</td>
<td>No</td>
</tr>
<tr>
<td>Who</td>
<td>Right actor</td>
<td>Is there an actor (role) performing the service?</td>
<td>Itility analytics team member</td>
</tr>
<tr>
<td></td>
<td>Right beneficiary</td>
<td>Is there a beneficiary (role) for whom the service is performed?</td>
<td>Customer</td>
</tr>
<tr>
<td>When</td>
<td>Right start</td>
<td>Is there a clear starting point in time for the execution of a service?</td>
<td>After the domain expert has set hypotheses</td>
</tr>
<tr>
<td></td>
<td>Right end</td>
<td>Is there a clear ending point in time for the execution of the service?</td>
<td>Validating the results of hypotheses testing with the customer</td>
</tr>
</tbody>
</table>

*Table 3: Assessment of the ”Validate hypotheses” business services on the modularity criteria*
To ensure the ability to easily include multiple business services into a service composition, the business domain specifications and business service specifications need to be defined according to the same standards. In Table 4, the specifications of the business domain “Data analysis”, and the service “Validate hypotheses” are provided according to the standards of the BASE/X framework. In Table 5, the specifications of the business service itself are provided.

<table>
<thead>
<tr>
<th>Business Domain Specification</th>
<th>Business Domain name: Data Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domain Description</td>
<td>Includes business services that have the functionality to extract value from all types of Big Data and to visualize this value in an understandable format for the customer</td>
</tr>
<tr>
<td>Service criteria</td>
<td>The services contribute to the preparation/cleaning of data, the value extraction from data, or visualization of data</td>
</tr>
<tr>
<td>Responsible for Domain</td>
<td>The analytics team of Itility</td>
</tr>
</tbody>
</table>

*Table 4: Business Domain Specification for “Data analysis”*

<table>
<thead>
<tr>
<th>Business Service Specification</th>
<th>Business service name: Validate Hypotheses</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Service Description</td>
<td><strong>This business service triggers the validation of hypotheses to verify whether or not they encapsulate potential business value</strong></td>
</tr>
<tr>
<td>Service Domain</td>
<td>Data analysis</td>
</tr>
<tr>
<td>Service functionality in terms of value-in-use</td>
<td></td>
</tr>
<tr>
<td>Business resources used by service</td>
<td>The members of the analytics team</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Service Classification</th>
<th>Core or Enriching</th>
<th>Commodity or Differentiating</th>
<th>Internal or External</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Core</td>
<td>Differentiating</td>
<td>Internal</td>
<td>Remarks</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Quality of Service (QoS)</th>
<th>Parameter</th>
<th>Maximum duration</th>
<th>Value</th>
<th>One business week</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>Business value</td>
<td>Value</td>
<td>At least one new business insight</td>
<td></td>
</tr>
</tbody>
</table>

*Table 5: Business service specification for "Validate hypotheses"*
With the extended service description for “Validate hypotheses” and the service catalog (Figure 22), the focus has been predominantly on the connection between business services to enable standardization and agility in the creation of the value-in-use for the customer throughout the whole customer experience eco-cycle (Figure 20). In line with the scope of this research, the business service “Validate hypotheses”, which encapsulates the first two phases of the Itility Big Data value chain (Figure 13), is investigated on a lower aggregation level.

By investigating “Validate hypotheses” on a lower aggregation level, this research zooms in on the building block services (BBSs) that the analytics team needs to be capable of to deliver this particular business service. The difference between business services and BBSs is that the business services are customer facing (inter-organizational), whereas the BBSs represent internal services that contribute to the creation of the business services (intra-organizational). Possibly, multiple layers of BBSs are needed in order to arrive at the right service granularity for standardization and reuse of its functionality. From the results of the semi-structured interviews (Appendix 4), it has already been concluded that a wide variety of Big Data analytics techniques is used, that there is no defined process structure for the usage of these techniques (by choice), and that every team member uses different techniques. The use of a catalog with all needed BBSs can, as explained in section 6.1 and depicted in Figure 15, solve these issues by providing a complete overview of the techniques, providing structure between the techniques, and by sharing knowledge among team members. Therefore, an overview of all BBSs that are currently used by the analytics team is created for the business service “Validate hypotheses” see Figure 24. The included techniques are derived from the results of the semi-structured interviews, provided in Appendix 4. Similar to the service catalog in Figure 22, the BBSs overview is divided into business domains, and even
subdomains, for reasons of clarity. In addition the techniques are classified in one of the Big Data value chain phases (Figure 7) to provide structure for the service composition in a later phase of this research.

![Building block services for “Validate Hypotheses”](image)

**Figure 24: Building block services for the business service “Validate hypotheses”**

It is important to realize that for the BBSs the customer of the included techniques is actually Itility itself. This is because all the techniques contribute to the creation of a service that Itility will sell to its customers and in this way, the services fulfill the customer-facing criteria of the BASE/X framework. In the proceedings of this research, the focus remains on the business service “validate hypotheses” and the agile layers of the BASE/X framework are designed based on the BBSs in Figure 24.

### 7.3.3 Business Models

Now that the set of business services needed to set hypotheses is provided, the first agile layer of the BASE/X framework can be defined. This concerns the business model layer which is central in tactical business design. A business model provides an overview of the contribution of every actor in a business network to the delivery of the value-in-use for a concrete customer segment, and of the benefits and costs for these actors. It makes sense that in order for a business model to be feasible, it has to provide more benefits than costs for all actors. Business models are agile since they can be created whenever a business opportunity arises by forming new service compositions to execute and they can also be dismissed if a business opportunity ceases.

**Segmentation**

Segmentation can support Itility to tailor its service offerings to deliver a specific value-in-use for different groups of customers. Generally speaking, market segmentation is performed based on
traditional demographic traits like for example age, gender, and income, or based on non-
demographic traits such as values and tastes (Yankelovich & Meer, 2006). For Itility these traits
do not serve well for customer segmentation. The experience that Itility delivers to the customer
predominantly depends on their desired Big Data maturity level, as these levels correspond to
different levels of the abstract value-in-use of business optimization. Therefore, segmentation of
customers is based on the four Big Data maturity levels (Figure 8), as depicted in Table 6.

<table>
<thead>
<tr>
<th>Abstract value-in-use</th>
<th>Customer segment</th>
<th>Concrete value-in-use</th>
<th>Business model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seamless Business Optimization (SBO)</td>
<td>Descriptive</td>
<td>SBO through knowing what happened</td>
<td>Beginner (/B)</td>
</tr>
<tr>
<td></td>
<td>Diagnostic</td>
<td>SBO through knowing why things happened</td>
<td>Intermediate (/I)</td>
</tr>
<tr>
<td></td>
<td>Predictive</td>
<td>SBO through knowing what will happen</td>
<td>Advanced (/A)</td>
</tr>
<tr>
<td></td>
<td>Prescriptive</td>
<td>SBO through decision support / automation</td>
<td>Expert (/E)</td>
</tr>
</tbody>
</table>

Table 6: Customer segmentation

It is also interesting to note that the BBSs that need to be performed in order to deliver the value-
in-use predominantly depend on the customers’ data as it determines which kind of analytics
techniques can be applied. This does not directly influence the experience because for the customer
it does not matter which techniques are applied as long as the business value is provided. But since
it does influence which BBSs need to be performed, also a segmentation is done on the 5V
characteristics of Big Data as described in Section 4.1.1.

