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COMPARING EXTERNAL DATA MONETIZATION OF TWO ANALYTICS PRODUCTS

Case study in the telecommunications industry

Master's Thesis
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Abstract of master's thesis

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Abstract

Monetizing growing amounts of company data is an intriguing idea for many practitioners. Data monetization becomes particularly relevant in industries where the traditional business is declining, pushing companies to seek new revenue sources to stay competitive. However, most companies still struggle with their data monetization efforts, implying a need to investigate the issues hindering data monetization potential and enablers driving success.

The novelty of the research field and its industry-specific nature suggest conducting explorative studies. This thesis examines the topic in the data-intensive telecommunication industry, focusing on identifying challenges and enablers related to external data monetization with analytics products in a case company. Two analytics products are compared based on expert interviews using a seven-step process framework for external data monetization. The process phases include 1) opportunity mapping and data strategy preparation, 2) potential planning and use case definition, 3) legal and compliance alignment, 4) data collection and preparation, 5) technological arrangements, 6) data pricing strategy and 7) market entrance planning.

The results show that the main challenges with analytics productization in a case company include data pricing for maximal profit accuracy, combining data sources and ensuring reliable results, as well as modeling, justifying and communicating customer value. Also, securing sufficient management's support and investments and balancing with constant organizational changes complicate analytics productization.

The analysis implies that enhancing market understanding by focusing on certain customer segments helps create more relevant use cases, ensure sufficient demand, and model customer perceived value. Moreover, measuring customer case and piloting success improves the customer value proposition's concreteness, further supporting pricing, marketing, and sales argumentation. Then again, treating data as an asset and investing in consistent data architecture and data management supports external data monetization with multiple data sources for reliable results and value. Finally, emphasizing education about external data monetization and analytics products will likely boost future initiatives' success.

The explorative case study results contribute to theory by using analytics product as an external data monetization offering and testing a practical process framework for academic purposes, similarly providing direction for further research and validation in other organizations and markets.

Keywords external data monetization, analytics productization, telecommunications

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Tiivistelmä

Yritysdatan kasvava määrä ja sen monetisointi on kiinnostava aihe monille yrityksille. Datan monetisointi on erityisen olennaista aloilla, joilla perinteinen liiketoiminta on laskussa, pakottaen yritykset etsimään uusia liikevaihdon lähteitä pysyäkseen kilpailukykyisinä. Useat yritykset kuitenkin painivat edelleen datan monetisointiyritysten kanssa, mikä viittaa tarpeeseen tutkia datan monetisointia haittaavia ja mahdollistavia tekijöitä.

Tutkimusalan uutuus ja aiheen toimialakohtainen luonne puoltavat eksploratiivista tutkimusmenetelmää. Tämä tutkielma tarkastelee aihetta dataintensiivisellä tietoliikennealalla, keskittyen analytiikkatuotteiden datan monetisoinnin haasteiden ja mahdollistavien tekijöiden tunnistamiseen tapausyrityksessä. Kahta analytiikkatuotetta vertaillaan asiantuntijahaastattelujen pohjalta käyttäen seitsenportaista ulospäin suuntautuvan datan monetisoinnin prosessiviitekehystä. Prosessivaiheet käsittävät 1) mahdollisuuksien kartoittamisen ja datastrategian valmistelun, 2) potentiaalin suunnittelun ja käyttötapauksen määrittelyn, 3) laillisuuden ja vaatimustenmukaisuuden linjauksen, 4) datan keräyksen ja valmistelun, 5) teknologiset järjestelyt, 6) datan hinnoittelustrategian ja 7) markkinoille tulon suunnittelun.

Tulokset osoittavat, että datan tarkka hinnoittelu, datalähteiden yhdistely, luotettavien tulosten varmistaminen, sekä asiakasarvon mallintaminen, perusteleminen ja viestiminen ovat suurimpia haasteita. Myös johdon tuen ja investointien varmistamisen haasteet sekä jatkuvat organisaatiomuutokset vaikeuttavat analytiikan tuotteistamista.

Analyysin perusteella markkinaymmärryksen lisääminen keskittymällä tiettyihin asiakassegmentteihin auttaa luomaan relevantimpia käyttötapauksia, varmistamaan riittävän kysynnän ja mallintamaan asiakkaan kokemaa arvoa. Lisäksi asiakastapausten ja pilotoinnin onnistumisen mittaaminen parantaa asiakasarvolupauksen konkreettisuutta, edesauttaen hinnoittelua, markkinointia ja myynnin argumentaatiota. Toisaalta datan käsittäminen omaisuutena sekä panostaminen johdonmukaiseen data-arkkitehtuuriin ja -hallintaan tukee monia datalähteitä hyödyntävän ulospäin suuntautuvan datan monetisoinnin tulosten luotettavuutta ja arvoa. Myös koulutuksen lisääminen todennäköisesti edesauttaa tulevien hankkeiden menestystä.

Eksploratiivisen tapaustutkimuksen tulokset antavat panoksensa teoriaan kuvaamalla analytiikkatuotteiden käyttöä ulospäin suuntautuvan datan monetisoinnin tarjoamana ja testaamalla käytännön viitekehystä akateemisesti, samalla antaen suuntaa jatkotutkimukseen ja validointiin muissa organisaatioissa ja toisilla markkinoilla.

Avainsanat datan monetisointi, analytiikan tuotteistaminen, tietoliikenne

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Helsinki, 26.4.2021

Iiris Savolainen

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Abbreviations and Acronyms

API = Application Programming Interface

B2B = Business to Business

B2C = Business to Consumers

GDPR = General Data Protection Regulation

ICT = Information Communications Technology

MVP = Minimum viable product

PoC = Proof of Concept

ROI = Return on investment

TSI = Telia Service Intelligence

1 Introduction

Big data has been a hot topic and expected to have significant potential in data-driven decision-making for several years now. The growing amount of available data also motivates companies to strive for methods to utilize it for economic benefit (Hartmann et al., 2016; Najjar & Kettinger, 2013). This process of using data to obtain quantifiable economic benefit is referred to as data monetization (Gartner, 2020).

Consulting company research reports, online newspaper articles and blog posts consider data monetization a significantly growing market. For instance, the Grand View Research (2020) argues that the global data monetization market was valued at USD 1.30 billion in 2019 and is expected to grow at a 24.1% compound annual growth rate from 2020 to 2027. Consequently, companies' ability to monetize their data effectively is believed to result in a significant competitive advantage in today's digital economy (Wixom & Ross, 2017).

Researchers identify multiple approaches for monetizing company data. For instance, internal data monetization by improving companies' internal processes and external data monetization with selling information offerings such as data or analytics to third parties are well-established approaches. Particularly the external part is widely underutilized, although it presents a considerable opportunity for data-massive companies to tap into and provide relevant value for their B2B customers (Laitila, 2017).

A promising strategy for external data monetization is the development of analytics products (Woods, 2016-a). However, many companies still struggle with their analytics productization efforts (Baecker et al., 2020). Because interest in this area is relatively recent, there is little research on the most pressing challenges and essential enablers in analytics productization. Moreover, external data monetization strategies and processes tend to be industry-specific, whereby the identification of general principles for successful analytics productization processes are difficult to come by. Hence, there is a considerable need for explorative case studies.

This thesis studies the analytics productization efforts at a case company Telia. Telia operates in the telecommunications industry, one of the most promising areas to grow with external data monetization due to its data-intensive nature (Costa & Zeinalipour-Yazti, 2019). Nevertheless, the company has not been able to fully tap into the external data monetization potential in the telecommunications industry. To explore reasons for this, the thesis compares two analytics products developed at Telia, one of which is considered successful while the other is still struggling with its monetization.

The case company benefits from the thesis by gaining more in-depth insight into their two productization processes with respect to the existing theoretical and practical framework. More specifically, the thesis helps to identify issues hindering Telia's external data monetization potential that could be avoided in future productization efforts. Similarly, the thesis supports embracing the identified enablers. At a more general level, this thesis contributes to theory by increasing understanding of using analytics products as an external data monetization strategy and emphasizing the process aspect of external data monetization.

1.1 Research problem

The case company Telia has not been able to fully tap into the external data monetization potential in the telecommunications industry. This is problematic in the current market environment where telecommunications companies are forced to seek new growth opportunities to substitute declining revenues from traditional operator business. From a competition perspective, failing to invest and develop profitable initiatives would be fatal in the future digital landscape.

Telia has developed some analytics products for external customers, but their success varies significantly, implying challenges in analytics productization. The research problem stems from this success inconsistency, especially from a less successful analytics product with poor customer demand and controversial debate about its future. Hence, the research questions are as follows:

RQ 1: What are the *challenges* in the external data monetization of the two analytics products?

RQ 2: What are the *enablers* of successful external data monetization of the two analytics products?

RQ 3: What are the *key aspects to consider for future* analytics productization success?

1.2 Structure of the thesis

Chapter 1 of the thesis provides a rationale for the study, introduces the research problem and questions, and explains the structure of the thesis. The main part of the thesis consists of a literature review and an empirical part. The literature review in Chapter 2 begins by addressing and defining the fundamental concepts of big data and analytics that are essential regarding external data monetization and analytics products. These concepts are also discussed in the telecommunications context. Then, the chapter moves on to define data monetization and discuss different approaches to it. After that, the chapter focuses on the external data monetization approach, providing input to external data monetization literature. The scope of selling data and insights is extended to selling analytics products outside the company by discussing external data monetization offerings. Then, the chapter introduces a seven-step external data monetization process applicable to analytics products. Finally, it describes analytics productization and some examples of it. The literature review provides a theoretical framework for the empirical part that focuses on the case company.

Chapter 3 explains the methodology used in the empirical part. The case company Telia and single case study method, along with the two analytics products and multiple units of analysis concept, are introduced. Also, data collection and analysis are explained in detail. Then, Chapter 4 discusses the empirical findings and implications for the case company, aiming to recognize and represent the challenges and enablers within the external data monetization processes of the two products. Moreover, it provides support for future analytics productization efforts with recommendations. Chapter 5 concludes the thesis with a summary and derives more general implications for theory and practice. Finally, it expresses the limitations of this thesis and suggests topics for further research.

2 Literature review

This chapter reviews the existing literature to formulate a basis and a theoretical framework for the empirical part. To ensure reliability, this literature review is conducted using multiple data sources. They include academic journal articles, blogs, books, conference proceedings, encyclopedia articles, theses, newspaper articles and company whitepapers. Data collection was conducted mainly using academic literature database Scopus, academic search engine Google Scholar, search engine Google and online research tool Aalto Finna (Learning Centre and Aalto University Archive). The material selection relied mainly on the following keywords: ‘data monetization’, ‘external data monetization’, ‘big data’, ‘analytics productization’ and ‘telecommunications’. Moreover, the article abstract, publisher and publication year affected material selection to ensure up-to-date and reliable data.

2.1 Telecommunications big data and analytics

Before reviewing data monetization, external data monetization offerings and processes related to them, it is essential to define data and analytics as concepts and in the telecommunications context as they are the key input and starting point for data monetization. Today, most data in our digital economy can be considered big data – a concept that is discussed in the following subchapters.

2.1.1 Big data in the telecommunications context

Data is often called the new oil. Fred (2017) summaries definitions for data as separate, meaningless bits of knowledge unless interpreted appropriately. Thus, the parable to oil can be quite accurate. The exponentially growing amount of data in companies is often referred to as big data, which is also a significant research area in today’s digital economy. In general, **big data** is defined as a large dataset that is almost impossible to manage and process using traditional data management practices and tools (Akoka et al., 2017). As the concept of big data is rather abstract, the definitions are mainly gathered by describing big data characteristics, evolved and expanded over time. Originally, big data was described using the 3V model (Volume, Velocity and Variety) (Johnson et al., 2017). Later, dimensions of Value and Veracity have been added to the definition (Claudio A. Ardagna et al., 2016). The model has recently been supplemented with two more additional criteria

(Variability and Visualization), resulting in a 7V model (Faroukhi et al., 2020). The 7Vs of big data are briefly explained in the following paragraphs. However, this thesis doesn't distinguish between big data and other types of data in the later chapters but simply refers to data.

As mentioned, the amount of data, i.e., volume, may be the most determinative aspect of big data, describing the big or enormous scale of data. The big data volume relates to the continuous generation of data from various new technologies and applications presented later in this subchapter (Faroukhi et al., 2020; Liang et al., 2018). The volume of data is both an opportunity and a challenge – it enables more representative sample sizes but also leads to higher maintenance and storage costs (Fred, 2017). Secondly, **Velocity** describes the rapid changes and speed of new data generation, storing, processing and becoming outdated (Faroukhi et al., 2020; Fred, 2017). It relates to companies' ability to process the voluminous data with speed (Johnson et al., 2017). The velocity opens doors for new kinds of discovery and real-time analysis (Akoka et al., 2017) that might provide essential results in certain time-sensitive domains and industries, allowing them to better and more timely respond to changes in their environment and enhance performance (Johnson et al., 2017). Then again, **Variety** relates to different types and forms of data (Fred, 2017) derived from both internal and external sources (Faroukhi et al., 2020). A common categorization divides data to structured and unstructured data. According to Taylor (2018), structured data has known data types and pre-defined data models. Conversely, unstructured data covers everything outside structured data – no pre-defined data models or regular data types, residing typically in wider data lakes, noSQL databases, applications etc. Most of big data is unstructured that is much more difficult to reach and process due to more complex formats (Fred, 2017; Taylor, 2018).

Veracity concerns the validity, accuracy and uncertainty of the generated data (Fred, 2017). Assuring the data quality by addressing anomalies and inconsistencies in the data is a prerequisite for reliable analysis and results that can be acted on (Faroukhi et al., 2020; Fred, 2017). On the other hand, **value** signifies the information and insights derived from big data by processing and analyzing it (Faroukhi et al., 2020; Fred, 2017). The value aspect relates to Liang et al.'s (2018) view of data as a digital commodity or asset. Using analytics helps increase the value of data – the next subchapter discusses big data value and analytics in more detail, building a bridge to the data monetization chapter.

Variability relates to the meaning of data which is continuously changing in the context of big data (Faroukhi et al., 2020). **Visualization**, then again, describes illustrating the relationships derived from complex data to provide a meaningful and interpretable result (Faroukhi et al., 2020). This aspect of big data can also be viewed as part of the analysis process, making it somewhat different from the other characteristics.

Besides the 7V model describing big data's features and nature, it is often relevant to specify data sources. At a general level, be IoT applications, mobile and social networks can be considered the main data sources generating an enormous amount of data (Akoka et al., 2017; Liang et al., 2018). From the companies' point of view, big data sources can be either external or internal based on whether the data is generated within the company (**internal data**) or acquired from the outside (**external data**) (Buytendijk et al., 2013). External data sources consist of 1) data providers and third parties from whom the commercial data is purchased, 2) customers or business partners providing external, otherwise unavailable data and 3) social media and open or public data sources. (Buytendijk et al., 2013; Huang et al., 2015) Internal ones, on the other hand, include 1) business support systems (BSS), or transaction and IT systems such as ERP and internal workflows and 2) operations support systems (OSS) formed by tracking-sensors, crowdsourcing technologies, i.e., generating new internal data.

