Leveraging data analytics for value creation in after-sales: Case study of an international manufacturing company

Lappeenranta–Lahti University of Technology LUT

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Examiner(s): Associate professor Lea Hannola

Post-doctoral researcher Lasse Metso

ABSTRACT

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The role of data analytics in after-sales operations has become increasingly critical for manufacturing companies seeking to enhance value creation, optimize processes, and gain a competitive edge. This thesis explores how data-driven decision-making can be leveraged within an international manufacturing company to improve after-sales services and enhance internal handover processes between capital project sales and after-sales teams.

The study examines the integration of data analytics into after-sales functions, focusing on its application in customer segmentation, predictive maintenance, and proactive sales strategies. By transitioning from reactive service models to data-driven proactive approaches, companies can not only improve operational efficiency but also foster stronger customer relationships, increase revenue potential, and reduce service costs.

The research employs a mixed-methods approach, combining an extensive literature review, a quantitative data analysis, and qualitative insights gathered from industry professionals through interviews. A data analytics tool was developed as part of the empirical study to provide greater visibility into after-sales opportunities and support strategic decision-making. The findings indicate that structured data utilization enhances internal handovers, improves after-sales performance, and strengthens customer retention.

TIIVISTELMÄ

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Tuotantotalous

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Data-analytiikan hyödyntäminen arvon luomiseksi osana huoltoliiketoimintaa: Case-tutkimus kansainvälisestä teollisuusyrityksestä

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Avainsanat: Huoltoliiketoiminta, data-analytiikka, arvonluonti, ennakoiva kunnossapito, asiakassegmentointi, pääomaprojektin luovutus operatiivisille tiimeille, valmistava teollisuus.

Data-analytiikan rooli myynnin jälkeisissä toiminnoissa on noussut yhä kriittisemmäksi teollisuusyrityksille, jotka pyrkivät parantamaan arvonluontia, optimoimaan prosesseja ja parantaa kilpailuetua. Tässä diplomityössä tutkitaan, miten dataan perustuvaa päätöksentekoa voidaan hyödyntää kansainvälisessä teollisuusyrityksessä myynnin jälkeisten palvelujen parantamiseksi ja sisäisten luovutusprosessien tehostamiseksi.

Tutkimuksessa tarkastellaan data-analytiikan integrointia myynnin jälkeisiin toimintoihin ja keskitytään sen soveltamiseen asiakassegmentointiin, ennakoivaan kunnossapitoon ja proaktiivisiin myyntistrategioihin. Siirtymällä reaktiivisista palvelumalleista dataan perustuviin ennakoiviin lähestymistapoihin yritykset voivat paitsi parantaa toiminnan tehokkuutta myös edistää vahvempia asiakassuhteita, lisätä tulospotentiaalia ja vähentää palvelukustannuksia.

Tutkimuksessa hyödynnetään useampaa eri tutkimusmenetelmää, jossa yhdistyvät perusteellinen kirjallisuuskatsaus, kvantitatiivinen data-analyysi ja alan ammattilaisilta haastattelujen avulla kerätyt kvalitatiiviset näkemykset. Osana empiiristä tutkimusta kehitettiin myös data-analytiikkatyökalu, jonka avulla saadaan parempi näkyvyys projektimyynnin jälkeisiin huoltoliiketoiminnan mahdollisuuksiin ja tuetaan strategista päätöksentekoa. Tulokset osoittavat, että jäsennellyn tiedon hyödyntäminen tehostaa sisäisiä projekti luovutuksia, parantaa myynnin jälkeistä suorituskykyä ja vahvistaa asiakaspysyvyyttä.

PREFACE

As five years of studies, student events, summer jobs, and other great experiences are seemingly coming to an end with the finalization of this thesis I would like to look back on what it has given me.

First and foremost, the greatest privilege has been the opportunity to be part of such a memorable community. With a heartfelt thanks, I express my gratitude to all the people that made Lappeen Ranta such a warm place to live in and return to. All those endless nights regarding both studies and activities that definitely weren't studies, those smiling faces at the guild room asking, "are you still here?", the trips we attended along the years, and all the other memories we created along the way. To you I would like to say, Thank you.

Secondly, I wish to reflect on the enriching experience of my exchange studies in Belgium. During this time, I had the opportunity to meet amazing people, travel, and experience new cultures on a deeper level, but also had time to reflect on myself. In hindsight this has been vital in shaping who I currently am and will become. I wish everyone had the same opportunity to take time for themselves and spend some months abroad as I did.

Lastly, I would like to thank all the people that help me in creating this thesis, with special thanks to Lea, David, and Peter, each of whom played a significant role in shaping the project. Thank you.

Helsinki 25.3.2025

Sakari Setälä

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1 Introduction

This master's thesis will focus on after-sales value creation by utilizing data analytics to improve data-driven decision-making with international manufacturing companies. The thesis also takes a closer look at a case company's after-sales business processes and data usage with the goal to evaluate their current status and suggest possible improvements. The goal of the thesis is to review the case company's capital sales to after-sales handover process from a data analytics viewpoint, expose the most significant development targets, and propose possible outcomes for those targets. Also, as part of the thesis, a data analytics and visualization tool was created that allows users to concisely view capital projects by market area and project value, which aims to help identify potential after-sales opportunities. Prior to the thesis, getting this level of visibility was so complex or labour-intensive it was limited to only a narrow portion of projects opposed to a holistic overview created by the data tool.