From these characteristics, it can be concluded that volume and velocity only play a minor role in
which data analysis techniques can be applied. Because these characteristics are handled by
infrastructure, which is needed for every customer, these characteristics are not suitable for
segmentation. Veracity refers to the extent in which the data can be trusted and consequently, how
meaningful the extracted results are. As this characteristic is handled after during the hypotheses
validation with the customer, this is also not a suitable characteristic for segmentation. The variety
of the customers’ data is a suitable characteristic for segmentation, as different analytics techniques
need to be used for different types of data. As a logical example, text mining techniques can extract
value from textual data, but not from numerical data. The last V characteristic, Value, is also a
suitable characteristic for segmentation as in Section 4.2.2. it became clear that for every maturity
level different analytics techniques are required to extract the corresponding value.
The two suitable characteristics for segmentation are divided into different levels. Variety is divided into textual data, numerical data, and hybrid data, which includes both textual and numerical data. Value is divided into descriptive, diagnostic, predictive, and prescriptive, in line with the Big Data analytics capabilities from Figure 8. A hybrid level is not needed for the characteristic value, since the higher maturity levels already include the capabilities (and thus analytics techniques) of the lower levels as explained in section 4.2.2.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
<th>Level 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variety</td>
<td>Numerical</td>
<td>Textual</td>
<td>Hybrid</td>
<td></td>
</tr>
<tr>
<td>Value</td>
<td>Descriptive</td>
<td>Diagnostic</td>
<td>Predictive</td>
<td>Prescriptive</td>
</tr>
</tbody>
</table>

*Table 8: Levels for segmentation per characteristic*

It is important to realize that for all segments the customer experience eco-cycle is the same, as the segments only need a different set of BBSs to fulfill the corresponding value-in-use. For this reason, one general business model is created that serves all segments. The segmentation becomes more relevant at the service composition layer, as it structures the internal processes of Itility.

*Service-dominant business model radar*

The business models are designed using the service-dominant business model radar, depicted in Figure 25, as proposed by the BASE/X framework. This radar includes five main elements that need to be defined, which are: co-produced value-in-use, value proposition, co-production activity, costs & benefits, and actors.
The co-produced value-in-use can be derived from the service-dominant strategy canvas for Itility (Figure 21) and is in this case: Seamless business optimization. This abstract value-in-use encapsulates the concrete value-in-use for all customer segments as described in Table 6.

The actors in the radar are similar to the actors in the service-dominant strategy canvas and include a focal organization, a customer, and the core partners. Usually, also enriching partners are included, but since no enriching partners have been identified there are none to include. The focal organization is identified as the analytics team of Itility, the customer is the organization seeking for the co-produced value-in-use, and finally the core partners are the IaaS provider, the analytics toolset provider, the domain expert, and the customer service software provider.

The value proposition represents components of the value-in-use that are delivered by an actor. The customer delivers its data to be analyzed by the analytics team. The analytics team itself delivers data science skills to extract value from the hypotheses that are set by the domain expert, hereby delivering domain expertise. The IaaS provider and Analytics toolset provider respectively deliver their infrastructure and tools. Finally, the service software provider delivers service software to ease customer support.

Next, the co-production activities represent the activities that the actors need to perform to create the value-in-use. For the customer this activity is to provide Itility access to their data, and the activity of the domain expert is to set up hypotheses and to support the validation of the hypotheses. Itility itself orchestrates the business network and needs to analyze data to validate hypotheses.
which will include performing different analytics techniques for every data (and thus also customer) segment. The activities of the IaaS provider the Analytics toolset provider, and service software provider are to provide access to their value proposition.

Finally, the costs and benefits are defined. These can be both monetary and non-monetary and are described for each actor in Table 9. For each actor, the benefits must outweigh the costs.

<table>
<thead>
<tr>
<th>Actor</th>
<th>Benefits</th>
<th>Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer</td>
<td>1. Validated hypotheses with business value</td>
<td>1. Operational costs</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Fee (to Itility)</td>
</tr>
<tr>
<td>Itility</td>
<td>1. Fee (from customer)</td>
<td>1. Operational costs</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Fee (to all four core partners)</td>
</tr>
<tr>
<td>IaaS provider</td>
<td>1. Fee (from Itility)</td>
<td>1. Operational costs</td>
</tr>
<tr>
<td>Analytics toolset provider</td>
<td>1. Fee (from Itility)</td>
<td>1. Operational costs</td>
</tr>
<tr>
<td>Domain Expert</td>
<td>1. Fee (from Itility)</td>
<td>1. Operational costs</td>
</tr>
<tr>
<td>Service Software provider</td>
<td>1. Fee (from Itility)</td>
<td>1. Operational costs</td>
</tr>
</tbody>
</table>

Table 9: Overview of all costs and benefits for each actor

After all elements for the service-dominant business model radar have been defined, the results are combined in the radar in Figure 26. Note that core service providers are depicted in the radar, but do not deliver any services in the service catalog (Figure 22). This is because they provide infrastructural services to enable the value creation by Itility, which are not customer facing.

Figure 26: Service-dominant business model radar for "Validate Hypotheses"
7.3.4 Service composition

Finally, the service composition layer from the BASE/X framework is defined. This layer represents the sets of business services that can realize the value-in-use of a business model. This is in line with the tactic design loop as depicted in Figure 18. The service composition is also involved in the confrontation of means. This means that the introduction of a new service composition can trigger the creation of new business services, or that changes in the business service catalog might lead to changes in service compositions (Grefen et al., 2013).

A service composition can either be with or without control flow. A composition without control flow is just the set of business services needed to realize a business model, whereas a composition with control flow places these services in the order of execution, similar to a business process.

Looking at the complete process (outside scope) of delivering the value-in-use to the customer on a high aggregation level, the service composition with control flow is quite similar to the customer experience eco-cycle in Figure 20. The difference is that this control flow, depicted in Figure 27, is defined from the point of view of Itility instead of the customers’. This control flow is provided in order to show all business services for which Itility can create a more detailed control flow on a lower aggregation level to standardize their processes.

By narrowing the scope back down to the business service “Validate hypotheses”, a similar kind of control flow is made on a lower aggregation level. For the creation of this control flow, the scope is narrowed down further to the business model dealing with the numerical (variety) and predictive (value) data segment. First, the relevant BBSs for the chosen data segment have been selected from the BBSs in Figure 24 to create a service composition without control flow, see Figure 29. Subsequently, the business services from Figure 29 are put into order of execution to create a service composition with hybrid control flow in Figure 28, which is a combination of a service composition with and without control flow. In Figure 28, the order of business domains from the service catalog is maintained (control flow), while within these business domains the analytics team members can choose which techniques to apply and in which order (without control flow).
Validate hypotheses: service composition without control flow

<table>
<thead>
<tr>
<th>Prepare</th>
<th>Organize data</th>
<th>Analyze data</th>
<th>Visualize hypotheses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Determine data type</td>
<td>Clean missing values</td>
<td>Remove linear combinations</td>
<td>Machine learning</td>
</tr>
<tr>
<td>Format the data type of variables</td>
<td>Remove zero-variance variables</td>
<td>Feature engineering</td>
<td>Identify and handle anomalies</td>
</tr>
<tr>
<td>Create train &amp; test data set</td>
<td>Identify dependent variable</td>
<td>Moving average &amp; trend analysis</td>
<td>Create (mock-up) dashboard</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Test model</td>
<td>Create report</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Train model</td>
<td>Create shareable presentation</td>
</tr>
</tbody>
</table>

Figure 29: The service composition without control flow for the business service “Validate hypotheses”