In the telecommunications industry, companies generate significant volumes of internal data daily (Zahid et al., 2020). Huang et al. (2015) argue that 97% of the total internal data volume comes from the operations support systems, more specifically telecommunications radio and core equipment. According to Costa & Zeinalipour-Yazti (2019), the data typically comes from telephony and data communications, radio and backbone infrastructure. In contrast, Zahid et al. (2020) identify smartphones, social media, IoT and next-generation communications networks (5G) as primary data sources in the telecommunications industry. Data generated or derived from these sources can be labeled as traffic, commerce, mobility, IoT and user data (Costa & Zeinalipour-Yazti, 2019). Additionally, call detail records, user clickstream, mobile network usage, geographical user data, network performance, network monitoring, customer/subscriber profiles, hardware, and VoIP data are used (Zahid et al., 2020).

2.1.2 Big data analytics in the telecommunications context

As mentioned, data is meaningless unless interpreted appropriately. Interpreting data by using specific tools and techniques and combining it with previous knowledge then results in information (Fred, 2017). The process of deriving and extracting this value from big data sets is called big data analytics (Zahid et al., 2020).

Big data analytics can be defined using an analytics maturity perspective. In general, analytics can be viewed as descriptive, diagnostic, predictive, or prescriptive. This spectrum is based on the computational and mathematical models used in each type of analytics, as well as the progressiveness of the outcome ranging from merely visualizing the data or reporting to forecasting future events based on past data (Claudio Agostino Ardagna et al., 2018; Moro Visconti et al., 2017). Big data can be considered a critical input, especially for predictive and prescriptive analytics in the most mature or advanced end of the spectrum, whereby the big data analytics discussion focuses on advanced analytics (Fred, 2017). In other words, advanced analytics solutions provide predictive insights and prescriptive recommendations by analyzing and transforming big data (Mattila, 2018). Descriptive business intelligence applications are usually unable to process unstructured data, at least directly (Barc, 2020).

Different statistical, processing, and analytics techniques are typically implemented on unstructured data residing in non-relational NoSQL databases when using advanced analytics (Grover et al., 2018; Zahid et al., 2020). Some of the scientific methods often used on big data include statistical methods to explore causalities and reduce volume, data mining to extract patterns, machine learning to produce algorithms that develop based on behavior, artificial neural networks to analyze images and recognize patterns, and social network analysis to reveal social relationships (Moro Visconti et al., 2017). However, Lismont et al. (2017) notice that utilizing more advanced techniques such as neural networks and support vector machines (SVM) is still quite rare in companies.

As most of the telecommunications industry data consist of big data or unstructured data, this thesis refers to analytics as mainly advanced analytics. In telecommunications, analytics typically include diverse domains such as machine learning, statistics, pattern recognition, and business intelligence to some extend (Zahid et al., 2020). Some of the most relevant types of analytics in the industry include detection and real-time analytics as well as experience and retention analytics (Costa & Zeinalipour-Yazti, 2019).

Moreover, many telecommunications companies view big data and data analytics as an important strategic direction and journey, making significant investments in the area (Taga et al., 2018). However, Zahid et al. (2020) argue that the lack of expenditure is one of the main problems in developing relevant big data analytics initiatives. On the other hand, return on investment (ROI) on big data investments stays typically unclear (Taga et al., 2018). Assessing the value of data, enhanced or revealed with big data analytics, is discussed more in the next chapter.

2.2 Data monetization

Deploying analytics on big data aims at extracting value from it. The phenomena can also be considered data monetization. This chapter defines the concept and introduces different approaches to it. Then, it identifies external data monetization offerings and presents a process for implementing them for optimal value creation. This process is utilized in the empirical analysis with analytics product as an offering type in the next chapter.

There are no universally agreed definitions for data monetization as it is such a recent topic in the literature. The concept interpretations vary significantly despite the overall importance (Hanafizadeh & Harati Nik, 2020). One of the most referred definitions, however, is from Gartner's online glossary. It defines data monetization as a process of using data to obtain quantifiable economic benefit (Gartner, 2020). This benefit can be derived from both raw data and mined resources (Faroukhi et al., 2020). Alternatively, Wixom (2014) defines it as “the act of exchanging information-based products and services for legal tender or something of perceived equivalent value” and Fred (2017) as revenue generation with and out of data and data-derived and information-based products and services.

As the basic definition for data monetization varies, the ways to categorize different types of data monetization vary also. Gartner (2020) identifies two categories in data monetization. The first considers using data to improve business performance measurably and inform decisions, referred to as an **internal** or indirect method. In other words, internal data monetization aims at improving and optimizing companies’ current internal business and operational processes, services and practices as well as enhance business decisions (Liang et al., 2018; Wixom & Ross, 2017). Conversely, the second category is called a direct or **external** method. It refers to selling, for instance, data or analytics as information offerings or goods (Hanafizadeh & Harati Nik, 2020) to third parties. Liang et al. (2018) frame this as developing and innovating new products, practices and business models by analyzing big data. However, the terms direct and indirect are not universally agreed to match with terms internal and external. For instance, Moore (2015) defines **direct** as selling or trading data and **indirect** as creating new information-based products and services. Then again, Faroukhi et al. (2020) call selling or sharing data as **explicit** and enhancing their own data-based products as **implicit** data monetization. Table 1. summarizes these varying definitions.

Table 1: Data monetization categorizations from the literature

Internal / Indirect	**External** / Direct	
	Direct / Explicit	Indirect / Implicit

This thesis focuses on the external part where companies develop and sell data or analytics to external parties without distinguishing between the sub-categories of direct/explicit and indirect/implicit external data monetization presented in Table 1. The next sub-chapter introduces three different types of these external data monetization offerings that can be used to execute external data monetization strategies.

2.2.1 External data monetization offerings

Offering refers to a product or service that is offered for sale (Cambridge Dictionary, 2020). In the external data monetization context, this means treating data or information-based offerings as goods. Here, the economic benefit comes from new value streams created with the offering (Baecker et al., 2020). These external data monetization offerings can be categorized in many ways, often based on different maturity factors. For instance, Hanafizadeh & Harati Nik (2020) and Laitila (2017) categorize external data monetization offerings based on their analytics maturity, i.e., how much the company has refined the data. Table 2 represents the three external data monetization offerings they identify. Moreover, they identify separate strategies for each type of offering, described more thoroughly in the next paragraphs.

Table 2: External data monetization offering types

<table>
<tr><th colspan="2">Offering type</th><th>Example</th></tr>
<tr><td colspan="2">1. Data</td><td>Selling raw or prepared datasets</td></tr>
<tr><td colspan="2">2. Analysis and insights</td><td>Analyzing data and selling the results</td></tr>
<tr><td rowspan="2">3. Analytics product</td><td>a. Data wrapping product</td><td>Enriching core products with additional data and analytics capabilities such as reporting or alerts, scaling delivery to multiple customers</td></tr>
<tr><td>b. Independent analytics product</td><td>Creating new analytics products that bring direct value to customers, scaling delivery to multiple customers</td></tr>
</table>

Executing external data monetization with **data** as an offering type is defined as selling data solely as an asset to create new revenue streams or extend the customer base (Baecker et al., 2020). This option can be considered the less mature strategy and companies have been selling their data for many years (Wixom, 2014). There are a few versions to execute the strategy; 1) selling full control to the data, 2) selling access to the data while keeping the control, and 3) using a data-as-a-service approach of trading data in real-time based on predefined criteria (Baecker et al., 2020). Categorization can also be done based on the maturity of the data offering dividing them into 1) raw data and 2) prepared data sale (Buff et al., 2015). The former is not processed in any way but might bring value to transactions or secure the non-replicability of the data. In contrast, the latter has been transformed, enhanced, cleansed, etc., to make it more consumable for specific use cases. Raw data might lack some usability, but it is still better to take into monetization consideration rather than just leaving it in company databases (Laney, 2017).

Today, most companies don’t have a comprehensive inventory of all their data and information (Laney, 2017). Hence, considering data offerings is an essential first step in the external data monetization spectrum. It forces companies to identify the current data they possess, think about potential demand and use cases for it and assess the value of their data for the prospective purchasers (Laney, 2017). Especially understanding the use of the data after its being sold is essential in assessing the value of the data and the risks related to asset sale strategy, further utilized in the pricing of the offering and setting up contracts, especially in cases of sensitive or regulated data such as customer data (Buff et al., 2015). Hence, it is essential to prevent companies from missing their external data monetization opportunities.

Then again, using **analysis and insight** as an external data monetization offering can be considered one step more mature external monetization strategy. Baecker et al. (2020) define it as selling information or knowledge that is derived from analytics or different visualizations. This means that the company investigates the data and only sells the results of the analysis. Selling analysis and information offerings solves a few risks related to selling raw or even prepared data offerings, data access and control. These risks include, for instance, unknown reuse of data or privacy issues of identifying single data points that, in the worst case, could compromise the company's own business (Laitila, 2017; Spijker, 2014). Moreover, generating insights creates more value for both customers and the company (Spijker, 2014) – the company can charge more for more refined offerings and utilize the insights also in their own operations. However, using analysis or insights is the least studied external data monetization offering, possibly due to its vague nature.

Finally, the **analytics product** option aims at creating entirely new offerings to customers based on data. Naturally, this requires most effort from the company but enables excellent economies of scale and significant opportunities for increasing the number of potential customers and maximizing revenues and margins (Buff et al., 2015; Parvinen et al., 2020). Analytics product can be viewed simply as a data-driven product (Hanafizadeh & Harati Nik, 2020) or as an opposite to general analytics tools, possibly more commonly known as business intelligence tools, such as Qlik or Tableau. They implement a specific type of analytics in a well-understood business context. (Woods, 2016-a) The choice of analytics and specification of the business context is defined by the company providing analytics product as customers might not always understand the possibilities in their context and have the analytics capabilities or resources to develop their own analytics. Typically, analytics products include basic descriptive reporting or more advanced analytics using different algorithms, machine learning, and statistical modeling that aims at predictive and prescriptive support (Buff et al., 2015).

Analytics products usually work as self-service, directly informing and supporting customers' business processes and decisions. They use different visualizations, reports, dashboards and graphic interfaces that often result in enhanced ease of use and usefulness. (Buff et al., 2015) In this sense, an analytics product can be any value-adding platform or service used to scale the delivery of data and insights to multiple customers (Laitila, 2017). Thereby, it can be seen as an opposite to customer-specific analytics implementation or manual gathering of insights on a case-by-case basis. Hence, it is essential to identify needs and use-cases common for multiple customers – there needs to be a common problem to solve (Woods, 2016-b). For clarity, this thesis refers to scalable service offerings also as analytics products.

There are many ways to categorize analytics product offerings. Baecker et al. (2020) include 1) using data as an input for a new analytics product and 2) using insights from the data to recreate the existing products as analytics product options. On the other hand, Wixom & Ross (2017) consider two approaches to analytics product innovation; 1) wrapping data around company's core products as additional analytics features and 2) creating data and analytics capabilities independent of the core products (Wixom & Ross, 2017). In *data wrapping*, companies enrich their existing products and services with additional data and analytics capabilities or information as a value-added component (Gartner, 2020.; Wixom & Ross, 2017). This additional value creation can be done with reporting, alerts and other information brought together with the core products. Typically, these additional information capabilities are free of charge for the customer, and the value for a company is gained somewhat indirectly (Hanafizadeh & Harati Nik, 2020) via increased core product prices, market share and switching costs (Wixom, 2014). The second option of *independent data and analytics capabilities* aims at creating information-based solutions that bring value to customers as an individual product or service (Wixom & Ross, 2017). The authors note that this approach requires new research and possibly new business models to succeed, which can simply be measured by the customers' willingness to pay for the product.

In addition to analytics products, Buff et al. (2015) identify the option to create **action offerings** at the high end of consumption path maturity. They define it as services helping customers act on the insights via consulting, onsite support and process automation or outsourcing, all of which depend on people and hence, are less scalable options. Action offering providers either use data and analytics to create recommendations or execute customers' business tasks based on insights from reporting and analytics (Buff et al., 2015).

The next subchapter introduces a process for external data monetization. Even though this thesis focuses on analytics product as an external data monetization offering, the process is derived from overall external data monetization literature, concentrating on telecommunications. This process can be considered a useful framework for studying issues in executing external data monetization efforts.

2.2.2 External data monetization processes

Before going into the external data monetization context, let's define what is meant by a process in this thesis. A process includes steps, but the order of the steps is not strictly defined. In fact, many processes have phases that happen simultaneously and iteratively. In new product development, the process is rather non-linear (La Rocca et al., 2016). However, a process aims at identifying the overall starting sequence of actions at a general level. On the other hand, in this thesis, a process seeks to offer a guide that practitioners, especially case company Telia, can take actions on.

An external data monetization process aims at transferring data into value and identifying the main elements involved. However, there are many ways to consider and identify these processes that differ in concreteness and scope. One notable contrast that can be found in the literature is whether the process emphasizes the technical or the commercial point of view. The **technical point of view** focuses mainly on big data characteristics, deep diving, for instance, to data management and data architecture or infrastructure aspects. This can be considered a data refinement process of data-driven operations that emphasize refining asset to value via suitable models. For example, Faroukhi et al. (2020) suggest a process for aggregating and exploiting data in the digital data lifecycle. They identify data generation, data acquisition, data pre-processing, data storage, data analysis, data visualization and data exposition/monetization as parts of creating value from big data. Ardagna et al. (2016), on the other hand, expand the area from creating value from big data to creating big data analytics and discuss big data pipeline at a more general level by addressing data preparation, data representation, data analytics, data processing and data visualization & reporting. They highlight the need for the right analytics and the right infrastructure. Also Najjar & Kettinger (2013) and Sun et al. (2012) argue that analytical and technological capabilities, including hardware, software, networking, mathematics, and whether it is an on-premise or cloud solution, are key topics in delivering analytics product or other data monetization.

The **commercial aspect** then takes a step to a more general and abstract direction, extending the big data lifecycle to include data pricing and trading on top of data collection and analytics (Liang et al., 2018). In fact, some general level external data monetization processes could be called rather business models or strategies but are called process in the context of this thesis. One key difference between technical and commercial approaches is that the commercial ones consider the use cases or the monetization method (internal or external) as a key aspect. In contrast, technical viewpoints typically ignore them or include them as the last step of the value creation process as data exposition (Faroukhi et al., 2020) or sharing data to monetize it (Moro Visconti et al., 2017). However, Faroukhi et al. (2020) note that only a small fraction of the studies address the exposition or monetization phase. In other words, the commercial approach considers investment decisions as a prerequisite for initiating the technical process. Another main difference is that the technical point of view typically ends when the technical solution is ready but lacks preparing exposition of the technical solution to customers via pricing and market entrance planning.

There is no established universal or certified process for any data monetization, let alone analytics productization that is a relatively little investigated external data monetization area. Consequently, the process for external data monetization, applicable for analytics productization, is derived from practical company whitepapers. It is complemented with technology-focused data monetization and commercial data pricing and trading literature to create as comprehensive view as possible. The process used in this thesis is designed explicitly for the telecommunications industry, matching the case company Telia's position. The phases of the process are presented in Table 3 and studied further in the following paragraphs.