Validate hypotheses: service composition with control flow

<table>
<thead>
<tr>
<th>Prepare</th>
<th>Organize data</th>
<th>Analyze data</th>
<th>Visualize hypotheses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Determine data type</td>
<td>Identify dependent variable</td>
<td>Factor analysis</td>
<td>Create (mock-up) dashboard</td>
</tr>
<tr>
<td>Format the data type of variables</td>
<td>Remove linear combinations</td>
<td>Feature Importance</td>
<td>Create report</td>
</tr>
<tr>
<td></td>
<td>Clean missing values</td>
<td>Identify and handle anomalies</td>
<td>Create shareable presentation</td>
</tr>
<tr>
<td></td>
<td>Feature engineering</td>
<td>Moving average &amp; trend analysis</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Create train &amp; test data set</td>
<td>Test model</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Train model</td>
<td></td>
</tr>
</tbody>
</table>

Figure 28: The service composition with control flow for the business service “Validate hypotheses”
Part V – Implementation

8. Prototyping

After the benefits of using a catalog have been described and a service catalog for one specific data segment is designed while traversing the business pyramid of the BASE/X framework, a prototype is created for implementation at Itility. For designing the prototype, the other two pyramids of the BASE/X framework come into play, see Figure 30. The operations pyramid supports the execution of the business pyramid, whereas the platform pyramid supports the architecture of the information system pyramid. For Itility this means that a platform is needed to design an architecture which supports the usage of a service catalog.

![Figure 30: The three BASE/X pyramids (Grefen, 2015)](image)

8.1 Process model

As recommended by Grefen et al. (2013), a business process management system (BPMS) platform is used for the prototyping of a service composition. According to Rudden (2007), these platforms have the ability to process more with less effort and higher quality. Rudden also states that through structuring business processes, a BPMS platform provides efficiency, effectiveness, and agility, which are benefits that contribute to the goal of this research and additionally, shows alignment with the BASE/X framework.

For the creation of the prototype of the service catalog, first the platform Bizagi is used. Claessens (2016) showed that Bizagi has a suitable combination of functional requirements, user requirements, and design restrictions in which the service compositions for delivering the value-in-use can be modelled. The most important advantage of Bizagi is that it is a process modeler, which enables the design of a modular system by breaking down processes into sub processes until the right granularity is reached. According to the reference architecture of the BASE/X framework in Figure 31, this modularity is needed to enable the loose coupling of services and to enable
flexibility in combining multiple business services into a service composition through the Enterprise Service Bus.

Just as for the first three layers of the BASE/X framework, first a model is created that covers the whole value-in-use delivery process, see Figure 33. In this Bizagi model, the columns represent the stages in the customer experience eco-cycle (Figure 20) and the rows represent the departments of Itility. For reasons of simplicity, any business service not provided by the analytics team is performed by “another department”. As a next step, all the business services from the high-level service composition for creating the value-in-use (Figure 27) are mapped to the right actor and stage of the customer experience eco-cycle. Support is provided to the customer after the customer requests for it. In addition, a service catalog database is connected to the business service “validate hypotheses”. In this database, all operational elements to perform this service are defined. The customer facing service “validate hypotheses” is further specified in Figure 32 for the data segment where value is predictive and variety is numerical.

This model shows in more detail how Itility can deliver this customer-facing service. The sub process consists of the composition of the level 1 BBSs with control flow, deducted from Figure 28, needed to perform “validate hypotheses”. The level 1 specification is needed since the BBSs in this sub process do not have the right granularity for standardization and reusability yet. In this model, the service catalog database is depicted within the boundaries of the sub process, to provide the needed information to all BBSs.
Figure 33: Bizagi model of the customer-facing services for the value-in-use delivery process

Figure 32: Bizagi model for sub process of “validate hypotheses”, representing the level 1 BBSs composition to perform this service.

Figure 34: Legend of the Bizagi elements used for modelling

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As the level 1 BBSs from Figure 32 are not of the desired granularity for standardization yet, a second level of BBSs is needed. Basically, the level 2 BBSs represent the building blocks that Itility needs to perform the level 1 BBSs. When looking at the level 1 BBS “Train model” for example, there still is a wide variety of models that can be trained such as a decision tree, neural network, and a genetic algorithm. As for reaching agility it is needed to be able to reuse the functionality of each of these singular models, these models are modelled as level 2 BBSs in the sub process of a level 1 BBSs. An example for the level 1 BBS “Train model” is provided in Figure 35, where any of the models for training can be initiated is included. The level 2 BBSs can include for example code snippets, queries, and clear instructions to actually train a model, and thereby “building” the level 1 BBS “Train model”. Note that there are many more possible models suited to train, but they are not all included for reasons of clarity.

![Figure 35: Bizagi model for sub process of "Train model", representing the level 2 BBSs composition to train a model](image)

The above described process models on three different aggregation levels (customer-facing services, level 1 BBSs, and level 2 BBSs), provide Itility with a complete structure of the processes that need to be initiated to deliver the value-in-use to their customer. As identified during the semi-structured interviews in Appendix 4, this structure is lacking at this moment since every analytics team member has his own way of working. Even though Itility intentionally didn’t provide this structure, it is needed to climb to the third maturity level of the CMM in Figure 14, where an organizations processes are defined. From this third maturity level on, Itility is able to start growing towards the fourth level, for which the use of a service catalog can play a huge role.
8.2 Automated catalog management tool

In the previous section a complete overview of the structure of the processes to deliver the value-in-use was obtained through the process models designed in Bizagi. This section continues by incorporating this complete overview into the Automated Catalog Management Tool (ACMT) that can automatically generate service compositions for Itility. This tool is established in Microsoft access by Tufan (2016) in a case study with the BASE/X framework for the creation of a similar type of service composition generation.

Since the service catalog layer of the BASE/X framework is part of the confrontation of means and the tactical design loop (Figure 18), two inputs are needed for the automated service composition generation. According to the tactical design loop, the business model layer should provide the business model that needs to be serviced. In addition, the business service layer should provide all the business services needed to fulfill the value-in-use of that business model. In the Bizagi model in Figure 33, already a general service composition was formed to deliver seamless business optimization to the customer. Within this service composition another composition of BBSs is needed to define the sub process of “validate hypotheses” (Figure 32), which is different for every data segment. This means that there are two types of compositions needed for Itility to deliver the value-in-use to their customers. For this reason, also two ACMT’s are designed. The first one for the customer facing service composition to deliver the value-in-use to the customer, titled Service Composition ACMT. This ACMT should typically be managed by a business engineer, who recognizes the needs for the client and is able to translate these needs into the right Big Data analytics techniques for Itility. The second one automates the BBSs composition to deliver the customer facing services, titled BBSs ACMT. This ACMT should typically be managed by a data scientist, who is able to perform the Big Data analytics techniques that are provided by the business engineer. Note that one person could have both the business engineer and the data scientist role.

Data model

For understanding and creating a service catalog, it is first needed to have an overview of all data elements and how these element are connected to each other. For this reason, a data model for the service catalog database, designed according to the BASE/X principles by Tufan (2016), is provided in Figure 36. This data model provides the structure of the business services and related entities, such as business domain, service provider, and service composition.
The entities business service and business service domain are already explained and applied to the scope of this research in Table 5 and Table 4. Respectively, they represent the modular pieces of customer-facing functionality and a group of business services to improve the structure of the service catalog.

The entity resources represents the resources needed to perform the business services. These resources can either be materialistic, such as money or machines, or they can be human resources, such as knowledge and skills. Within the scope of this research, these resources include the infrastructure and analytics toolset, which are both provided by a core partner, and labor.

The service provider is only the analytics team of Itility, as the team members are validating the hypotheses. It the case of Itility it is not needed to add any of the core service providers since they only deliver infrastructural value to Itility and not directly to the customer. The domain expert already used his expertise to set up the hypotheses and will come into play again after Itility has validated or rejected these hypotheses.

A service composition has already been defined in section 7.3.4 and represents the set of business services that is needed to deliver the value-in-use of a business model.

The business actor entity represents all the actors that can participate in a business service. This includes actors who perform the business service, who is the customer, and who is the beneficiary.
8.2.1 Service Composition Automated Catalog Management Tool

The Service Composition ACMT to create a composition of the customer facing services is applied first to Itility. This tool serves as a database which includes all the relevant information needed to create the service composition. For this prototype, the information that is identified in this research project is included, such as business services, business domains, and actors. For Itility it is of course possible to add and edit the information.

When starting the tool, a main menu opens in which the user can choose the operations that he wants to perform, see Figure 37. Below an explanation of these operations is given. Screenshots of the operations are depicted in Appendix 7.

![Figure 37: Main menu of the Service Composition ACMT](image)

- Services: the user can add and edit the customer facing services here. For this prototype, all customer facing services as depicted in Figure 27 are included.
- Business domains: the user can add and edit the business domains here. For this prototype, all business domains from Figure 22 are included.
- Actors: the user can add and edit the relevant actors here. For this prototype, the customer, the Itility analytics team, “another Itility department”, and the core service providers are included.
- Resources: the user can add and edit the resources here. For this prototype, labor, Splunk Enterprise, and Microsoft Azure cloud storage are included.
- Service Providers: the user can add and edit the service providers here. For this prototype, Itility, “another Itility department”, domain expert, and the customer itself are included as they are the actors that directly contribute to the value-in-use creation.
- Service Composition: the user can add and edit service compositions here. For this prototype, the four service compositions from the customer segmentation in Table 6 are included. The selected service composition can be exported to an excel sheet.
- Service Catalog: this operation provides the user with a full overview of the services per business domain.

- Compositions per service: provides an overview in how many service compositions a particular service is included. This could be more than one since the services should be reusable.

- Exit database: the user can close the database by this operation.

When all the needed information is stored in the upper five operations accessible from the main menu, the service catalog is automatically generated. From this point, Itility is able to define a value-in-use and select the needed services from the catalog to deliver this value-in-use. This set of services can then be exported to an excel sheet and represent the service composition without control flow to fulfill the value-in-use.

8.2.2 BBSs Automated Catalog Management Tool

Second, the BBSs ACMT to create a composition of the BBSs is applied to Itility. This tool serves as a database which includes all the relevant information needed to create the BBSs composition to perform the customer facing services which are specified in the first ACMT. The BBSs ACMT is similar in structure and interfaces throughout the tool, but differs in content which correspond to a different nature of operations as a BBSs composition must be made instead of a service composition. The main menu for the BBSs ACMT is provided in Figure 38.

![Figure 38: Main menu of the BBSs ACMT](image)

In a similar fashion to the service composition ACMT, in this tool the BBSs composition, without control flow, to deliver a customer-facing services can be extracted. One important difference is that the form for defining BBSs is slightly different as it must specify whether it is a level 1 or level 2 BBS and the reusable functionality should be included here, see Appendix 8.
8.2.3 Combining the ACMT’s

When the needed information is added in both tools, Itility is able to compose the compositions to increase the agility in Big Data analytics. Firstly, as described in Section 8.2, the business engineer recognizes the needs of the customer and determines to which business model the customer belongs. The business engineer can now combine the customer-facing services that are needed to fulfill the business model into a service composition using the service composition ACTM.

This service composition should be forwarded to the data scientist (could be the same person), who then knows which customer facing services need to be performed. In line with the scope of this research, the example continues with the customer facing service “validate hypotheses”. The data scientist can now use the BBSs ACTM to create the BBSs composition of level 1 BBSs (e.g. in Figure 32) that is able to perform the hypotheses validation. In addition, the same catalog can be used to find the level 2 BBSs (e.g. “Train decision tree model”) which the data scientist can perform himself to deliver the level 1 BBSs. The data scientist can simply use the queries, code snippets, and/or instructions that are provided along the level 2 BBSs and does not need to design or search for new solutions.

8.2.4 Compact Automated Catalog Management Tool user manual

As the ACMT is a new tool for Itility, guidance is needed to make the users understand how the tool works and which actions they are able to take. This is an essential step for exploiting the benefits of using the ACMT and will ensure that the service catalog is produced and managed in a standardized way. As explained by Tufan (2016), the ACMT has 4 main roles. These are the business strategist, catalog manager, service owner, and business service designer. A compact user manual is provided divided over the four different roles.

**Service catalog manager**

The service catalog manager is responsible for maintaining the consistency and performance of the service catalog. This role should ensure that all the services are of the right granularity according to the criteria of Table 3, and that all business domains and business services are respectively specified in the templates of Table 4 and Table 5. Together with the business strategist, the alignment between the service catalog and the strategy of Itility should be maintained. This could trigger the need for new services or the removal of services. Additionally, this role should assure that every service has a service owner.
**Business strategist**
The business strategist is responsible for aligning the business strategy with the organizational capabilities. In line with the strategic design loop in Figure 18, this implies that the business strategist should control that the strategy is well represented by the business services needed to execute this strategy. Together with the service catalog manager, the alignment between the service catalog and the strategy of Itility should be maintained.

**Service Owner**
The service owner is responsible for the availability, performance and quality of a set of business services. A service owner must keep the service catalog manager up-to-date about the services he is responsible for. In addition, this role is the point of contact for anyone needing help to perform a service.

**Business service designer**
The business service designer is responsible for designing or redesigning business services and to create service compositions. In order for the services to get included in the service catalog, the service designer must create these services according to the standards handled by the service catalog manager. For the creation of service compositions two inputs are required: the business model with corresponding value-in-use and the service catalog in which the services to serve that particular business model are stored. Possibly, the business service designer could add the control flow manually, which is not automatically provided by the ACMT.

### 8.2.5 Validation

Unfortunately there has been no time in this research to validate the use of the ACMT’s at Itility since the ACMT tooling was only received less than two weeks from the end of this research. But while working with the ACMT’s, it quickly became clear that there is one factor that would hold back the agility for Itility of delivering a solution, which is that only compositions without control flow can be generated. It makes sense that it is easier to work with a composition with control flow (Figure 28) than a service composition without (Figure 29). This way the analytics team members would still need to puzzle in which order to perform the BBSs. Also, the need for using two separate ACTM’s is considered devious, but it is not able get the required functionality from just one of them. However, the catalog function does provide a complete overview of all the business services and could be used solely for that purpose to find the needed level 2 BBSs which include the reusable pieces of code, queries and relevant information.
9. Results
In this chapter, the results of this research are provided, divided over the research questions. All included statements directly follow from Chapter 4 to 8. The combination of these conclusions answers the problem statement.

9.1 Research question 1
- What effect does the usage of a service catalog have on agility in Big Data analytics?

In Chapter 4, first the concepts of Big Data and agility were defined as background information for this research question. Big Data can include valuable information for business optimization by improved decision making, whereas agility implies the sense and response capabilities of an organization to react on changes. When combining these two elements it can be stated that by increasing agility in Big Data analytics, an organization will be able to deliver valuable information extracted from different types of data faster to their customers. As stated in 4.4.1, the usage of a catalog can contribute to this increase of agility by creating a systematic overview of all possible actions in combination with the characteristics of SOA. Loose coupling minimizes the effort to add or remove services from a catalog, reusability enables reusing the same services for multiple solutions, and interoperability enables the ability to use services that are designed by another actor. In addition to agility, also efficiency and governance can be increased by using a service catalog.