Table 3: External data monetization process for telecommunications industry (Instarea, 2017)

1.	**Opportunity mapping and data strategy preparation**
2.	**Potential planning and use-case definition**
3.	**Legal and compliance alignment**
4.	**Data collection and preparation**
5.	**Technological arrangements**
6.	**Data pricing strategy**
7.	**Market entrance planning**

The first phase of the process, **opportunity mapping and data strategy preparation**, emphasizes the identification of available data. In fact, discovering and identifying not only available but valuable data is the key (Fred, 2017). Data intensity in the telecommunications industry provides excellent possibilities for many kinds of data-driven initiatives (Costa & Zeinalipour-Yazti, 2019), especially unique external data monetization possibilities (Taga et al., 2018). This good data monetization potential is often derived from various data types such as customer, contract, traffic, network cell plan, media behavior and WIFI network data, depending on the company's core offerings. Identification of available data can be made through a thorough data audit for mapping the monetization opportunity for the data. The results should then be utilized in creating an internal data strategy. (Instarea, 2017) Creating a data strategy is an opportunity for companies to determine the data exposition; whether they should aim to trade on the data (external) or use it personally to refine their internal activities (Faroukhi et al., 2020).

The second phase, **potential planning and use-case definition**, is the innovation part of the process. Garrett (2018) defines use case simply as a description of a problem solved by combining data and data science and applying analytics without further considering the algorithms or models used to build the solution. Use-cases are relatively industry-specific and the potential in the telecommunications industry is significant. Some most valuable use-cases recognized in the telecommunications industry are third-party targeted marketing as a service, population analytics & location intelligence as a service, data access platform via API, citizen notification and smart city platform, and telco data processing & raw data access to a dataset. (Instarea, 2017) For companies, reviewing use-case suggestions can boost choosing the most suitable one and creating new valuable use-cases (Garrett, 2018).

On the other hand, the use cases are also industry or customer vertical-specific, e.g., banking, retail, advertisement, government and transportation (Taga et al., 2018). Taga et al. (2018) state that the external data monetization opportunities should be considered case by case, starting from individual needs. More specifically, they argue that it is vital to identify where the opportunity with the best potential lies in the value creation chain. Succeeding in this requires a well-developed partner ecosystem that includes partners ranging from B2B customers, start-ups and technology vendors across the value chain (Taga et al., 2018). Also Parvinen et al. (2020) emphasize discussing with multiple different partners to better understand the business opportunities and suggest expanding the search for suitable discussion partners outside the current value chains or networks as well. Then again, B2B customers often act as data providers by passively serving as sources for big data, analyzed for finding addressable issues (Zhang & Xiao, 2020).

On the other hand, La Rocca et al. (2016) highlight the importance of marketing, sales and customer management functions in interpreting the market context and customers' needs. More specifically, they, along with Zhang & Xiao (2020), call for customer involvement in new product development process to truly understand the customers and create customer value. Consequently, they suggest defining opportunity space and technical requirements jointly. This 'outside-in' approach is studied to be critical in ensuring solution fit for customers in the B2B context (Haas et al., 2012). Moreover, customers are increasingly motivated to participate in new product development to ensure customized solutions and early access to innovations (Chang & Taylor, 2016). However, customer needs can vary significantly and be somewhat tacit (Zhang & Xiao, 2020). Accordingly, Henry Ford's legendary quote, “If I had asked people what they wanted, they would have said faster horses.” suggests that customers often are unable to communicate their unmet needs regarding innovative products.

Legal and compliance alignment as a next step is relevant throughout the process and essential to include from the beginning as the risk of involuntary privacy violations is high in external data monetization efforts (Taga et al., 2018). Especially cases with consumer or personal data must be addressed appropriately (Fred, 2017). To ensure sufficient data privacy, regulators and national security, organizations are creating regulatory frameworks of various strict rules and restrictions nationally, internationally, etc. (Taga et al., 2018). A common example is General Data Protection Regulation (GDPR) by European Union, granting consumers the right to protect their own data. Furthermore, there are industry-specific laws and regulations. Especially the telecommunications industry is highly regulated, underlining the importance of this phase in the context of this thesis. (Instarea, 2017)

Hanafizadeh & Harati Nik (2020) divide legal-related matters into the five theme patterns; confidentiality, ethical issues, privacy, security, and rules, regulations & laws. To address these in this step of the process, at least a consent collection and anonymization approach should be defined (Instarea, 2017). The former, consent collection, is required by GDPR and concerns using customers' personal data in, for example, analytics products input. It also includes the option to withdraw consent once given (Taga et al., 2018). The latter, the anonymization approach, deals with privacy – most regulations require that individuals cannot be identified from the insights derived from data. The anonymization level must meet this criterion, requiring data masking and aggregation and standards for accessing data (Instarea, 2017).

The **data collection and preparation** phase can be considered the first execution or implementation phase as the three previous phases focused on planning, e.g., data requirements, data strategy and anonymization approach. In practice, data is now collected from various data sources and processed to some extent, at least to cover the anonymization level agreed in the previous phase. Faroukhi et al. (2020) describe this acquisition phase as a process of obtaining raw data and underline the importance of determining and having a place, i.e., data storage, to transfer all the data from the various sources. They also note the storage system characteristics impact future scalability and performance of the result, such as analytics product. Moreover, unstandardized data management, data infrastructure and data architecture negatively affect the overall adaptation and execution of analytics initiatives (Claudio A. Ardagna et al., 2016; Parvinen et al., 2020; Zahid et al., 2020).

Usually, some attributes are already available, whereas others need to be addressed and processed separately for a specific purpose. In fact, data collected from multiple sources is likely to be quite noisy and even redundant, causing meaningless results followed by possibly false business decisions if used as it is (Faroukhi et al., 2020). Consequently, paying attention to pre-processing and cleaning the data, as they are key elements in the big data context, enables creating reliable value with efficient, global and scalable models (Faroukhi et al., 2020). Similarly, Zahid et al. (2020) mention poor data quality and the overall complexity of integrating heterogeneous data as some of the main issues regarding the topic.

The fifth step, the **technological arrangement & development approach,** is a rather extensive part of the external data monetization process. In fact, this phase should be started parallel to other planning in the previous steps to ensure sufficient resource allocation, match the company's established product development processes, and possibly feasibility for future use cases and revenue streams. In other words, this phase focuses more on the development and deployment of a secure and reliable technical solution, and the planning regarding technology should be done before this phase. Development and deployment should cover at least a smooth data transfer, secure data architecture, and backend and frontend access. Also, basic processes such as billing and account management should be ensured, including granting customer-specific API keys to identify users, etc. (Instarea, 2017)

This step, or possibly the prior planning part, includes choosing whether to develop the technology internally or partner up with a suitable technology provider. Making the right technology choices to ensure technical feasibility is one of the most pressing challenges in this area, especially when the range of options and solutions expands exponentially (Taga et al., 2018; Zahid et al., 2020). According to Taga et al. (2018), most telecommunications companies with advanced external data monetization strategies use external partners such as specialized analytics firms in creating innovative analytics products. They continue arguing that sometimes acquiring start-ups for vertical integration in the value chain is worthwhile. However, in-house data analytics and system architecture skills are needed to some extent even if the analytics phase was outsourced to external partner or technology provider (Claudio A. Ardagna et al., 2016).

Suppose a company decides to develop the technology by themselves. In that case, they must consider all the technical aspects such as data analysis and data visualization from Faroukhi et al. (2020) big data value chain carefully. In other words, they must ensure data-driven operations (transforming data assets into value) by sufficient resources and supplies, such as people, perception, analytical and technical capabilities, and platforms (Hanafizadeh & Harati Nik, 2020). In effect, the big data analytics capability aspect is typically expensive, resource-intensive, and complicated (Zahid et al., 2020).

The next step of the process concerns **data pricing strategy**. The themes here vary from the potential customer base and suitable segments or verticals to consistent price optimization. Laitila (2017) describes pricing as evidence for the promised value of data and data-driven products. Also Najjar & Kettinger (2013) consider pricing the actual monetization part for the company, highlighting the importance of pricing strategy planning. In fact, advanced pricing strategies focus on maximizing profit rather than covering the costs (Liang et al., 2018).

However, Wixom (2014) note that pricing can be a challenging task in data-related businesses. Liang et al. (2018) explain the challenges with diverse data sources, complex data management, and data diversity. They identify economic principles such as costs and supply & demand relevant in determining the price for data. They highlight identifying and allocating costs related to development, analytics, collocation, and maintenance, as digital assets' re-production costs are typically minimal. Buff et al. (2015) emphasize the customer perceived value approach, especially evaluating the future value of increased opportunities derived from big data analytics and insights. Harmon et al. (2009 suggest five factors to estimate the value. The first one is utility & satisfaction of the price based on customer feedback, the second one market environment factors affecting customer behavior and the third one customer motivation, representing the reasons to purchase. Then, supplier value denotes customers' general perception of the vendor company, and the economic value represents customer demand and relation to the price. Then again, Liang et al. (2018) remind that innovating new products in an immature market with low competition allows companies to explore their customers' preferences and adjust prices accordingly.

Customer segmentation is a key element in creating a pricing strategy. In practice, companies need to distinguish whether to ensure buying potential for small companies or strive to capture large companies' revenue potential and find a balance between these (Instarea, 2017). To address different types of customers, companies can differentiate the prices by differentiating the features and the product quality (Liang et al., 2018). On the other hand, pricing scalability is also essential in the pricing strategy phase (Laitila, 2017).

Finally, the process concludes with **planning the market entrance,** including go-to-market and marketing strategies and piloting. Suppose an analytics product was developed with a partner. In that case, the partnership can be leveraged in the new product marketing – Crisafulli et al. (2020) argue that partnering strategy leads to higher competence perceptions and purchase intentions than independent strategy in the B2B context. Moreover, the sales aspect comes into the picture as the suitable key performance indicator are defined and aligned, and the salespeople on-boarded and trained for suitable use-cases (Instarea, 2017). In other words, this phase aims to enable and support strong revenues starting from the product launch as sales function is a key element in the customer-supplier interface, driving suppliers revenue generation and creating customer value (La Rocca et al., 2016). Haapaniemi (2017) studied that initially, consultative sales are the key to introduce the idea and the expected value and to create relationships with customers – e-shop or portal can be leveraged for additional purchases. Results from pilot projects can help communicate the perceived need and value for a larger customer pool (Laitila, 2017). The sales and distribution part is also possible to execute using an external partner (Haapaniemi, 2017).

Even though this thesis utilizes the seven-step process framework, it is worth highlighting that other viewpoints to external data monetization processes have been presented as well. For example, ensuring management's support and investments with calculations and business cases along the way is essential and challenging in the novel and relatively risky data monetization area (Laitila, 2017; Parvinen et al., 2020). The process could also be viewed from, for instance, a project management perspective, or the fundamental approach to value creation sources could be challenged. These perspectives are briefly discussed next.

Project management considers the process execution perspective, including piloting and the idea of proof of concept (PoC). *Proof of concept* typically refers to companies' research practices, aiming at justifying an experimental test case in real life (Jose et al., 2018). In other words, it investigates whether an idea can be turned into reality– it can focus on, for instance, technical feasibility or financial viability (Pratt & Rawson, 2020). PoC phase typically initiates the project – steps 1 and 2 of opportunity mapping and defining use cases could correspond to this approach. Moreover, PoC can be used to align initiatives with the company's strategic goals and get management's approval for further development (Instarea, 2017; Pratt & Rawson, 2020). Thereby, PoC can be followed by design and data integrations, resulting in a prototype or minimal viable product (MVP) (Instarea, 2017; Pratt & Rawson, 2020).

On the other hand, *Piloting* can refer to testing the prototype or the MVP with a selected customer and a potential user of the solution. Consequently, the company gets the initial results of the solution that helps determine the actual value and future revenue – whether customers are willing to pay for the product (Haapaniemi, 2017; Laitila, 2017). The initial results can also support future pricing and communicating the value proposition (Parvinen et al., 2020). According to Haapaniemi (2017), many telecommunications companies' initiatives are still in the piloting phase, indicating issues in finding valuable cases. Successful pilots are then moved to into production phase, where the larger-scale technological aspects are developed for fully going live (Instarea, 2017).

Today, companies are shifting from well-ahead planned, waterfall-like project management practices to a more *lean and agile* approach, where the development is done iteratively. The shift also relates to non-linearity – companies can't simply follow the external data monetization process description presented in this sub-chapter but use it as a framework for the actual execution. Considering agile ways of working and delivery become particularly relevant when working with complex big data – data-based value creation processes are still unclear (Faroukhi et al., 2020). On the other hand, Lamberg et al. (2019) point out that embracing agile mentality to become a modern company might seriously disturb technology companies' core processes via inconsistent organizational design, increased complexity of decision making, internal competition and rivalry of competing technologies. Therefore, critical consideration of agile development practices should not be ignored.

Also, the **value-creation approach** and the logic behind the process could be challenged. For instance, Garrett (2018) identifies two fundamental approaches to data monetization; 1) exploratory data analysis approach and 2) business problem-centric approach (Figure 1). The former approaches value creation by investigating the available data and testing various models and algorithms to develop suitable use cases, whereas the latter starts from the established business problem. Garrett (2018) argues that the business-problem-centric approach is more recommended in general but notes that finding suitable real data as a last step of the process typically causes issues with complex big data. In fact, Parvinen et al., 2020 encourage experimental and exploratory perspective to external data monetization innovation. The process used in this thesis can be considered as a combination of these approaches by presenting them as the two first phases.

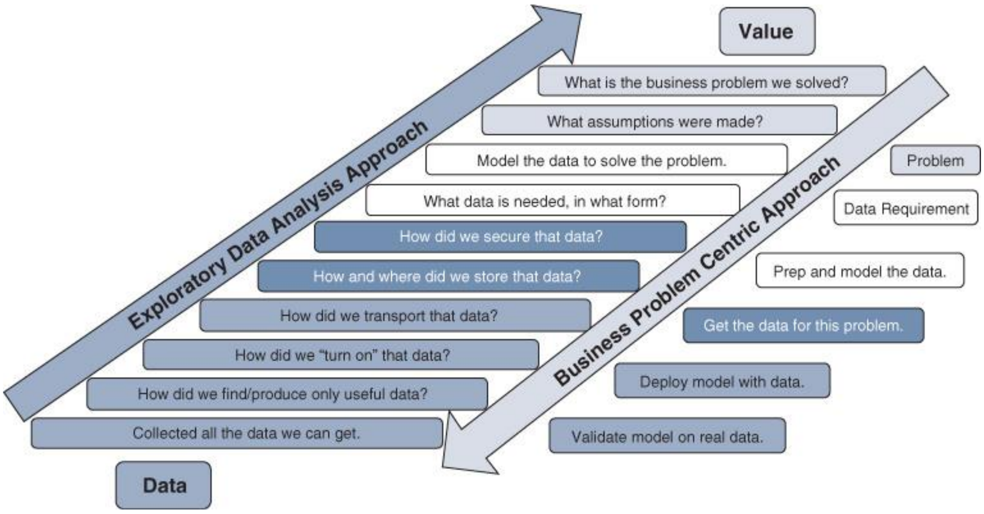

Figure 1. Detailed Comparison of Data Versus Problem Approaches (Garret, 2018)

2.3 Analytics productization

External data monetization processes aiming to create and launch an analytics product could simply be called analytics productization. The term, however, is not widely used in the existing literature. Therefore, it is now considered based on general productization literature and brought to analytics product context with suitable real-life examples. These examples provide a context for the methodology and empirical part where two analytics products created at case company Telia and their processes are compared.