Looking at the challenges, a significant time effort is needed to create a service catalog whereby the above mentioned positive effects on agility can actually be reached. If not designed and maintained correctly, the service catalog will only cost time, leading to lower agility.

9.2 Research question 2
- How can Itility use a service catalog to increase agility in Big Data analytics?

From the analysis of the AS-IS situation at Itility in Chapters 5-6, it can be concluded that Itility already takes actions to deliver the value extracted from Big Data faster to their customers, but that there is still room for improvement as it is sometimes contradicting with the high quality that Itility aims to deliver.

A service catalog would provide a systematic overview of all possible Big Data analytics techniques, which decreases the amount of time needed to develop or search for new analytics techniques. By having modular business services (analytics techniques), knowledge management is encouraged to stimulate the reusability of previously developed services in the creation of new
solutions. This would for example solve the need for multiple team members performing the same deep-dive, which is currently the case since they all have different Big Data analytics capabilities.

In addition, from the mapping on the Capability Maturity Model (CMM) it became clear that Itility does not have a standardized process for extracting value from data. Even though this was initially done by choice, it is getting more important for Itility to create these processes to control the growth of the analytics team and ensure that all team members can deliver solutions of desired quality. A service catalog can solve this problem by enabling Itility to create agile executable chains of standardized analytics techniques. By doing so, Itility can climb to the third maturity level of the CMM where new focus points for improving agility can be identified.

Similar to the conclusion of research question 1, the benefits of the service catalog can only be realized if it is managed properly.

9.3 Research question 3

- How can a service catalog be implemented at Itility?

Before the implementation, first a service catalog is designed for Itility according to the guidelines of the BASE/X framework (Grefen et al., 2013). According to this service-dominant business framework, a service catalog is designed including all the customer facing business services that Itility needs to be able to perform to fulfill the overall service-dominant strategy of the analytics team. In line with the scope of this research, the business service “Validate hypotheses” is worked out in more detail and its modular building block services (BBSs) are provided in two levels. The first level includes the BBSs needed to perform the customer-facing services, where the second level represent the modular and standardized building blocks including for example reusable code snippets. By modelling the value-in-use delivery process on multiple aggregation levels, Itility can fulfill the “defined process” criteria to grow to the third level of the CMM (Figure 14). From here, Itility can look forward to growing towards the fourth level, for which the design of a service catalog can help.

The service catalog has been created in two separate Automated Catalog Management Tools (ACMT). The first one is for the business engineer to define which customer-facing services should be combined to serve a customer. The second one supports the data scientist to select the right BBSs to deliver the customer-facing services which were provided by the business engineer.
Similar to the results of the first and second research questions, the benefits can only be extracted from the service catalog if it is managed correctly. For this reason, a compact user guide on how to work with the ACMT and how to keep the service catalog up to date is provided for each of the relevant roles.

Unfortunately the tool is not tested at Itility due to time constraints. Still, it could already be concluded that the use of this tool would be a bit devious, as it can only create service compositions without control flow. Looking beyond the compositions, the overview of all modular level 2 BBSs including reusable functionality for performing the level 1 BBSs can be helpful for the analytics team members and decrease the time they need to spend developing their own BBSs.

9.4 Additional result
The scope of this research project was to increase the agility in performing Big Data analytics, for which a service catalog has been made. During this research project however, all the layers of the BASE/X framework have been designed with a wider scope as well. This enables Itility to easily identify business services other than “Validate hypotheses” for which a similar type of service catalog can be beneficial by providing a systematic overview of modular BBSs. By doing so, Itility can increase its agility throughout the whole Itility Big Data value chain (Figure 13).

9.5 Problem statement
“What is the effect of the usage of a service catalog with standardized service components on the agility in Big Data analytics and how can such a catalog be implemented at Itility?”

The effect of the usage of a service catalog with standardized service components on the agility in Big Data analytics is theoretically supported through reusability, interoperability and loose coupling of services. It enables the analytics team members to share their knowledge and to reuse this knowledge into multiple solutions. This saves time in designing new solutions or searching for new ones. What could not be done in this thesis is to quantify this increase in agility. First of all since no data from Itility or literature is available on the current time spending, and secondly, because the solution of the service catalog is not tested at Itility due to time constraints. For the implementation of the solution design the ACMT was used (Tufan, 2016) in which a service catalog can be build which enables Itility to build service compositions and BBSs compositions to deliver the value to the client. This implementation has not been validated due to time constraints though and therefore no further solid conclusions can be stated.
10. Recommendations
Throughout this research project and based on literature, it has become clear that the usage of a service catalog can increase the agility in Big Data analytics at Itility. For this reason, the general recommendation is to start using a service catalog. During this research project, the BASE/X framework has been applied to Itility and a prototype has been created for the implementation of a service catalog. As the prototype has some drawbacks that negatively affect agility, it is recommended to find or develop another tool for using a service catalog. This section provides additional recommendations for developing and maintaining the service catalog based on the four interactions between the BASE/X layers from Figure 18.

10.1 Strategic design loop
For the alignment between the identity and the capabilities of Itility, the following is recommended:

1. All the team members of the analytics team should be aware of the service-dominant business strategy in order to align their actions accordingly. The service-dominant strategy canvas in Figure 21 can support in communicating the business strategy.

2. The core capabilities should be well defined for deciding which capabilities should be performed by Itility itself and which capabilities should be outsourced. The matrix from Figure 23 can support Itility to do so.

3. Itility should appoint a business strategist, ensuring that the service catalog matches the long-term strategy and that services are included in a standardized and modular fashion. This manages complexity by being able to assemble complex solutions from standardized modules.

10.2 Tactic design loop
Recommendations for the alignment between the market offerings and market demands of Itility:

1. Itility should create a customized customer eco-cycle for every customer including all interactions and needs from the client in order to be able to compose the best fitting service composition to fulfill their needs.

2. Itility should appoint a business service designer, who is able to translate business requirements into a service definition.

3. The team members of the analytics team should be trained to work with the catalog. This is needed to learn how the right service composition can be composed to fulfill the value-in-use for the customers.
10.3 Alignment of means
Recommendations for the alignment between the required and available capabilities of Itility:

1. Itility should appoint a service catalog manager for maintaining the consistency, performance and right granularity of the services in the catalog. This enables Itility to easily compose service compositions.

2. Itility should appoint services owners to the services in the catalog. This enables the users of the catalog to ask question or feedback directly from the right person.

10.4 Alignment of goals
Recommendations for the alignment between the identity and the market offerings of Itility:

1. Itility should appoint a business strategist, ensuring that the business models that are being offered are in line with the strategy and that no business models are lacking.
11. Conclusion

This chapter concludes the main results and provides an overview of the added value for different stakeholders. In addition, an overview of the limitations of this research project are given.

11.1 Conclusion on results

At first a literature review verified that increasing agility in Big Data analytics is a relevant subject to research since today’s world is highly dynamic and for organizations to survive, it is needed to make decisions faster and of better quality (Bharadwaj et al., 2016). As one of the main benefits of using Big Data has been identified as decision support by making decisions faster and based on (more) accurate information (Rouhani, 2015), this indeed is a relevant subject to research. Also, literature showed that the use of a service catalog comes with opportunities to improve agility by enabling for example loose coupling of services, interoperability, and reusability of services (Sarna & Herdiyanti, 2016).

These theoretically supported benefits for using a service catalog for increasing agility have been researched in a case study at the IT engineering office Itility, which uses Big Data to optimize the operations of their high-tech clients. After a thorough analysis of the AS-IS situation at Itility it was concluded that there is one issue that prevents increasing their agility at this moment. This issue is that there are no standardized processes for performing analytics. Even though this is done intentionally to provide all the team members with freedom to perform analytics, it places Itility on the second level of the CMM (Figure 14).

The service-dominant business design framework BASE/X (Grefen et al., 2013) has been applied to improve the agility in analytics. The framework seemed to have a good structure to establish a service-dominant mindset by focusing completely on creating the value-in-use for the customer, and not on the underlying assets needed for the creation. A strategy around this value-in-use was formed after which de customer-facing services that are needed to perform the strategy have been defined with the help of the customer experience eco-cycle (Figure 20). By breaking down these business services into the right granularity, Itility is enabled to deal with the complexity of providing solutions by simply assembling them from the business service catalog.

These solutions are represented by service compositions which are designed to fulfill a specific value-in-use, which is the case of Itility is determined by the type of Value that needs to be extracted and the Variety of the data as described in Table 8. For reaching the right granularity for
standardization in these service compositions, the customer facing services are specified in two more layers on a lower aggregation level. Firstly, the Building Block Services (BBSs) level 1 which is needed to assemble the customer facing service. Secondly, the BBSs level 2 which is needed to assemble the BBSs of level 1.

These three aggregation levels are modelled in Bizagi and provides Itility with a clear overview of the structure on how they can assemble the right elements to create the right service composition to deliver de value-in-use for a business model. This is exactly what was needed for Itility to grow to the third level of the CMM and reach a higher process efficiency.

Lastly, these Bizagi models are incorporated into the Automated Catalog Management Tool (ACMT) to automatically generate service compositions for Itility. As there were three aggregation levels for the creation of services, two separate catalogs needed to be designed. The first catalog creates a service composition on the customer-facing services level. The second catalog uses this service composition to create the BBSs composition on the second level and to find the needed standardized building blocks to perform the customer facing service on the third level.

The prototyping of the ACMT is in a very early stage as the tool was obtained during the final phase of this research project. This means that there hasn’t been time to test this prototype at Itility. The results of the prototypes designed in this research however, do provide insights on how a service (or BBSs) composition can be established if the right information is stored in a database. The tool itself is limited in functionality that Itility eventually wants to achieve, as the tool can only provide a composition without control flow. With these type of compositions you are in a similar situation as where you have all the parts to build an Ikea closet, but you don’t have the manual that shows you which parts to assemble first. In such a situation you don’t know where to start. Therefore, the usability of the ACMT for Itility can be questioned, definitely since during the process, multiple of these situations have to be faced. At least one time for creating the control flow in the customer facing services and subsequently, at least one time for creating the BBSs flow for all BBSs separately. An improvement to the ACMT or an additional tool is needed to support the analytics team to create this control flow, since it harms the agility in which Itility operates.

Concluding the above, the usage of a service catalog to increase agility in Big Data analytics is relevant and can indeed increase the agility by breaking down the services into standardized and reusable modules. In this research a solution is designed according the BASE/X framework. The
implementation of the ACMT however, is still in a very early phase, as there was no suitable tooling available in an earlier stage of this research and it is too time consuming within the scope of this research to create a new tool for this issue.

11.2 Contributions
First of all a contribution to literature has been made by applying a service catalog in a new business domain of Big Data analytics. This research proved that it is suitable to apply a service catalog in this domain since the activities that need to be perform can be broken down into standardized and reusable BBSs, represented by for example code snippets, queries, or clear instructions.

Second, a contribution has been made to the service-dominant BASE/X framework by showing that it is able to increase agility in the Big Data analytics domain. The BASE/X approach supports Itility to think in terms of value-in-use of their services and enables agility through enabling the composition of the previously mentioned standardized modules. Also, a new element has been added to the BASE/X framework, which is the Customer Experience Eco-cycle in Figure 20. As the experience of the customer is established during every contact moment between Itility and its customers, the customer experience journey has been mapped to identify all these contact moments. For Itility it was specifically termed as an eco-cycle, as their focus is on finding new opportunities to create more business value at their current customers. Subsequently, these contact moments have been included into the “Interactions” element in the service-dominant strategy canvas in Figure 21.

Thirdly, this research provides business value to Itility by providing insights on how agility can be increased and by providing a thorough analysis of the AS-IS situation in Big Data analytics. Firstly, a top-down approach for modelling their business processes is presented which can be used by Itility to define their processes and grow to the third maturity level of the CMM in Figure 14. This top-down approach starts by modelling the customer facing services and break these down into two lower aggregation levels of BBSs which have the right granularity for standardization and reusability. By also providing templates on how to standardize the documentation of the service (or BBSs) descriptions, Itility is able to create a complete overview of all business capabilities. Subsequently, these capabilities can be incorporated into the ACTM to have a complete database with all capabilities. This ACTM allows a dynamic service design for Itility through a flexible composition of reusable service modules in order to deliver the needed value-in-use for every business model or to create new business models. Finally, the user manual of the ACTM provides
Itility with the most essential insights for managing the service catalog by explaining actions that the different user roles need to take.

11.3 Reflection
If the same research project was needed to be performed once again, some points for improvement have been identified during this project. First of all, it would be better if less time is committed to support operations of Itility that are not directly linked with this master thesis project. Especially in the first 1.5 month too much time was spend on performing the Big Data analytics myself and throughout the research project at least one per week was spend on activities for Itility that were not related to this research project. Secondly, the research should’ve been performed more directly towards the scope, since some models have been created on a higher aggregation level to provide Itility with the opportunity to more easily extend the service catalog to other business services than “Validate hypotheses”. Thirdly, and in the researchers’ opinion most importantly, the right tooling for creating a service catalog should be obtained earlier than in the last two weeks of the research project. After knowing that the tool was going to be available, there has been too much delay in receiving access to it. Even though all the input for the tooling was already designed, it is time consuming to incorporate it into the tool and it left no time for user-testing at Itility which harms the quality of the recommendations that can be made. Therefore it would have been better to define the tooling at an earlier stage in the research project.

11.4 Limitations
The limitations of this research project are mainly related to the tooling of this project. Since BASE/X is a relatively new framework, no suitable tooling for creating a service catalog with capabilities of composing a services composition was available. When the tool that is used in this research project became available and it was decided to use this tool, the retrieval of the tool was delayed until approximately two weeks before the end of this research project. This greatly limited the possibilities to incorporate all the business services of Itility in the tool and made it impossible to test this tool at Itility for feedback. Within the time-constraints of this research project, it would not have been feasible to design a completely new tool for this.
References


### Appendix 1: Overview variety in Big Data analytics techniques

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*Table 10: Overview of Big Data analytics techniques (Klooster, 2016)*

Table 10 provides an overview of a variety (but definitely not all) of Big Data analytics techniques as found by Klooster (2016).
### Appendix 2: Big Data actions Catalog

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<td><strong>Methods</strong></td>
<td><strong>Techniques</strong></td>
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<td>Automated physical Data Vault design (Kmeta et al., 2014)</td>
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*Table 12: Agile BI actions catalog (Krawatzeck & Dinter, 2015)*

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<table>
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<th>Level 1</th>
<th>Level 2</th>
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<td><strong>Principles</strong></td>
<td><strong>Methods</strong></td>
<td><strong>Techniques</strong></td>
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*Table 11: Agile BI actions selection guide (Krawatzeck & Dinter, 2015)*
Appendix 3: Itility Big Data toolset

In Figure 39 an overview is given of all the tools that Itility is able to use to ingest, store, query, and visualize data. This extensive toolset enables Itility to always choose the right tools to provide value to the customer. The selection of the right tool depends on the criteria depicted in Figure 40. Also the preferences of the customer are taken into account, since it is for example possible that the customer has experience with some of the tools or that it fits better to their current infrastructure.