Simply put, productization refers to developing something, such as a concept or a service, into a product. Harkonen et al. (2015) describe productization as a process of analyzing needs and combining suitable elements for a repeatable and comprehendible solution that is commercially ready for sale, delivery, use and invoicing. In the service productization context, three productizing practices are identified; (1) specifying and standardizing the service offering, (2) improving tangibility and concreteness of the service offering and professional expertise, and (3) systemizing and standardizing processes and methods (Jaakkola, 2011). These aim to clarify the service offering, create replicability, and enhance understanding of the offering (Harkonen et al., 2015).

In the analytics context, productization could imply creating some graphic interface, platform or portal where the analysis results are continuously shown. Customers would then have access to it and consume the analysis in a self-service manner. In fact, many analytics products work in a Platform as a Service (PaaS) or Software as a Service (SaaS) model where users pay based on their usage (Haapaniemi, 2017). One key driver for analytics productization is the demand for high-level analytics democratization in customer organizations (Kapoor, 2017).

Next, the thesis introduces a few cases where analytics productization is considered beneficial in the telecommunications industry. Roughly, the most potential cases could be divided into 1) location-based analytics, 2) social media and usage-based analytics and 3) network optimization analytics.

First, *population analytics and location intelligence* solutions have a major potential to be productized (Instarea, 2017). Typically, such solutions gather individuals' data and create meaningful patterns for valuable stories for different industries. The productized analytics made on top of location data include footfall reports for the retail industry, transportation and traffic planning support for cities and transportation companies, and ATM-locating planning support for the financial industry (Instarea, 2017; Taga et al., 2018). Moreover, these can be used to produce citizen notifications and smart city platforms that help governments communicate better with the right people in the right area, such as construction or weather emergency notifications based on real-time location data (Instarea, 2017).

Second, *social media and usage-based analytics* use customer data to create insights that can be productized for B2B customers' use. These analytics products can help customers better personalize rewards and target advertising based on web-browsing history, app usage and social media behavior data. (Instarea, 2017; Taga et al., 2018) In other words, they help B2B customers to increase the effectiveness and ROI of their marketing efforts (Kapoor, 2017). This type of analytics often uses location data for even more precise digital advertising and mobile marketing.

The third typical case is *network optimization analytics*. Telecommunications companies use these widely for internal purposes, and these analytics can also be productized for B2B customers' own use. Examples in this include end-to-end wireless network visibility, self-coordination among network functions and entities, energy efficiency optimization and other real-time analytics products (Zahid et al., 2020). These analytics types could be considered to belong to the data wrapping category more than independent analytics capability as these relate strongly to the use of core products. Furthermore, this option's benefits can be mainly indirect – e.g., increased customer satisfaction and increased loyalty through improved transparency and service quality.

This chapter's productized analytics are only a few examples – for instance, the Internet of Things (IoT) and 5G technologies open new opportunities for analytics productization. However, this introduction gives a glimpse of what analytics productization can be in the telecommunications context. The next chapter explains the methodology used in the empirical part, including the case company presentation and introduction of the two analytics products.

3 Methodology

This chapter describes the research methodology in detail to help the reader interpret the results and findings discussed in the next chapter. The goal of the thesis is to explore reasons why the case company has not been able to fully tap into the external data monetization potential in the telecommunications industry and how the finding could be addressed in the most suitable way in future analytics productization efforts. An explorative case study approach comparing two existing analytics products is considered a good option to develop this in-depth understanding. The overall research method, research context, data collection and data analysis are explained more thoroughly in the following sub-chapters.

3.1 Research methodology

This thesis takes a qualitative approach to the research problem by identifying the challenges related to external data monetization of analytics products and examining the best ways to avoid them in the future. A qualitative approach is considered the best for this kind of explorative investigation of the phenomenon within its real-life context. Moreover, this approach is well suited for studying relatively new and little-studied topics such as external data monetization. Instead of testing hypotheses, studying independent and dependent variables, etc., qualitative research methods typically use theory-based concepts for understanding the phenomena and interpreting processes and meanings. (Silverman, 2014) The theoretical framework introduced in the literature review is accordingly used to examine real-life situations.

The thesis is conducted as a case study – an excellent method when striving for a close and in-depth understanding of a limited number of cases happening in their real-life context (Bromley, 1986). The case study method doesn't differentiate between the real-life context or other complex conditions and the phenomenon studied but considers them crucial in adequately understanding the studied phenomenon. In fact, case studies don't focus on isolated variables but intend to build a broader overview on top of those contextual or other complex conditions. (Yin, 2012) Most of the external data monetization phases, such as data preparation or pricing, have already been studied independently, but not to get a deep understanding of the overall process related to the concept. Also, the industry-specific nature of data monetization opportunities supports using the explorative case study method. Case studies typically offer opportunities for quantitatively generalizing and testing the findings and created hypotheses in the future (Silverman, 2014).

3.1.1 Case and context

Yin (2012) suggests choosing as important, interesting or significant case as possible. This thesis uses Telia as a case organization due to the outstanding data monetization opportunities in the telecommunications industry. Telia operates in the Nordics and the Baltics, serving both B2C and B2B customers. The scope of this thesis is limited to only Finland and B2B segment. Telia has a strong history in Sweden and Finland (formerly Sonera) starting from 1853. Nowadays, Telia Company consists of country organizations and common/global functions, employing over 20 000 persons.

Today, traditional voice connectivity and network operator business is declining due to saturating mobile markets, intense price competition and new voice and messaging services by Over-The-Top providers such as WhatsApp. Thereby, telecommunications companies are forced to seek new growth opportunities. (Deloitte, 2016) Telia aims to become a new-generation telco – in the B2C segment, it has entered the TV and Media business, and in B2B, expanded to ICT services, particularly IT services such as data center & cloud, security, device management and IT service management. Providing analytics and insights is a part of this ambition to become the digitalization partner of choice for Telia's B2B customers.

3.1.2 Units of analysis

The case study design selected for the thesis is a single case study with multiple units of analysis. This means studying multiple embedded subcases within an overall holistic case of one organization and one context (Yin, 2012). The units of analysis are the two analytics products and the processes related to their productization, enabling a comparative report style in the thesis. The analytics products are studied from product management's perspective, but other relevant aspects are included through stakeholder collaboration.

The first of the two units of analysis studied in this thesis is called **Crowd Insights**. In a nutshell, Crowd Insights is a population analytics or location intelligence service providing insights about crowd movement patterns generated by Telia's mobile network. It can be used to produce three types of insights: 1) Origin-Destination Matrix reports, 2) Routing reports and 3) Activity reports. These reports support customers' data-driven decision-making concerning their own business, e.g., public facilities situating, improving the commuting experience, new transportations routes and infrastructure changes. Telia has selected urban development, public transportation, retail and events & tourism as target industry verticals to tailor the offering for. Besides providing scalable analytics product offerings for urban development and retail sectors, data and insights offerings are also offered as project deliveries. Furthermore, these data and insights offerings can be consumed in multiple ways ranging from end-to-end answering to customers' business problems to only providing data sets and offering the insights together with a partner. As a scalable analytics product offering, Crowd Insights is fully independent as it is not wrapped around the core products, according to Wixom & Ross's (2017) approach.

In this thesis, Crowd Insights is considered successful analytics productization and external data monetization initiative, as customers are interested in the product and willing to pay for it. In fact, the product has multiple remarkable customers, and the Corona pandemic has further raised its significance. The same use case was originally initiated in two separate units seeking new business opportunities, but the development continued centrally at a global department accelerating innovation in emerging business areas such as IoT and cloud. The Finnish market, however, is commercially on a separate unit's responsibility. Figure 2. represents the Crowd Insights development on a high level, distinguishing the starting point, objectives, simplified progress and outcomes.

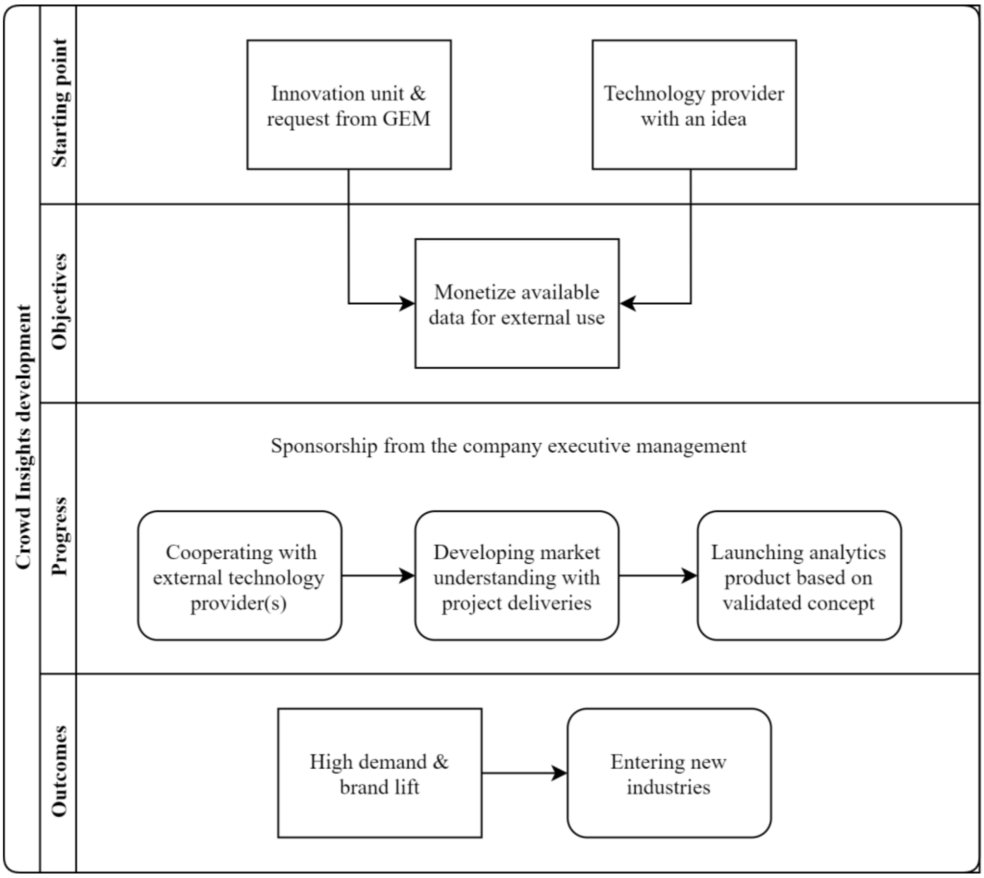

Figure 2. Crowd Insights development

The second unit of analysis is called **Telia Service Intelligence** (TSI). It provides real-time visibility about the current operational state of a customer's network consisting of fixed and mobile network connections. The service enables customers to identify the nature and scope of disturbances and breaks on a graphic UI and react promptly to protect their critical business processes, e.g., connected payment processes. It is targeted at large B2B customers with over 100 subscriptions. In this thesis, TSI is considered an opposite to Crowd Insights' success as it still struggles with its external data monetization – customers are interested in the product but not willing to pay for it. The current TSI offering has not got a sufficient customer base, limiting further product development. In fact, the TSI future is debatable and possible next steps are under investigation. Unlike Crowd Insights, TSI resembles more a data wrapping product or additional analytics feature created around Telia's core products. The development was initiated in a unit responsible for internally ensuring network service quality in Finland. The development has continued in a global department playing an essential role in Telia's ICT journey. Figure 3. shows the simplified TSI development – the events are discussed more thoroughly in the next chapter.

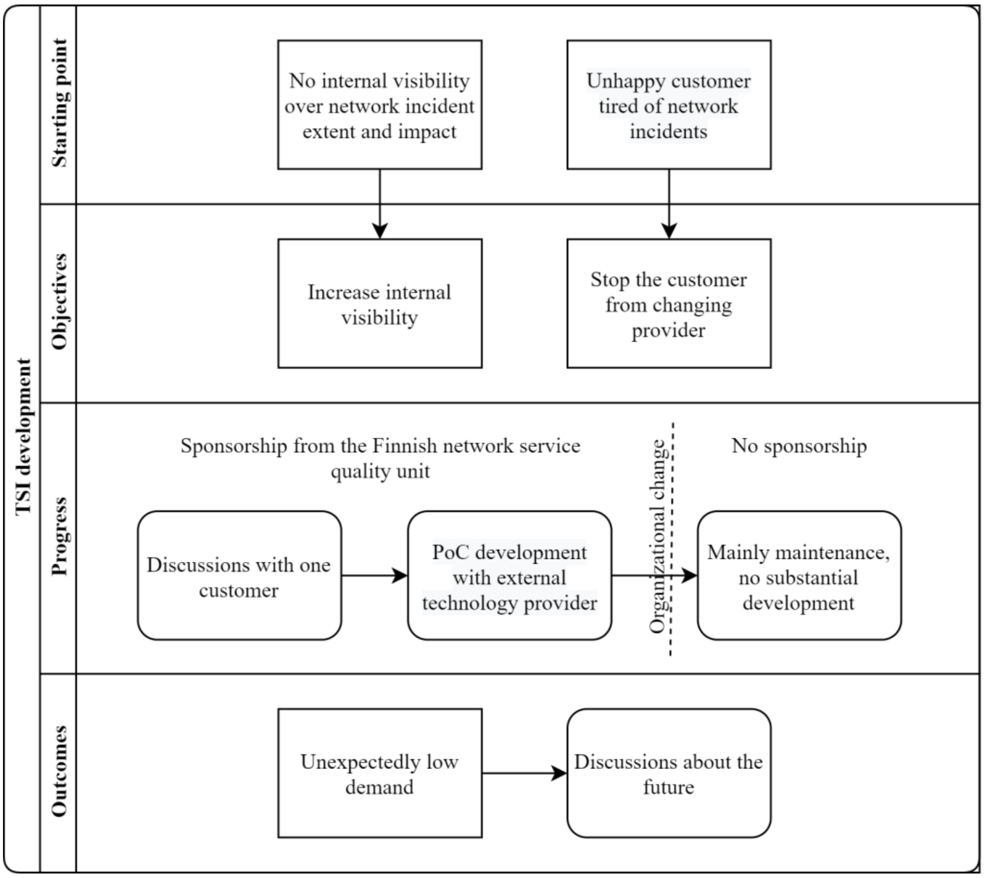

Figure 3. Telia Service Intelligence (TSI) development

3.2 Data collection & analysis

In the empirical part, the data sources include mainly semi-structured interviews, complemented with open-ended story sessions and case company digital artifacts. This use of multiple sources of evidence supports data collection principles concerning triangulation (Yin, 2012). In other words, it enhances the validity of the thesis. The interviews are used as the primary data source and *open-ended story sessions and digital artifacts* as secondary ones. The open-ended story sessions were held with product representatives of both Crowd Insights and TSI to understand the products better and guide the actual interview phase. Digital artifacts, on the other hand, were used to examine the current Telia context for external data monetization using analytics product offerings. These artifacts included Telia's established product descriptions, organization structure materials along with data, analytics, and innovation -related webinars.

The *semi-structured interview* method for primary data collection was used to enable explorative discussions, simultaneously covering the intended subject areas. All selected interviewees work at Telia and are or have been involved in the external data monetization process of Crowd Insights and TSI. The more precise selection aimed at covering all process phases described in the literature review for both products. The interviewee selection began using my own and my teams' connections at Telia and evolved based on early interviewees' suggestions. All the interviewees work on the product management side and have worked with multiple relevant stakeholders from, e.g., Telia's IT, legal and sales departments. The selected interviewees per product with their current titles and areas of expertise or main product responsibilities are presented in Table 4. There are fewer interviewees from the TSI context, as the analytics product was developed with much fewer resources and people.