In addition, the tools from Table 13 are used by the analytics team for identifying data structure, performing statistical analysis, writing algorithms, and business process mining.

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<thead>
<tr>
<th>Tool(s)</th>
<th>Main purpose</th>
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<tbody>
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<td>Excel &amp; Notepad</td>
<td>Identify the data structure before uploading in Splunk Enterprise</td>
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<tr>
<td>R &amp; Rapidminer</td>
<td>Perform statistical analysis, machine learning techniques/algorithms such as decision trees, neural networks, and random forest</td>
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<tr>
<td>Python</td>
<td>Write customized algorithms</td>
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<tr>
<td>Disco</td>
<td>Business process mining</td>
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*Table 13: Tools that Itility uses for Big Data analytics*
Appendix 4: Semi-structured interviews on current way of working

Goal
For making a thorough analysis the current way of working of the analytics team at Itility, detailed information is needed on how team members extract hypotheses to validate with the customer from a new data set, which is exactly in the scope of this research project. It includes the steps that are taken, performed analytical techniques, and used tools. To get this information, semi-structured interviews have been conducted with each team member of the analytics team at Itility individually.

Setup interview
Between the 22nd and 29th of April, eight members of the analytics team have been interviewed. At first, a short introduction about the interview is given to help the interviewee understand the goal of the interview. Next, the interviewees are asked for permission to record the interview and to include it in this research project. The questions asked including the goal of these questions are provided in Table 14.

Results
The result of the semi-structured interviews, provided the needed insights for the analysis of the current way of working at Itility. The steps that the individual members of the analytics team take to extract value from data, are given in Figure 42 to Figure 49. When comparing these figures, it becomes clear that the members of the analytics team are not performing analytics in a structured manner. This can be concluded due to the fact that all the members perform different steps in a different order and it also means that there is quite a variety between the capabilities of the team members. In Figure 50, a summary of additional performed steps, used templates, desired templates, and most consuming steps are given. Combined with the steps from the 8 individual models, this figure includes all the modular Big Data analytics techniques that Itility is capable of at this moment, which serves as input for the creation of the service catalog for Big Data analytics. In addition, Figure 50 provides insights in what kind of standardized templates can support the analytics team and it shows the most time consuming tasks in which standardizing can potentially increase agility the most.
<table>
<thead>
<tr>
<th>Question</th>
<th>Goal</th>
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| 1. Have you performed deep-dives while working at Itility and is there one that you can remember well in particular? | - Get insights in how many times the interviewee performed a deep-dive.  
- Bring up one deep-dive that can be worked out in more detail during the next question. |
| 2. Could you guide me step by step through the steps that you took to extract hypotheses with potential business value from the data set? | - Get an overview of the steps that the analytics team needs to take in order to extract hypotheses from new data.  
- The interviewee was asked to write down their steps in the template from Figure 41 |
| 3. Which tools did you use for each step?                               | - Get an overview of the tools that are used by the analytics team.  
- The interviewee was asked to add these tools to the corresponding steps in the template. |
| 4. Have you performed different steps or used different tools in other deep-dives? (The interviewee was given some examples if they couldn’t think of any themselves) | - Find additional steps/tools used to extract hypotheses from new data. |
| 5. Have you used any predefined models (e.g. scripts/queries/dashboards) during deep-dives?   | - Get an overview of predefined models that could potentially be included in the services catalog. |
| 6. Are there any predefined models that you would like to use?           | - Get ideas of what kind of predefined models an support the analytics team. |
| 7. Which steps in steps that you’ve drawn on the template are most time consuming? | - Get an overview of steps that consume most time and which might thus have more potential for increasing agility. |
| 8. In which steps do you see the highest potential for speeding up the execution? | - Get insights in which steps are least efficient at the moment. |

*Table 14: Questions from the Interview*
Receive Data Set

Formulate Hypotheses

---

**Figure 41: Template for writing down deep-dive steps**

- **Obtain raw data**
  - Team member 1: Search for variables (with info domain expert) using Splunk
  - Team member 1: Understand data
  - Team member 1: Categorize data
  - Team member 2: Visualize in tables
  - Team member 1: Visualize per variable/category
  - Team member 1: Formulate Hypotheses

**Figure 42: deep-dive process of team member 1**

- **Obtain raw data**
  - Team member 2: Clean Raw Data
  - Team member 2: Thorough Prescriptive Analysis using Rapidminer, R
  - Team member 2: Make distinction actionable (deep-dive requirements)
  - Team member 2: Statistical Analysis using Splunk
  - Team member 2: Test for information requirement using Splunk
  - Team member 2: Dashboard
  - Team member 2: Formulate Hypotheses

**Figure 43: deep-dive process of team member 2**

- **Obtain raw data**
  - Team member 2: Extract understanding of data over time using Rapidminer, R
  - Team member 4: Analyze rows, columns, dimensions using Splunk
  - Team member 2: Searchable table: Rapidminer for quick prototyping
  - Team member 2: Formulate Hypotheses using Splunk
Figure 44: deep-dive process of team member 3

Figure 45: deep-dive process of team member 4

Figure 46: deep-dive process of team member 5
Figure 47: deep-dive process of team member 6

Figure 48: deep-dive process of team member 7

Figure 49: deep-dive process of team member 8
### Summary of used templates, desired templates, additional performed steps, and the most time consuming steps

<table>
<thead>
<tr>
<th>Used Templates</th>
<th>Desired Templates</th>
<th>Other Used Techniques</th>
<th>Most Time Consuming</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Dashboards</td>
<td>&quot;Datased&quot; (set boundaries for data types)</td>
<td>(TM) Sentiment Analysis</td>
<td>Searches in Splunk</td>
</tr>
<tr>
<td>Splunk</td>
<td>Anomaly Detection</td>
<td>(TM) Word Correlation (e.g. for errors)</td>
<td>Make results understandable for Client</td>
</tr>
<tr>
<td></td>
<td></td>
<td>R</td>
<td></td>
</tr>
<tr>
<td>App for debugging data collection</td>
<td>Check for Data Completeness</td>
<td>(PM) Identify throughput, opening time, utilization</td>
<td>Check for completeness of Data</td>
</tr>
<tr>
<td></td>
<td>Searches in Splunk</td>
<td>Disco</td>
<td>Vizualise fields (separate and combined)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(TM) some R scripts, not generic enough at the moment</td>
<td>Standard Statistics</td>
<td>Determine Correlations</td>
<td></td>
</tr>
<tr>
<td>XG boost</td>
<td>Specify format of every log file separately to create TA's</td>
<td>(TM) TIDIF</td>
<td></td>
</tr>
<tr>
<td></td>
<td>For Data Gathering</td>
<td>(PM) IT guardian Ease</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Teems</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Disco</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(ML) feature Importance</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>R</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(TM) n-grams</td>
<td>Correlation Matrix (R)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(ML) Factor Analysis (R)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(TM) Sentiment Analysis</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure 50: Summary of the answers to questions 4, 5, 6, and 7.**

For Figure 50, the abbreviations mean the following: TM = Text mining, PM = Process mining, ML = Machine learning. In addition, the specific tool that is used for an element is stated in blue.
Appendix 5: Service-dominant strategy canvas workshop

Goal
The service-dominant strategy canvas workshop was organized to gather information for answering the questions as depicted in the service-dominant strategy canvas in Figure 19. With this information, the service-dominant strategy for the analytics team of Itility is defined.

Setup workshop
The workshop took place on the 26th of May and was attended by nine members of the analytics team and Paul Grefen, the first supervisor of this research project. During the meeting, first a general refresher on the importance of strategy was given. Subsequently, the attendees were introduced to the concept and all elements of the service-dominant strategy canvas. After the introduction, the attendees were divided into two groups to brainstorm on how the service-dominant strategy can be defined for the analytics team of Itility.

Results
The results of the brainstorm of both groups are given in Figure 51. Even though it was difficult for both groups to define the strategy for the long-term instead of short-term, the results provided insights that supported the design of the service-dominant strategy canvas, see Table 15.

<table>
<thead>
<tr>
<th>#</th>
<th>From team</th>
<th>Insight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1 &amp; 2</td>
<td>Customers are medium or large sized companies that collect data</td>
</tr>
<tr>
<td>2</td>
<td>1 &amp; 2</td>
<td>The experience delivery should be fast and seamless, by relieving the customer as much as possible</td>
</tr>
<tr>
<td>3</td>
<td>1 &amp; 2</td>
<td>The actual value delivery itself (e.g. dashboards and alerts) are also interactions</td>
</tr>
<tr>
<td>4</td>
<td>1 &amp; 2</td>
<td>An analytics toolset provider and an IaaS provider should be included as core partner</td>
</tr>
<tr>
<td>5</td>
<td>1 &amp; 2</td>
<td>Data analytics is a core service</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>The service software provider should be included as a partner (Zendesk as stated by 1)</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>Relations with core partners should be short term and against a variable rate to be flexible</td>
</tr>
<tr>
<td>8</td>
<td>2</td>
<td>Support should be a core service, as it contributes to creating a seamless experience</td>
</tr>
</tbody>
</table>

Table 15: Insights gained from the workshop

That is was difficult for the groups to define a long-term strategy becomes clear when noticing that both of the results predominantly consist out of the current partners and activities. In addition to this workshop, multiple feedback sessions contributed to creating the final service-dominant strategy canvas from Figure 21.
Figure 51: Results of service-dominant strategy workshop (team 1: left, team 2: right)
Appendix 6 – Mapping of Business Services on the Business strategy.

As explained in section 7.2, an organization should be able to execute its service-dominant strategy through the business services as defined the corresponding layer. For this reason, a mapping between has been made to verify if the set of business services can perform all the elements of the service-dominant strategy canvas, see Table 16. From the mapping, it can be concluded that this indeed is the case.

<table>
<thead>
<tr>
<th>Business Domain</th>
<th>Business Services</th>
<th>Mapping from strategy canvas element</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profiling</td>
<td>1. Customer profiling</td>
<td>1. Core service → profiling &amp; Interactions → profiling</td>
</tr>
<tr>
<td></td>
<td>2. Collect data</td>
<td>2. Interactions → data collection</td>
</tr>
<tr>
<td></td>
<td>3. Define business rules</td>
<td>3. Interactions → business rule definition</td>
</tr>
<tr>
<td></td>
<td>4. Validate Hypotheses</td>
<td>4. Interactions → validation hypotheses</td>
</tr>
<tr>
<td></td>
<td>5. Validate PoC</td>
<td>5. Interactions → validation PoC</td>
</tr>
<tr>
<td>Data analysis</td>
<td>1. Validate hypotheses</td>
<td>1. Core service → data (pre-) processing</td>
</tr>
<tr>
<td></td>
<td>2. Create Proof of Concept (PoC)</td>
<td>2. Core service → data (pre-) processing</td>
</tr>
<tr>
<td></td>
<td>3. Provide Data Science on-site</td>
<td>3. Enriching service → Data Science on-site</td>
</tr>
<tr>
<td>Provide Infrastructure</td>
<td>1. Provide IMAP environment</td>
<td>Both business services belong to: Core service → IaaS</td>
</tr>
<tr>
<td></td>
<td>2. Provide sandbox</td>
<td></td>
</tr>
<tr>
<td>Reporting</td>
<td>1. Create dashboard</td>
<td>All four business services belong to: Core service → visualization</td>
</tr>
<tr>
<td></td>
<td>2. Create alert</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. Create report</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4. Create presentation</td>
<td></td>
</tr>
<tr>
<td>Support</td>
<td>1. Handle Incidents</td>
<td>1. Core service → support</td>
</tr>
<tr>
<td></td>
<td>2. Handle Changes</td>
<td>2. Core service → support</td>
</tr>
<tr>
<td></td>
<td>3. Handle Questions</td>
<td>3. Core service → support</td>
</tr>
<tr>
<td></td>
<td>4. Provide Data Science training</td>
<td>4. Enriching service → Data Science training</td>
</tr>
<tr>
<td></td>
<td>5. Provide desired state management</td>
<td>5. Enriching service → Desired state management</td>
</tr>
</tbody>
</table>

Table 16: Mapping of the business services of the analytics team on the Strategy canvas

When there would be business services in the services catalog that do not match with the strategy, either these services need to be removed or the strategy should be widened in order to include these business services. When business services for an element in the strategy would be lacking, either these business services should be added to the catalog or the strategy should be narrowed down to remove the need for this business service.
Appendix 7 – overview of operations in the Automated Catalog Management Tool

In this appendix, examples of operations are provided which the users can perform in the Automated Catalog Management Tool as described in Section 8.2.1.

![Figure 52: Service Composition ACMT - Business service definition for "Validate Hypotheses"](image1)

![Figure 53: Service Composition ACMT - Business service definition for "Validate Hypotheses"](image2)

![Figure 52: Service Composition ACMT - Service domain definition for "Data analysis"](image3)

![Figure 53: Service Composition ACMT - Service domain definition for "Data analysis"](image4)
Figure 56: Service Composition ACMT - Actor definition for "Itility Analytics Team"

Figure 55: Service Composition ACMT - Resource definition for "Labor"

Figure 54: Service Composition ACMT - Service provider definition for "Itility Analytics Team"
Figure 57: Service Composition ACMT - Service Composition definition for “Seamless”

Figure 58: Service Composition ACMT - Compositions per service for “Validate Hypotheses”
Appendix 8 - overview of BBSs form in the BSs ACMT

### Building Block Services (BBSs)

<table>
<thead>
<tr>
<th>BBSs Specification</th>
<th>Train Decision Tree model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer-facing Service</td>
<td>Validate Hypotheses</td>
</tr>
<tr>
<td>Functionality</td>
<td>Train a decision tree machine learning model to retrieve predictions</td>
</tr>
<tr>
<td>Service Provider</td>
<td>Hility Analytics Team</td>
</tr>
<tr>
<td>Business Resources Used</td>
<td>Labor; Microsoft Azure Cloud Storage; Splunk analytics toolset</td>
</tr>
<tr>
<td>Actor Performing Service</td>
<td>Hility Analytics Team</td>
</tr>
<tr>
<td>Beneficiary of Service</td>
<td>Hility Analytics Team</td>
</tr>
<tr>
<td>Informed Actors</td>
<td>Hility Analytics Team</td>
</tr>
<tr>
<td>Code Snippet or Query</td>
<td>E.g. a code snippet to train the decision tree in R</td>
</tr>
<tr>
<td>If level 2: None creator + Instructions</td>
<td>Team member 1: Instructions on e.g. how to train the model and what do the outcomes mean</td>
</tr>
</tbody>
</table>

**Figure 59: BBSs ACMT – Level 2 BBS specification for "Train decision tree model"**