Table 4: *Interviewee introductions*

Product	Title	Area of expertise / product responsibilities
Crowd Insights	Senior Business Development Manager	Commercial launch and offering in Finland
Crowd Insights	Head of Customer Delivery & Support	Legal anonymization and technical implementation processes
Crowd Insights	Commercial Product Manager	Business case and technology partners
TSI	Development Manager	Technological, data and analytics arrangements, project management
TSI	Commercial Product Manager	Commercial offering

In total, seven interviews were conducted with the five selected experts. The topics and the question patterns varied based on the area of expertise and external data monetization participation phases. Moreover, the exact interview questions depended on the prior open-ended story sessions for each product. Appendix A presents the general interview structures used and themes covered per each external data monetization phase. All interviewees were provided with informed consent, and each participated in the study voluntarily. The interviews were held in Finnish or English and took place in a specific business communication platform used at Telia.

The interviews were recorded to help to analyze the material thoroughly. The recordings were then transcribed manually or utilizing an automatic transcription feature for a more exact analysis of the interview data. The theoretical framework introduced in the literature review was used to structure the key elements from the transcribed interview data and analyze this case study evidence. More specifically, the data from the two units of analysis were compared with each other in each part of the framework. The next chapter presents the case company findings using this framework.

4 Analysis & findings

This chapter describes the analysis and findings made from the interview data, focusing on the interview results and implications for the case company Telia. In other words, this chapter provides answers to the research questions presented in chapter 1;

RQ 1: What are the *challenges* in the external data monetization of the two analytics products?

RQ 2: What are the *enablers* of successful external data monetization of the two analytics products?

RQ 3: What are the *key aspects to consider for future* analytics productization success?

The findings are presented chronologically using the seven-step process framework introduced in the literature review. Each subchapter presents one process phase – they first discuss the identified main challenges and enablers at the case company Telia and then reflect them in both analytics product contexts. The main challenges and enablers are summarized in tables, followed by future considerations of dealing with the main factors. The key findings are supported with interview citations. After the framework sub-chapters, further fundamental findings and underlying process factors that emerged during the interviews and analysis are discussed. The chapter ends by summarizing the main findings and recommendations for the case company.

4.1 Opportunity mapping and data strategy preparation

At the case company Telia, many different aspects related to operator business are measured and data collected continuously for different business purposes. This huge data volume is widely known in the organization, especially in the analytics product context. Especially operating support system (OSS) data and its value potential are acknowledged; for instance, mobile phones as sensors or data sources are evidently perceived as valuable due to their vast, continuous, and inclusive nature. Still, Telia is incapable of utilizing the data and tapping into its data monetization opportunities fully. In other words, data is not treated as an asset that is needed to kick off with data and analytics initiatives successfully.

The existing way of treating data at Telia occurs particularly as a lack of a standardized approach to the data value. For instance, a common data strategy would enable and support identifying data availability for different data and analytics initiatives – currently, the collected data is mainly used only for the original business purposes. Combining data sources for added value has not been studied or acted on notably, even though the great data monetization potential in the telecommunications industry is significantly related to the availability and use of various data sources and types. Thereby, data value assessment is rather a product, initiative, or project-specific and hence, might conflict with other products or strategies. Moreover, the approach to evaluate data value and opportunities in product contexts is customer-specific and reactive instead of utilizing data mapping results or data catalog to create a data strategy. One could state that data value is more connected to the estimated customer perception and price than assessed data opportunity potential.

> *"Traditionally, we aim at fulfilling all customer requests no matter what. It doesn't include thinking about whether it is valuable or not – the value is what we have sold to the customer.--- There is no systematic (data) strategy, it's more reactive and causal." -TSI*

> *"These (the data solutions), of course, aren't aligned with what the data generation has been meant for. Virtually, they might conflict with them." -TSI*

The reactive approach to data monetization and analytics initiatives is demonstrated in the TSI context. The project was business problem-driven, initiated based on both internal and external requirements: 1) internal request from a new technology lead to solve an internal visibility issue, 2) promise to an external customer to solve their problems, and 3) project manager's own hunch about the potential. Thereby, the TSI approach to the data monetization value-creation process could be claimed to be business problem-centric that evolves from established business problem to data requirement and preparation, then to getting the data for the problem and finally deploying the model with data and validating it with real data. However, finding suitable data as a last step of the process typically causes challenges with complex big data – some data is of poor quality and some might not be available at all. Also, having both internal and external requirements led to loosely defining the data value and monetization opportunity, probably resulting in belated challenges in modeling the TSI value proposition.

> *"It goes always begins with what is the information I want. A customer tells us that, and then we see if it's available and adequate. If it's not available, how to get it. Typically we need to develop new probes to collect the data, and that is a slow process."-TSI*

Conversely, the Crowd Insights' value-creation process was proactive and resembled a more exploratory data analysis approach. The data value and opportunity were explicitly evaluated for external use cases as the initiative took off in a unit specified to innovation and new business and product ideas. In fact, company executive management requested them to see how Telia could profitize the currently available data. In Finland, the trigger came from an external technology provider who had identified the value that Telia's data could have with their technology. Thereby, the data opportunity was considered first. The more detailed and addressable business problems were defined and decided on later in the process, enabling more objective consideration of the data value and opportunity and more iterative identification of business needs. Table 5 brings together the identified main challenges and enablers related to this process phase.

> *"The aim was to find new business opportunities. --- The technology provider contacted us and they had the technical solution for data collection and providing analytics. Then again, we had the actual data and they asked if we wanted to go and try." -Crowd insights*

Table 5: Opportunity mapping and data strategy preparation challenges and enablers

Challenges	Enablers
Lack of data asseting and common data strategy	Explorative approach to data monetization
Reactivity and business problem centricity	

To summarize, there is a significant need for paying more attention to opportunity mapping and data strategy preparation in the future. First, treating data as an asset on a company level could support more proactive innovation in the external data monetization area. In fact, a common data strategy could help determine the data exposition, i.e., whether the best data monetization potential is in internal or external initiatives, thereby increasing chances for success. Evaluating data availability and creating a data catalog on a company level could reduce the challenges on the analytics product or initiative level. Also, increased transparency, documentation and communication between initiatives could help to avoid conflicting product data strategies and even redundant investments in different analytics technologies. Finally, an explorative approach to data monetization should be emphasized more and not only react to established customer demands. There should be a business problem to be solved, but that should not restrain the objective opportunity mapping and data value evaluation.

> *"Crowd Insights has its own tools, but the data collection and the data itself are the same. Data assets and strategy are important. Now there are independent initiatives in different units and organizational silos, which is not good – it is a hidden factory with no accountable value."-TSI*

4.2 Potential planning and use-case definition

Previously, there had been some individual, nonrecurring data and insight deliveries to specific customers, but productizing analytics had remained limited at Telia. As analytics products are used to scale delivery to multiple customers, identifying common business needs and sufficient demand is particularly crucial for external data monetization success. However, some of Telia's analytics product use cases have eventually turned out to be irrelevant to the anticipated customers, resulting in lower customer demand than initially expected.

Irrelevant use cases can be considered a product of an unsuccessful identification of target customers' needs. This identification is challenging for various reasons, such as customers' inability to phrase their needs and evaluate unknown future opportunities. Understanding the customer business problems and needs requires in-depth cooperation between customers and Telia that calls for selecting target customer segments and focusing on their business problems. The business problems should then be reflected on Telia's role in the value creation chain and ability to deliver on the problem. However, there are implications of hesitating to decrease the generalizability and focus on the most potential segments and problems. Then again, customer demand being lower than expected could be a result of insufficient validation of the identified customer needs and demand in the market before productizing the analytics.

> *"Customers often don't have a clear idea of where the information would be utilized. Therefore, this is mainly a learning journey. It was essential to select, which customers to discuss with."-Crowd Insights*

TSI is an example of an analytics product that, in a sense, failed to meet the needs of a sufficient customer pool, resulting in unexpectedly low demand. From product management's perspective, the issues derive from a limitation of the solution – the use case covers only a part of the identified customer need, virtually one component of the process of interest. Value chains around customer's business processes and Telia's potential to create additional value were discussed but specializing in certain industry's needs was not prioritized for further investments. Moreover, covering customer's business processes and needs would have required partnering with other service providers, which neither was proceeded in the TSI context.

The TSI use case was refined collaboratively with customers, but the input was limited to two pilot customers making it a highly customer-specific development. The lack of higher-level industry segmentation thinking poses a challenge in later generalizing the need and use case. TSI is targeted at large B2B customers with more than 100 subscriptions, but that does not include considering the implications to customer's business. The need was perceived as common but not validated with multiple customers, leading to no certainty of sufficient demand for the productized analytics. This rushing to an analytics product offering based on the small pilot customer pool's needs with no prior use case testing could be considered rather risky. In fact, as the TSI use case is not a widely recognized data monetization opportunity, developing market understanding, focusing on the most prominent segments and validating the customer need would have been particularly critical.

> *"TSI shows only one component or part of the IT system. It is not interesting from the customers' perspective. They are interested in their own business." -TSI*

> *"We had customer discussions, where the customer very openly described Telia's disturbances' effects on its business processes. We evaluated our opportunities to*

> *affect that. --- Our resources were not enough. To provide these kinds of solutions, one needs to partner up with other use case providers." -TSI*

On the other hand, Crowd Insights has been able to develop highly relevant use cases for selected industries and business problems. The industry or customer vertical-specific nature of use cases was considered more thoroughly, and identifying the most promising customer segments in the market has been a priority from the beginning. This approach has truly enabled developing an understanding of the customers' business processes and common issues in the industry.

The market understanding has been built using multiple secondary and primary sources. First, as the overall use case of population analytics with location data is the most recommended data monetization method in the literature, public sources such as academic experiments offered a beneficial starting point for identifying the most potential directions to start an investigation. Another significant secondary source was benchmarking from different markets both via own research and chosen technology providers' prior experiences in similar use cases in other countries. Especially the latter was identified as a crucial success driver in the beginning. Finally, internal consideration along with a market survey of public perception led to narrowing down to certain most promising customer segments, especially the public sector.

As market needs stem from individual needs, customer discussions represented the most important primary source. Daily collaboration as a joint learning journey was identified as critical for evaluating unknown future opportunities and helping customers phrase their needs. Extra emphasis was put on customer input accuracy by searching for the best matching roles and contact persons in the organizations – Crowd Insights use cases were defined with the business development side and roles such as CDO, not with typical contact roles responsible for daily operations that typically require more ready-made solutions.

Analytics productization has been rather iterative in the Crowd Insights context to ensure sufficient demand for scalable analytics product. In fact, individual, project-like deliveries to specific customers, identifying a common need and demand of multiple customers, and creating a commercial concept are considered a working prerequisite for analytics productization. This method is still used when investigating new industries or customer sectors. Additionally, consulting industry experts have been critical to generalizing individual customer input, increasing understanding of the most promising customer segments, and reflecting on Telia's potential to fulfill the needs. This collaboration within the partner ecosystem was considered crucial in the Crowd Insights context from the beginning. Finally, other use cases have been tested as previous initiatives that have supported finding the best directions to proceed. For instance, a previous, more personalized use case initiative with location data was turned down by the management, setting direction to more generalized and anonymized use case for the common good. Table 6 summarizes the general challenges and enablers related to this process phase.

> *"We aimed to read and understand what had been done in other markets. Especially our technology partner acted as a quite significant source of information as they had also been in a service provider position in another market." -Crowd Insights*

> *"Especially when entering new segments, it is not wise to directly develop an end-user service, but we should aim to learn more with a customer project. --- As we work with a few similar pilot cases and see common elements, we should aim at creating a commercial sales concept. --- After validating the concept, sales and demand, we proceed to productize it." -Crowd Insights*

> *"Working only independently won't lead to good results. --- Besides individual customers, we should discuss with industry experts e.g., consultants to get a wide understanding of the customer sector." -Crowd Insights*

Table 6: Potential planning and use case definition challenges and enablers

Challenges	Enablers
Lack of market understanding and focusing on certain segments	Segmentation and specialization
Small-scale validation of customer need and demand	Engaging with a partner ecosystem

To summarize, developing accurate market understanding, selecting the most promising customer segments, and identifying their value creation chains and ecosystems are critical for creating use cases and validating the concepts. In the future, segmentation and use cases could be considered from the following three perspectives to avoid ungeneralizability and irrelevancy; 1) figuring out the general direction and use case, 2) understanding individual customer needs and 3) specializing in the most relevant customer industry verticals.

From the first perspective, reviewing the use-case suggestions provided for the telecommunications industry in academic reviews and other material could boost choosing the most suitable use case or derive new valuable use-cases from them. Having a recognized use case idea as such or as a parent idea could help communicate the initiative to stakeholders and convince them of the potential in the telecommunications context. Thereby, chances for investments, other resources and support across the organization could potentially be improved. Reviewing public sources can also boost narrowing down to the most promising segments. Secondly, literature and secondary sources typically cannot be directly implemented in real-life contexts on other markets and organizations. Therefore, customer discussions to jointly reveal customers' needs should be continued. To ensure customer involvement and engagement both in time and money to get an accurate view of the future demand, charging even a small amount from the piloting could be considered – this has proved to work at least in Crowd Insights context. From the third perspective, identifying the most relevant customer industry verticals should be considered from the start as business problems tend to be industry-specific. Focusing on certain segments increases use case relevancy, validates the concept and helps to ensure sufficient customer pools. Focusing on certain industries and business problems also eases partner collaboration. However, partnerships to solve customers' business problems require a general change of thinking regarding partnerships and collaboration.

> *"Information from secondary sources is never the same as own learnings. That is why big aspect of the work has been daily collaboration with customers. --- We didn't conduct free pilots as we thought it wouldn't give enough evidence of real customer interest." -Crowd Insights*

> *"Virtually, one component provider cannot easily make these kinds of solutions, but partnering with other use case providers is a must. --- The lack of partnerships might be more Telia's problem as an organization." -TSI*

4.3 Legal and compliance alignment

The criticality of legal and compliance-related matters is widely acknowledged at Telia, which possesses a lot of personal data. Especially risks related to compromising GDPR and mishandling privacy issues are extra emphasized. The privacy matters are related to public perception risks that could potentially harm Telia’s brand on top of the financial penalties that could follow neglecting regulations. There are clear internal processes and guidelines to address the legal and compliance aspects appropriately to address the risks.

The clear legal frameworks, such as GDPR, support external data monetization and analytics productization as they clearly state what is allowed and what is not. Moreover, they enable understandable communication of privacy to third parties such as consumers, minimizing the public perception risks. The established standard processes include, for instance, standard internal Data Protection Impact Assessment (DPIA) and internal privacy office consultation possibilities for privacy-related changes. Minimizing risks is built within the Telia data management system – the idea of privacy by design where the data is provided to product development only with valid business reasons, readily anonymized and aggregated. On the other hand, the security side is mainly handled by the Telia IT unit, ensuring appropriate access control, segregation of duties, and system updates. Finally, technology provides security audits are part of the practices.

Then again, product management is responsible for following and taking actions on the established processes and guidelines. For instance, defining a suitable anonymization approach and selecting and making agreements with technology providers are done product-specifically. However, development activities sometimes are challenging as the privacy and legal professionals' reaction can be more opinionated than cooperative.

> *“The brand and public perception were the most important ones (concerns). What if Telia’s customers think that we're misusing their personal data and the confidence that they have for us as an operator. That could be potentially a catastrophe for the whole operator.” -Crowd Insights*

> *“GDPR provides a clear playground. For us, it has been an opportunity as we now know what we can and cannot do, and there is a strong justification for it. That is why we dared to go forward with this.” -Crowd Insights*

> *"When we started talking about this to legal (unit), it was like no, no, no, no. For quite some time." -Crowd Insights*

TSI can be seen as a neutral use case with respect to public perception as the analysis is done only with B2B customer's own employees' and devices' data and results showed only per customer. Thereby, TSI has mainly followed the established standard legal & privacy processes, not requiring extra effort in this phase. The product-specific anonymization approach contains filtering out personal aspects of the data and encrypting the personal identifiers. Then again, the security perspective and the fact that agreements with external parties such as technology providers rely only on trust for goodwill have been highlighted. Therefore, the data is fully processed and analyzed on Telia's own cloud and servers. The agreements on ways of working with the technology provider are in place to ensure confidentiality.

> *"It relies on trust that nothing leaks outside the factual connection. --- Basically, the use of information is also based on contracts. --- Everywhere where data is processed, it's humans who do that. There can be slips or on purpose. --- When you go to Google, it's Google that is in control. That risk was not taken with TSI." -TSI*

Then again, Crowd Insights is a more sensitive use case with greater public perception risks as it uses and analyzes consumer customers' mobile data to provide insights to B2B customers. A fair number of actions were conducted to minimize these risks. First, the Crowd Insights project included a market survey to guide the use case development work and ethics. Secondly, there was a third-party evaluation of the solution from a legal perspective, and finally, an external review of the code to make sure it performs as intended. Most importantly, a solution-oriented collaboration with Telia's legal department and internal pre-GDPR work are identified as some of the main success factors in the early development stages.

In the Crowd Insight product context, the anonymization approach includes 24 hours delay, removing observations of less than 5 per cell tower per hour, rescambling unique identifiers and throwing the encryption keys away. This ensures that no individual persons can be tracked, and the anonymization can't be undone. The security risks related to data are not addressed notably in the product context, as they are more in the IT unit's responsibility. Crowd Insights technology provider uses public cloud, highlighting the importance of thorough supplier investigation – the fact that German authorities already approved the technology provider's solution was critical in order to proceed with the initiative at Telia. Table 7 summarizes the main challenges and enablers derived from the analytics product comparison for the process phase.

> *"She (contact person from the legal unit) was extremely business-oriented and solution-minded. I worked a lot together with her in finding solutions to the problems that we faced." -Crowd Insights*

Table 7: Legal and compliance alignment challenges and enablers

Challenges	Enablers
Public perception and financial risks	Solution-oriented collaboration
	Clear guidelines and frameworks

Thereby, the recommendations for the future follow the current practices and ways of working. For instance, legal and privacy checks should be conducted normally. However, it would be critical to further ensure continuous up-to-date access to data from the security perspective as it appears to have weaknesses on a company level. Use case sensitivity analysis should remain a top priority from the start, especially in cases that deal with personal data. Previously suggested data catalog and strategy could support product development parties to assess the personal data aspect and sensitivity. Thoroughly considering use case sensitivity is evident in forming a suitable anonymization approach and involving relevant stakeholders if needed. In fact, transparency and communication to relevant stakeholders should be emphasized to avoid conflicts and surprises. Early contact with stakeholders in the legal and privacy unit could increase engagement and result in a solution-oriented collaboration that is crucial in turning an initial no to yes, thereby raising the probability of proceeding with the use case idea.

> *"There are situations where people change roles but the access rights from the past role remain the same. We don't have anyone to oversee that the access to data closes along with the change of role." -TSI*

4.4 Data collection and preparation

Although the data exists in the various databases and warehouses, unstructured data management and data architecture at Telia hinder combining data sources for added value. Especially, poor or nonexistent data masters make it difficult to match different data to certain customers or products – there is no single company-wide data master, and the existing ones change continuously, rarely being fully up to date. Moreover, the initiatives to standardize data management and data architecture, such as a common data lake for mobile network data storing, have not yet succeeded fully as not even the professionals working with it understand all the differences in the data coming from various source systems. The data volume and velocity further complicate data management and architecture. For instance, real-time data processing causes issues on which data to save and which to let flow through, and the overall data volume on how to store and process data cost-effectively.

The data measurement and collection techniques vary significantly between different technologies, subsidiaries and countries, causing challenges with data quality. In other words, the data collection landscape is rather siloed. The low quality, missing values and different levels of measurement granularity make it difficult to process, analyze and eventually monetize the data and require emphasis on normalization. Moreover, the low quality affects analysis result reliability, calling for extra attention on verifying the results. After all, the results and data streams are built by humans, increasing the need for constant awareness about the analysis results.

> *"Even those guys (working with common data lake) don't have a full understanding of the differences in the data. It all looks different in different countries." -Crowd Insights*

> *"The diversity of measurement points causes a problem of combining information and showing all the status information on one screen." -TSI*

> *"We have data with a life cycle of seconds, minutes, hours, which is this real-time need. There is no point in saving it somewhere – and there's a ridiculous amount of it. --- The second there is something irregular (in the real-time data flow) it should be possible to connect to the saved, collected data with customer and product info (data master)." -TSI*

TSI faces significant challenges related to cross-use between different siloed technologies and IT as it uses mobile network data and fixed network data, enriching them with customer and product data masters, change notifications, incident alarms and network coverage data. First, getting a precise status from a large environment is challenging. Secondly, connecting the data from different technologies to one customer or product is demanding in the current environment. Thirdly, data quality issues stemming from the diverse measurement techniques and units complicate cleaning and preparation remarkably. In fact, normalizing the data, changing formats, handling missing values, and connecting the data with data masters are crucial to ensure reliable results. Then again, real-time analysis of countless data items further complicates data processing.

> *"You always need to evaluate if the results are what they were meant to be. There might be those missing values and wrong formats. --- We have many data sources that give results on different granularity levels. Then we need to normalize it to a rough level and get the results from there." -TSI*

Crowd Insight uses only mobile network data containing very stripped-down sub-sets with only a few data items. Moreover, data is not enriched but only aggregated to counts. However, Crowd Insights faces issues of using data from multiple countries that have their own systems with different configurations, parameters, and setups. Thereby, the data stream is inconsistent even though coming through the common data lake, leading to challenges with analysis result reliability. Besides the quality issues, the data volume causes challenges, especially concerning the cost-effectiveness of data processing. Table 8 presents the main challenges identified in the analysis of the two products – no substantial enablers were recognized for the process phase.

> *"It (setup) looks different in each country. The data stream that should be similar is not the same." – Crowd Insights*

> *"The scalability, however, is a bit complex – processing hundreds of events for millions of users in several countries every day turns into billions quite quickly. --- Cloud platform was more scalable for us and turns out it's also fairly cost-effective. It allows us to manage peaks and works quite well if we need to reprocess something." -Crowd Insights*

Table 8: Data collection and preparation challenges and enablers

Challenges	Enablers
Unstandardized data collection, data management, and data architecture	
Data quality effects on result reliability	
Data volume and velocity	

From a product perspective, sharing information about the ways of working and practices around data collection and preparation could boost future analytics productization efforts. However, the main contribution would be needed on a company level to ensure more standardized data collection, data management and data architecture. Systematically improving possibilities to link data sources from different technology silos, countries and subsidiaries would be critical to support future data monetization initiatives, where the value typically comes from using various data sources in new use cases. These improvements should include at least effort on data master and common target architecture for coordinated systems. More specifically, ensuring up-to-date customer and product master could boost combining different measurement data, for instance, for a wider analysis of a specific customer. Then again, common target data architecture and harmonized data measurement and collection between countries and technologies could improve possibilities to utilize data consistently and reduce data quality issues stemming from various setups. Moreover, the current efforts on common data architecture and overall data management should be continued to reach the intended value and to cope with processing increasing data volume and velocity.

> *"There is no real target architecture for the different countries. --- Telia would very much benefit from having a common process, system and data architecture. ---. The data lake was a very nice idea, but I think in reality, they have a bit more to go and to do." -Crowd Insights*

4.5 Technological arrangements

Conducting technological arrangements for analytics products internally is not perceived as possible nor reasonable at Telia, following the telecommunications industry's overall trend of outsourcing technological development to specialized analytics firms. The main reasons for this at Telia include lack of internal analytics tools, the inability to link data sources, lack of agile ways of working, advancement of the algorithms needed, and insufficient in-house analytics competence. In fact, competent professionals are scarce in the market and insurmountably difficult to attract to Telia. Moreover, external technology providers' efforts on the analytics development were considered more scalable, offering cross-pollination and cost-bearing opportunities.

However, there appear to be challenges also related to the use of external technology providers. Especially in the past, the immaturity of the analytics market and the unavailability of suitable technology providers limited selection and comparison possibilities. Other external technology provider challenges concern scalability, transparency and interactivity of the solution. Particularly lack of transparency and interactivity can result in a black-box situation, where Telia has very limited visibility to the solution, narrowing down possibilities to contribute to the development and making it difficult to communicate and sell the solution to third parties as a trustworthy one. Moreover, ordering everything separately exposes to misunderstandings between Telia and supplier as well as problems with convincing and ensuring sufficient internal funding. TSI and Crowd Insights resembling MVP suggests a wider trend at the case company of not prioritizing and enabling further development. Lack of investments causes issues also in building partnerships with the external technology providers that would support more engaged development and value creation. Finally, Telia's external analytics providers and solutions appear to be nonaligned with each other, allowing wasted resources and value-creation potential.

> *"I think this (external partner approach) is competence-wise because to develop these kinds of big data analytics, you need to attract different types of data analysts, data engineers, data scientists. And they are scarce in the market, so attracting them to Telia could be quite hard to do and get off the ground." -Crowd Insights*

> *"It's hard to work with this kind of statistical data when you have a black box. It's hard to sell it. You need to be able to show what kind of methods and what kind of calculations have been made and assumptions taken." -Crowd Insights*

> *"We haven't been able to develop further from the version 1.0, which is a shame. --- We haven't been able to bring in further development with which the value could be increased."-TSI*

The issues of using an external technology provider materialize especially in the TSI context. In fact, the solution's real-time nature and level of advancement pose challenges even with an external provider. For instance, filtering everything normal out nearly real-time but instantly matching data with data master if anything abnormal happens is demanding. Moreover, dynamic analysis and comparing the normal status per profile with generic decision trees of past phenomena or trends increase the complexity.

In the TSI context, technical platform security and evaluated cost-benefit ratio were highlighted in technology provider selection. However, the supplier collaboration is a black box situation, causing a dilemma between low transparency & interactivity and moderate internal funding. Moreover, the relationship with the selected analytics company has not grown into a true partnership model due to difficulties to ensure investments and, hence, lack of engagement in development. In fact, solution and value-creating elements have not been possible to develop.

> *"At the moment, TSI is a black-box for Telia – a problem. If we wanted to bring in new data, product or service, it needs to be ordered from the supplier. However, they are so expensive that Telia doesn't want to invest that much in them." -TSI*

Crowd Insights, on the other hand, has been able to overcome the black box issue by changing the technology provider. Initially, an external provider was selected emphasizing prior experience in similar use cases and GDPR compliance. Later, tackling challenges related to scalability, transparency, and flexibility were prioritized. Now Telia can develop new features and pass them for the technology provider to scale, cost-efficient cloud platform enabling scaling. All in all, common use case and industry knowledge sharing with another company enabled more educated partner selection, and using well-known, fairly simple algorithms to create dynamic statistics lowered the partner criteria.

Moreover, Telia had invested in the new supplier company for other business purposes, which encouraged and enabled further cooperation and building deeper partnership along with other support from the management. Nowadays, the relationship between Crowd Insights and the technology provider is partnership-like with a revenue split model. Nevertheless, Crowd Insights' core product has neither been developed substantially during the past few years, which could become a problem in the long run. Table 9 summarizes the general challenges and enablers of this process phase.

> *"So it (algorithm) is not cutting edge as such, it's more a scalability question." -Crowd Insights*

> *"Basically, this (non-black box) allows us to do some custom development. If we want to, they can make it standard. This is a big influence for us. We have an open books agreement where we pay for the resources and then we have a revenue split which makes this very partnership like supplier relationship." -Crowd Insights*

Table 9: Technological arrangements challenges and enablers

Challenges	Enablers
Lack of transparency and interactivity in a black-box situation	Management's support for investment and collaboration
Lack of investments and partnership for further engaged development	Partnership-like flexible and transparent development

The case company could benefit from having a more precise strategy concerning analytics in the future. Particular focus should be put on determining the total realized investments in in-house competence and tools and external solutions. It could support a better assessment of the most relevant in-house competence areas in the analytics domain and how they align with external technology provider competencies. Better alignment of the external technology providers and analytics solutions could help avoid overlapping and unnecessary investments in different parts of the organization. It could also support focusing on certain technology providers and building strong partnerships with them, increasing the engagement, collaboration and mutual benefits. Partnership-like development is also likely to progress from black-box situations to more transparent and flexible collaboration.

> *"Analytics strategy need to be managed to get results and avoid unnecessary costs of development overlapping (tools etc.)." -TSI*

4.6 Data pricing strategy

Digital asset pricing is considered a pressing challenge in the data and analytics landscape as data and derived products are perceived as intangible resources with no direct customer-specific costs. In fact, a higher amount of analytics product users decreases the overall cost per customer. Thereby, the customer-perceived value approach, where the focus is on maximizing revenue rather than covering the costs, is regarded as more rational than the traditional cost-based pricing.

However, modeling customer value to find a suitable pricing point is considered problematic due to limited support both externally and internally at Telia. Externally, the overall immaturity of the data and analytics market and the lack of common practices complicate finding the suitable price point. Virtually, they include narrow price benchmarking opportunities, such as other data or information products' prices, and lack of continuous budgets for information purchases in organizations. Internally, modeling customer perceived value based on internal stakeholder opinions as a secondary source can decrease the result reliability. For instance, consulting standard sales and customer representatives instead of discussing with customers can lead to biased and inaccurate price point suggestions as they might not fully understand their customers' motivation in the analytics product context.

Optimal pricing is considered to be accurate as well as scalable and simple. This could enable minimizing wasted revenue potential per customer and streamlining the sales and pricing process for further maximized revenue. However, determining the approach to data pricing strategy can be challenging as the accuracy and simplicity conflict easily. Finding a price point that accurately models customer perceived value seems to require exploring customers' preferences, motivation, and willingness to pay for the product and adjusting prices accordingly in the immature market. Then again, the case-by-case customer-specific pricing process is slow and very resource-intensive, limiting possibilities to use it. On the other hand, scalable and simple pricing typically requires selecting the best parameters that are hard to come by, and using automated tools, that are poorly available at Telia. Managing complex pricing structures manually is irrational, leading to using simpler, other than optimal parameters and using a more fixed than scalable pricing structure.

> *"Data is yet an intangible asset that doesn't erode. Cost-based pricing makes no sense. It's not necessarily negative for us if one customer gets the (same) data with 1000€ and another pays 10 000€ for it."-Crowd Insights*

> *"A certain type of immaturity in the whole market and the early stage that we are in concerning trading information leads to lack of common practices that makes pricing difficult." -Crowd Insights*

> *"Pricing is not wise to make very complex if price structure is managed manually. We weren't able to automate it (pricing) based on different parameters." -TSI*

The customer-perceived value approach to pricing has been particularly difficult with TSI. It appears that the limited focus on prior overall customer segmentation and market understanding for the use case multiply to the issues in modeling customer value. Furthermore, utilizing the available pricing benchmarks in the market has remained relatively limited. In fact, the fixed price point, reflecting customers' willingness to pay for the product, was found through iterating and evaluating value and price suggestions made by internal stakeholders such as sales and customer representatives of large B2B customers with over 100 subscriptions. The use of secondary source input to review customer needs could be considered a challenge in result reliability – did the customer representatives understand the value proposition? How well can they know their customer's motivation in the analytics product context? Stakeholder consultation resulted in a wide range of price suggestions, eventually leading to select something in between. Thereby, the price point could be claimed to be poorly justified.

With TSI, the pricing simplicity is highlighted as the product sale relies on standard sales processes. In other words, there are no resources for exploring customer-specific preferences for the most accurate pricing. Moreover, TSI pricing simplicity is perceived as essential to attracting interest in the standard sales department, especially when sales stakeholders are crucial in delivering the value proposition to potential customers. However, utilizing suitable parameters for simple and scalable pricing has been challenging due to the lack of automated parameter tracking tools. Initially, the scalable part of the price was meant to be bind with the number of customer's subscriptions. Still, an irrational amount of manual work and difficulty to automate tracking resulted in using the number of TSI users and access rights per customer as the parameter.

> *"We tried to iterate what the price could be. --- Some thought that if the price is clearly rather high, it gets noticed in the sales more easily. There are these different points of view to pricing, to keep it quite simple."-TSI*

> *"We ended up having a fixed part and scalable part that would scale the price based on the customer size. The more the customer has subscriptions, services, etc., the more the benefit increases in a sense. --- Eventually, we ended up scaling it based on the number of users (of TSI) only." -TSI*

Pricing is regarded as one of the most demanding tasks in Crowd Insights analytics productization. The customer's perceived value is considered more in-depth – the objective is to understand in which situations and how customer value realizes in customer's business. Then again, the efforts made in understanding the market, focusing on certain segments and learning jointly with the customers have been remarkable benefits in perceiving the value. The available resources have played an essential role in enabling this more persistent approach to modeling customer value.

Pricing accuracy is prioritized when formulating prices for new business needs or sectors, virtually referring to project deliveries prior to developing an analytics product. Deciding on the price level in case-by-case customer discussions, where the customer expresses their willingness to pay and suggests the price enables quite accurate pricing with minimal wasted revenue potential. However, standardized analytics products require a more scalable and simple pricing strategy that relies on selected parameters along with the project delivery findings derived from customer-specific pricing exploration per selected industry segment. The main factor used to assess the willingness and ability to pay is the organization size. Exact parameters, however, depend on the type of customer; municipalities are evaluated through, for instance, population, budget, and organization targets, whereas private businesses are typically evaluated through revenue. Still, setting the price for scalable analytics product is not a fully automated process and requires some manual effort and consideration. Simplifying and speeding up the pricing process and pricing model with suitable parameters is needed as the current process is too slow and resource-intensive for a long-term solution. Table 10 brings together the general-level identified challenges and enablers derived from the analytics product comparison for the process phase.

> *"We intend to figure out how each customer could possibly use the information, what they aim to do with it to understand what is the benefit and the value they get from it and thereby, set the price point." -Crowd Insights*

> *"This (simplification) is the direction we want to go when we understand well enough what they do (in the industry). In cases where our information is used for non-standardized use cases, it is still a case by case, cat and mouse game." -Crowd Insights*

Table 10: Data pricing strategy challenges and enablers

Challenges	Enablers
Modeling customer value and revenue potential with limited supporting sources	Efforts on use case definition and segmentation
Pricing scalability & simplicity; parameter selection, and lack of automated tools	Resources for exploring customer value and adjusting prices
Pricing accuracy; resource-intensive and slow process	

In the future, more emphasis should be put on understanding the customer-perceived value to increase pricing accuracy. Especially considering the future benefits derived from the analytics product insights is essential. Thereby, focusing on specific segments and learning jointly with the customers remains relevant. Customer segmentation based on common business needs could also support using internal sources as it enables focusing on discussing with the right customer representatives and evaluating the wide range of price suggestions. After understanding the specific need and use case, the customer discussion findings should be utilized in selecting the most suitable parameters for scaling. Discussions primarily with selected customers and secondarily with internal stakeholders stay particularly relevant as long as the data and information pricing market remains immature.

Adding internal support to data and analytics pricing on a company level could attenuate the identified challenges. For instance, aiming at internal transparency of customer discussion findings concerning digital asset pricing could help in the situation where the benchmarking opportunities in the overall market are limited. At least the common elements that impact the customer perceived value, such as market environment factors and supplier value denoting customers' general perception of the vendor company, could be gathered together. Secondly, internal support for external data monetization pricing could be improved and simplified by enhancing internal data monetization – to support data-driven decision-making within the company. For example, considering cost allocation regarding the analysis tools, maintenance, etc., on a company level could help individual projects to find a minimal economic price to utilize as a starting point for price consideration. Furthermore, it could improve equal and transparent investment assessments of the internal analytics environment vs. external analytics purchases.

Increasing pricing simplicity and scalability without compromising accuracy is demanding. However, internal efforts on automated tracking of the pricing parameters could support using the parameters that best represent the customer value. It could enable simplified and fast pricing processes with optimal revenues for final analytics product pricing and preliminary project deliveries required in future analytics productization efforts.

> *"I hope that at some point we find a way to create simple pricing where we don't have to each time consider customer's willingness to pay and liquidity." -Crowd Insights*

4.7 Market entrance planning

Telia has standardized B2B sales and account management functions for a consultative sales approach. However, they seem problematic for bringing new types of products, such as analytics products, to the market – typically, standard sales personnel don't have prior experience or a profound understanding of the analytics area. Moreover, the current analytics product revenues tend to be relatively small, which might decrease sales motivation in a commission model. As a result, getting attention from the standard sales and account management functions is challenging.

Also, the unfamiliarity with the analytics product concept results in challenges in creating the initial customer interest – explaining the new type of analytics product to customers and justifying the value is found difficult. Customers' similar unfamiliarity, old habits of using Telia's tools, and poor combability to established products further complicate the initial sales argumentation. Furthermore, new ways of working and untraditional decision-making principles with a new type of data source sometimes cause customer reluctance. Solution sales with dedicated sales personnel for analytics products are considered an effective way of dealing with customer suspicions and creating the initial customer interest. Still, the approach is eventually likely to face significant scalability issues.

To support more efficient sales of analytics product, extra effort in phrasing and justifying customer value is required. Especially in the B2B context, story-like argumentation and content marketing with prior customer results as evidence is perceived superior compared to straightforward and price-centric marketing. However, there are some challenges related to the story-like success-based approach. First, figuring out suitable methods for measuring results and actual impact on a customer's business is typically quite demanding when it comes to data and analytics products where the value is often indirect through enhanced decision-making. Secondly, extra support and collaboration with suitable marketing and communications stakeholders are not typical at Telia, even though content marketing collaboration is regarded as having a critical role in defining the value proposition, core message, target groups & roles, and the overall go-to-market approach. Creating analytics product descriptions and sales materials independently with only an internal marketing framework and guidelines is thereby considered a challenge. The challenges in measuring and communicating the success and results to the sales personnel and customers have led to issues in concretizing and justifying the customer value, hindering the argumentation and sales power.

> *"If we wanted to make truly scalable sales, this kind of approach (case-by-case solution sales) obviously wouldn't work." -Crowd Insights*

> *"They (sales) should look around and experiment with the customer what this kind of service could offer to them and is this the kind of topic to be discussed further. --- However, it is a bit challenging service to start a discussion." -TSI*

The issues with the standard sales function are particularly critical in the TSI context. The product is fully dependent on the standard process – it is just one product in the product lists even though it is a new product type. In other words, TSI significantly relies on the standard sales personnel's argumentation and abilities to create the initial interest regardless of their unfamiliarity with the analytics product concept and the limited concreteness of the value proposition. The situation would require an extra emphasis on sales onboarding, but the initial issues in justifying the customer value itself complicate communicating the suitable use cases and the value proposition to sales personnel. Furthermore, the value proposition has not been clarified with extra marketing collaboration besides the standard sales material frameworks. Neither measuring and communicating the success and results has been acted on. In fact, TSI feedback is gathered through customer discussions, but the focus has been more on improvement requests than discussing the perceived value and implications to companies' business. This has led to a situation where the sales personnel struggle to understand the customer value proposition and sell the product, eventually leading to very moderate sales and revenues.

> *"Starting to use new tool always requires effort before you see whether it brings you value or not." -TSI*

> *"Both communicating the value and the value itself are challenges as the current value remains limited." -TSI*

> *"It (measuring) relies more on customer feedback and discussions. --- Results are not involved in the conversation. The focus is more on improvement suggestions, how TSI could be developed from a customer perspective. It is very difficult to tap into the value concretely." -TSI*

Then again, Crowd Insights is introduced to the market and customers with dedicated solution sales resources that work only with the product. This solution sales method has enabled raising the level of focus, understanding, and consultative approach to another level. Moreover, it helps connect and engage with the most promising target groups or roles in customer organizations such as CDOs instead of normal contacts. Solution sales scalability issues are considered with plans to raise the level of collaboration with the standard sales once the analytics concept understanding increases both amongst the potential customers and in the standard sales unit. Currently, standard sales leads are only encouraged and occasional sales campaigns for the most promising customer segments are launched. Sales scalability is also driven through specific external go-to-market partners that have established customer relations and possibilities to customize the analysis if required.

Besides the solution sales approach, widespread stakeholder collaboration and a marketing strategy emphasizing the market visibility from the product launch are considered essential factors in creating the initial customer interest and selling the product. Especially collaboration with internal communications and external content marketing partners is regarded as crucial for refining the value proposition and formulating optimal sales argumentation approach to deliver the core message to the right target. Eventually, Crowd

Insights' go-to-market approach has resulted in incoming contacts and requests from customers and their partners. Nevertheless, Crowd Insights still struggle with measuring the success and concretizing the value proposition due to difficulty to prove the causal relationship between the analysis results and the possible cost savings or new revenue. It is the case, especially in some of the scalability-driven delivery models where Telia only provides the data – the analysis and conclusions are entirely done by the customer or a possible second partner. Table 11 summarizes the main challenges and enablers identified for this process phase.

> *"What is the concrete benefit the customer has got? It still partly hinders selling the service. --- The more we can do it (measure concrete value), the stronger our message is and the easier it is to win sales and the higher price point we can get." -Crowd Insights*

Table 11: Market entrance planning challenges and enablers

Challenges	Enablers
Standard sales and market immaturity	Solution sales approach
Attracting sales interest and providing support for sales argumentation	Content marketing and internal stakeholder collaboration
Justifying customer value; measuring and communicating success and results	

As functioning sales is critical in getting strong revenues from the product launch and realizing the promised value of external data monetization, more emphasis could be put on sales planning in the future. More specifically, increasing sales support for a more solution sales-like approach could be needed as standard sales function seem to be immature for effectively advocating for the new types of analytics products. Then again, open discussion and collaboration between solution sales and standard sales are evident in enabling future scalable sales. Emphasizing standard sales education concerning new product types could also boost sales motivation and argumentation. Moreover, sales scalability can be improved using specific go-to-market partners with established customer relations and an understanding of the industry's needs.

Supporting sales functions and increasing customers' willingness to pay for the product, in general, could be done through more convincing argumentation of the value proposition. As content marketing with stories and prior results is perceived most efficiently in B2B marketing and sales argumentation, involving relevant stakeholders from the marketing functions could make a more general procedure to formulate the best possible core message. Moreover, extra emphasis should be put on gathering the material from customers' experiences and piloting results. Thereby, measuring success should be higher on the priority list in piloting cases, and the measurement issues should be addressed appropriately.

Buying the service after a test period or deeming the results to provide new interesting information can be considered success criteria. For more insightful feedback, customer perceived value and implications to customer's business should actively be brought up in the customer discussions. After the open-ended identification of the most significant success factors, quantifying the measurement could be beneficial. In fact, creating parameter-based success and customer experience measurement could be a potential asset in refining the value proposition and concretizing sales argumentation. For instance, the product usage or connection to customer satisfaction are identified as potential parameters. Finally, including an external technology provider in the customer message could enhance customer's perceptions of the product quality, as the case company is not known for any traditional competence in the analytics product area.

4.8 Underlying process factors

Besides the aspects included in the external data monetization framework, the interview analysis revealed other underlying factors about the case company environment affecting external data monetization and analytics productization success. These should not be ignored to truly understand the different outcomes of TSI and Crowd Insights initiatives. Furthermore, these factors could be essential to improve Telia's analytics product landscape for future success cases.

The identified underlying and impactful factors consist of organizational structure, organization culture, and management's support and investments. Virtually, it seems that the organization culture doesn't encourage open innovation and initiative but relies more on centralizing these functions to specific departments. In fact, the company culture seems to emphasize management support in product development and investments extensively.

Management's support typically results in both financial and time-wise investments as well as effort from supporting departments such as IT and marketing. The organizational structure, culture, and their connection to management's support and investments seem particularly explicit when comparing TSI and Crowd Insights.

> *"I think one super important success factor for us was that we had the whole group executive management as our stakeholder. --- They were putting quite clear expectations on us and steering our direction. Every milestone decision to go or no-go was taken by the group executive management. --- If you want to challenge, you have to talk to them (GEM)" -Crowd Insights*

Then again, constant organizational changes and changes in the line management seem to increase the uncertainty around product development continuity and success. In effect, different business priorities in the new unit steer the investments and determine which initiatives are developed further. It appears that challenges concerning organizational changes' effects on external data monetization initiatives are sometimes accidental due to a lack of transparency about employee skills and engagement in certain initiatives. The effects of organizational changes are particularly visible in the TSI context. Thereby, more emphasis should be put on increasing openness and transparency from a product management side. On the other hand, more consideration could be expected from the company management side.

> *"When people are being moved around, managers don't necessarily know what products, services, and competence there are behind the people. Sometimes these end up in a grey area that is in no one's interest. --- When investments are needed for development in the new organization, managers have different perspectives and needs and don't see enough value for spending their budgets." -TSI*

Finally, it seems that lack of profound understanding of analytics at different organization levels is a significant root cause for other challenges identified in the thesis. Virtually, this relates to new kinds of value creation methods and resources required to deliver results in the analytics area. Thereby, sufficient in-house understanding of data analytics, especially understanding the value-creating elements and methods, should be further emphasized at the case company. It appears crucial, particularly with management, as they grant investments in analytics development, whether it is a value-adding feature order from external partners and improvement in the internal analytics landscape. The investments and budgets further define how much analytics products are developed – should they be enhanced to highly-tailored or advanced analytics for specific validated use cases or kept a more general MVP. Thereby, investing in raising the comprehension level regarding analytics is likely to result in more educated use of analytics as a value creator.

> *"If you talk about things (analytics) to someone with no basic knowledge or understanding for comprehending and building on it… --- It is mostly on conception and vision whether something should be developed or not. --- Managers don't understand. For them, visualizing a data point and showing trends is analytics enough." -TSI*

4.9 Summary of main findings and recommendations

To conclude, this subchapter summarizes the most pressing challenges in the external data monetization of the two analytics products at the case company Telia. More specifically, the most evident challenges that emerged during the interviews and the identified root causes are briefly revised.

Based on the interviews of both analytics products, **pricing** was considered one of the most problematic areas of the external data monetization process. The main reasons varied from difficulties in phrasing and modeling customer perceived value to creating automated parameter tracking. In other words, there are challenges to distinguish whether to go for scalable parameter-based pricing with potential accuracy and revenue losses or for a case-by-case precise but complex pricing process. The pricing challenges were fundamentally bundled with a lack of pricing tools and, on the other hand, educating and cooperating with standard sales unit and processes. Then again, **combining data sources** for reliable analysis results and value was identified as another main challenge in the process. More specifically, the issues were associated with fragmented data management and data architecture at the case company. It appears that issues with data maters, varying measurement techniques between technologies and different configurations in different countries act as the main reasons for the overall data challenges. Moreover, data is not treated as an asset, and considering data value and potential as such is not comprehended or prioritized essential. Finally, lack of **management's support and investments** was considered to significantly complicate the analytics productization process, especially with a data wrapping product, such as TSI, where value is created around core products. The financial investments seem to be linked to development activities ordered from an external technology provider, but the lack of support can also occur as limited stakeholder collaboration with, e.g., marketing and sales functions.

The most fundamental root cause resulting in various challenges appears to be the **level of understanding** of the nascent external data monetization and analytics productization concepts. This could explain, for instance, insufficient support on utilizing multiple data sources for additional value creation and difficulties to model and communicate the value to both internal and external stakeholders. The lack of fundamentally comprehending new value creation methods and data offerings is not limited to management but to various stakeholders ranging from sales to customer organizations and even product management functions.

The root causes should be handled appropriately to affect the challenges expressed in the interviews. The company could support external data monetization and analytics productization by emphasizing the education of all relevant stakeholders. Moreover, further utilization of dedicated solution sales for new kinds of products with distinct value creation methods should be considered more thoroughly. On the product management side, it would be essential to increase the level of **market understanding** already in the early phases of analytics productization as it forms a basis for making value propositions. Customer segmentation based on common business processes and challenges along with investigating the relevant partner ecosystem around them would enable creating more in-depth and relevant use cases. Clear use cases validated with sufficient piloting before concept creation and analytics productization along with measuring success could critically help justify and concretize the value proposition, further enhancing pricing and sales argumentation.

The next chapter provides a summary that ties the findings to the initial research problem and objectives. It also clarifies the connections to the literature review. Furthermore, it discusses the analysis findings and reflects them on a more general level, resulting in implications for theory and practice. The discussion evolves to identifying the thesis limitations concerning the empirical study that helps evaluate the analysis findings.

5 Discussion & conclusions

This chapter summarizes the thesis – it reviews the original research problem and objectives, the literature review and the empirical part findings. Moreover, it presents more general implications derived from the case study setting. These implications are addressed both from the theoretical aspect and from the practitioners' point of view. Lastly, the thesis discusses the overall limitations of case study research and the findings and suggests topics for further research.

5.1 Thesis summary

This thesis studied external data monetization with analytics products empirically with a theoretical background. The exact research problem was derived from a case company dilemma of not being able to concretize the promised external data monetization potential in the telecommunications industry. Thereby, the thesis objectives were to identify the challenges and enablers related to external data monetization with analytics product offerings. Also, specifying relevant future considerations of the identified factors was perceived desirable. As external data monetization is relatively industry-specific, an explorative case study conducted with a theoretical framework was selected as the research method.

The literature review was essential to form the background and understanding of the main concepts and build the theoretical framework for the empirical study. One of the main points was that big data, in general, is a complex topic and poses various challenges in many related areas. The complexity can be described with, for instance, seven big data characteristics and multiple data sources. On the other hand, big data provides significant opportunities in the data monetization and analytics productization area, especially in the data-intensive telecommunications industry. According to a data monetization definition, the opportunities relate to the process of using data to obtain quantifiable economic benefit. External data monetization approach of selling data, analysis & insights, and analytics product offerings to third parties were regarded as having particularly many untapped opportunities. Here, analytics product was considered the most mature offering, providing the best revenue and scalability opportunities for companies. The seven-step external data monetization framework described the process of realizing the big data opportunities and potential using both technical and commercial elements, taking into account the topic complexity. The focus areas included 1) opportunity mapping and data strategy preparation, 2) potential planning and use case definition, 3) legal and compliance alignment, 4) data collection and preparation, 5) technological arrangements, 6) data pricing strategy and 7) market entrance planning. The analytics productization perspective deepened the significance of analytics product offerings. It emphasized the importance of clarifying the service offering, creating replicability, and enhancing the understanding of the offering for successful external data monetization. For instance, considering previously recognized use cases for the telecommunications industry is perceived as relevant.

The empirical case study comparing two analytics products was conducted with expert interviews. The interview analysis suggested that the main challenges concerning opportunity mapping and data strategy preparation relate to lack of data asseting & common data strategy and reactivity & business problem centricity. In contrast, an explorative approach to data monetization appeared as an enabler. Potential planning and use case definition related challenges stemmed from lack of market understanding & focusing on certain segments and small-scale validation of customer need & demand. The enablers, accordingly, seemed to consists of segmentation & specialization along with productizing only validated concepts. From a legal and compliance alignment perspective, public perception & financial risks were seen as challenges and solution-oriented collaboration and clear guidelines & frameworks as enablers. Data collection and preparation related challenges included unstandardized data collection, data management & data architecture, data quality effects on result reliability, and data volume & velocity. No significant enablers were identified for the phase in the case company context, suggesting a need for further support in the area.

The technological arrangement challenges related to lack of transparency & interactivity in a black box situation and to lack of investments & partnership for further engaged development. On the other hand, management's support for investment & stakeholder collaboration was perceived as a technological arrangement enabler. Data pricing strategy challenges were considered particularly demanding, relating to scalability & simplicity with parameter selection & lack of automated tools, and to accuracy, associated with resource-intensiveness & slowness. Also, modeling customer value & revenue potential in the market with limited supporting sources was a challenge. On the other hand, the enablers included efforts on use case definition & segmentation and resources for exploring customer value & adjusting prices. Finally, challenges in the market entrance planning area consisted of unfamiliarity in the standard sales & the market, attracting sales interest &

providing sufficient support for sales argumentation, and justifying customer value via measuring & communicating success & results. Solution sales approach along with content marketing & stakeholder collaboration were perceived as enablers. Then again, the underlining process factors concerned organization culture emphasizing strong management's support, continuous organizational changes, and limited level of understanding of the analytics and data monetization concepts on different organization levels.

From a commercial perspective, the main considerations for future analytics productization efforts, in essence, related to understanding the market, specializing in the most prominent segments, and exploring the customers' motivation in-depth to suitably address the issues that matter to their business and model the customer-perceived value. Joint learning with customers and allocating resources for sufficient concept validation could prevent unsuccessful analytics productizations. Besides, measuring customer cases and piloting success could improve the customer value proposition's concreteness. These factors appeared to enhance pricing, marketing, and sales argumentation that build on the customer-perceived value. From a more technical point of view, treating data as an asset and investing in consistent data architecture and data management were perceived as evident for overall analytics development. For instance, enabling the combining of data sources and ensuring data quality for reliable results is critical. From an underlying process factor perspective, emphasizing education of the related concepts on different company levels and acknowledging the organizational culture's and inconsistency's effects on initiatives progress should not be neglected. To conclude, improving the external data monetization and analytics productization landscape from commercial and technical perspectives is considered essential for future initiatives' success.

5.2 Implications for theory

This thesis presents the main concepts and categorizations introduced in the existing big data, analytics, and data monetization literature. It complements this emerging research field by narrowing the focus to external data monetization and deepening the understanding of its different offerings and methods. More specific contributions arise from concentrating on analytics products as an external data monetization offering and combining analytics productization literature to more general data monetization releases.

A significant amount of data monetization theory deals with determining the data monetization concepts, but this thesis perceives external data monetization from a processual perspective, providing additional elements to existing theory. In fact, the thesis utilizes a practical process framework and complements it with suitable product development literature focusing on other digital assets. Data monetization has already been discussed from a processual point of view, but the focus typically has remained on the technical perspective. Thereby, this thesis provides a more inclusive process framework consisting of both technical and commercial elements, truly addressing it as a productization process. The more inclusive approach better reflects the real-world demands and realities.

As external data monetization strategies and processes tend to be industry-specific, the explorative case study method provides critical knowledge from a telecommunications perspective. Moreover, the thesis academically demonstrates that the practical framework suits analytics productization in the telecommunications industry. The thesis findings and discussion, on the other hand, provide some in-depth insights into the process framework from the case context. For instance, pricing planning could be addressed earlier, and securing management's support should be emphasized more in the process. The results and hypothesis can then be utilized for further generalization efforts and theory validation.

5.3 Implications for practice

Data monetization is considered an excellent opportunity to gain a competitive advantage in data-intensive industries but is critically challenging to execute among telecommunications practitioners. Therefore, addressing the topic further from a telecommunications company perspective is presumably desired. The main practical implications of the thesis are two-fold. First, the thesis provides an introduction to big data and analytics in the telecommunications industry, especially to data monetization with its various value creation methods. External data monetization with analytics products is presented further, and some of the most recommended analytics productization use cases are briefly introduced. Thereby, the thesis helps practitioners understand the nascent field of data monetization, supporting ideation of analytics productization concepts in companies.

Secondly, the thesis provides a structured processual framework to approach external data monetization in the telecommunications industry, particularly adjusted to support analytics productization efforts. It gathers the core elements and phases of a successful monetization and introduces the key aspects presented in the academic and practical literature. The framework is empirically validated with two analytics products in a case company context, offering more in-depth discussion on the process phases. The empirical validation's main contribution was to identify the challenges and enablers in the analytics productization processes essential to note in other similar efforts. Moreover, the thesis supports addressing the challenges suitably, embracing the enablers and suggests ways to consider them in the future. Practitioners can thereby address the findings and case company implications as a hypothesis in their own organizational context. Virtually, they could identify issues that possibly hinder or boost their external data monetization potential and analytics productization efforts. In addition, they could adjust the suggested ways to address the challenges and enablers identified in the case company to their organizational context.

5.4 Limitations & further research

This thesis increases understanding of external data monetization with analytics products via in-depth case study exploration. However, studying only one case organization has its limitations concerning generalizing results (Yin, 2012). Therefore, the case study results should not be taken as an ultimate truth but rather a hypothesis that could be studied with further case studies in other organizations. The findings gathered from multiple case study contexts could then be compared for a more generalizable theory.

Studying only two units of analysis and drawing conclusions from only them has its limitations concerning relevance to the case company, especially as the two units of analysis are not fully comparable as they have different purposes, target groups, and product types. In other words, the thesis does not fully reflect the real-life situation in the entire case organization concerning external data monetization success factors and challenges – typically, real-life is much more complex and varying than any research setting. Moreover, the case company's situation might have changed from the time when the two analytics productizations began, further limiting the result reliability for the company. The number of interviewees per analytics product was rather restricted as well, and the interview results reflect only the subjective views of the interview participants with possible bias. In fact, the interview pool was limited product management perspective, possibly leaving some company-related aspects hidden. Therefore, additional relevant stakeholders from, e.g., sales or IT department, could be interviewed for more inclusive discoveries within the case company.

The external data monetization process used in the thesis could be questioned as it stems from commercial company white papers, not academically verified processes. Then again, this is more a common caution than a limitation when studying relatively new topics. However, comparing the external data monetization process framework to other academic literature, the framework used could be claimed to miss some elements such as data generation (Faroukhi et al., 2020) and organization, operating model and culture (Taga et al., 2018). The framework used in the thesis is targeted particularly to EU markets as it, for instance, discusses GDPR, further limiting the generalizability of practical implications. The original framework included business case consideration at the data pricing strategy phase, but it was removed in this thesis due to a debatable place in the process and lack of interview material around the topic.

As the thesis framework covers rather many functions related to productization, it provides multiple interesting directions for future research. First, the thesis findings imply that sufficient market understanding, industry segmentation and customer co-creation form a basis for later commercial success. Therefore, it would be interesting to study further the most effective methods for investigating an immature market and interacting with individual large B2B customers and industry experts. Validating the methods with multiple cases could significantly boost the attention paid to the use case and market understanding phase in companies' practical implementations. Secondly, additional research on digital asset pricing would be needed to address the challenges identified in the area. Distinguishing the best practices to balance between accurate case-by-case pricing and scalable parameter-based pricing along with methods to automate the pricing processes could provide valuable insights for the future. Extra effort would be needed with data wrapping products bundled with core products with indirect value creation methods. In other words, creating commercial concepts that consist of multiple core and additional products and services could be studied further. Finally, the thesis suggests that organizational culture, organizational changes, and managers' understanding of analytics product concept and value are crucial to ensure investments and external data monetization continuation. Long-term research to further validate these hypotheses and the causal connection could provide vital information for practitioners' decision-making. It could also contribute to organizational and managerial literature from external data monetization and analytics productization perspectives.

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Appendix A: Interview structures

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0. General

Interviewee introduction; role at Telia & in product context

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1. Opportunity mapping and data strategy preparation

Starting the project, triggers & approach (data vs business problem)

Data availability identification

Prior data exploration and data value/monetization potential consideration (data strategy)

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2. Potential planning and use case definition

Idea generation & project initiation (data vs business problem)

- Internal vs external trigger

Critical evaluation of customer needs

Value chain identification & market understanding

- Fit & feasibility

Use case definition & stakeholders

Piloting

- Customer selection
- Measuring and feedback

Potential customer base & customer segmentation

3. Legal and compliance alignment

Legal stakeholders, responsibilities, cooperation & inspections

Privacy, GDPR and data anonymization approach

Technical security & confidentiality

Ethical issues

Effects on the development process

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4. Data collection and preparation

Describing the data

- Items in data sets, data sources

Data quality; complexity, noisiness

Pre-processing & cleaning the data (validity & reliability of the results)

Data architecture on a general level

- Collecting & storing
- Scalability & security

Stakeholders and responsibilities

Data management approach (standardization)

Main challenges in the area

5. Technological arrangements

Technological arrangements overview

Reasons for outsourcing

Priorities in choosing an external technology provider

- Describing the chosen provider

Technical solution and algorithm description (advancement)

Work distribution between Telia and external technology provider

Most important skills and competencies for Telia and external technology provider

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6. Data pricing strategy

Potential customer base consideration

- Segmentation
- The rationale for target customer/industry selection

Pricing strategy description

- Price structure
- Reasons/principles (economic vs. customer perceived value)

Customer perceived value estimation logic

- Parameters
- Stakeholders

7. Market entrance planning

Sales strategies and practices

- Stakeholders & collaboration
- Sales match with the customer contact person

Sales onboarding practices and WoW

- Sales approach

Collaboration with marketing (+content marketing & communications)