As part of the following introduction, the objectives of the study, its scope and limitations, and the structure of the thesis will be discussed in more detail. The importance of the study for both the case company and its respective competitors in their field will also be explained, along with a thorough look at the methods used in the thesis. This aims to give the reader a more comprehensive understanding of the thesis while simultaneously allowing them to give proper emphasis on the most significant sections.

1.1 Background and objectives

One can easily say that the amount of data being collected by companies has risen immensely as a result of the third industrial revolution, which incorporated the use of computers and the internet into our day-to-day lives. This trend is also evident when analysing Google search terms related to data collection and utilization, which have increased significantly over the past twenty years. Picture 1 visualizes the growing interest in the search term "Data analytics," which can serve as a useful reference for related terms and their relevance to companies. For companies like Facebook, data has become one of the most important revenue generators. Although some level of data-driven revenue growth can be already observed in almost every major company, regardless of market area or business sector, its

significance is likely continuing to grow in the future. The importance of data utilization is growing rapidly, as tools like artificial intelligence and other data-driven models are increasingly becoming a necessity rather than an option for companies aiming for future growth.

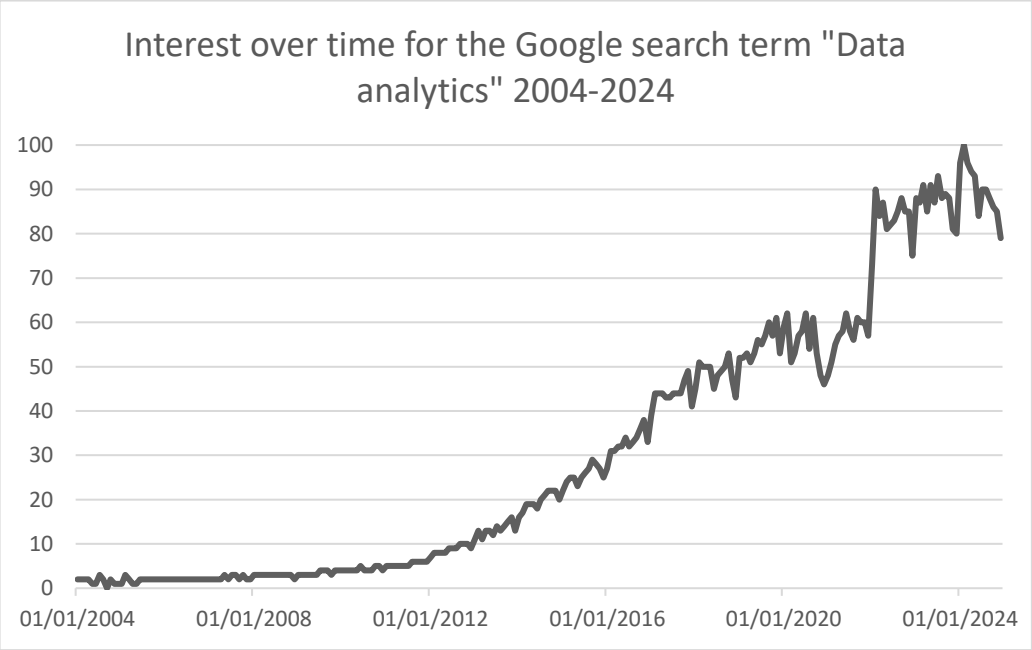

Figure 1: The interest over time of the Google search term "Data analytics" between 2004-2024. Numbers represent search global interest relative to the highest point of intrest. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term. (Google, 2025)

This thesis will be looking at how international industrial manufacturing companies can utilize their data in their value creation process. More specifically in how B2B-companies can utilize their data in capital project sales handovers from the original project team to the team(s) responsible for after-sales. The thesis will be viewing after-sales as a single instance that includes everything from functions such as maintenance, repairs, operations, training and support. When viewing large-scale manufacturing companies their sales can usually be roughly categorized based on the end customers' needs into two different types: Capital sales projects and operational sales. Capital sales projects or capital expenditure (capex) are large scale investments from the customer usually involving multiple sales cycles as several different possibilities of execution are explored. This can, for example, involve investing into a new production site or expanding an existing one. Oxford languages define it as, *''money spent by a business or organization on acquiring or maintaining fixed assets, such*

as land, buildings, and equipment." (Oxford English Dictionary, 2024). Operational sales projects, also referred to as operating expenses (opex), involve sales characterized by shorter sales cycles and a higher frequency of transactions. These projects typically involve equipment the customer already owns and uses but requires additional support or services to maintain operational readiness. Services like spare parts, maintenance and scheduled shutdowns are all good examples of operational projects from an after-sales viewpoint. The Oxford languages define it as, *"money spent on the ongoing costs of running a business or organization, such as wages and rent on premises."* (Oxford English Dictionary, 2023)

This thesis will combine a theoretical approach to data-driven value creation with a practical implementation of a data analysis tool that allows its users to view potential aftersales opportunities with a more comprehensive perspective. The practical review will consist of both a quantitative data analysis combined with qualitative support from extensive interviews from professionals within the case company. To achieve the objective of this thesis and address the research problem, the following research questions must be explored and answered:

1. What role can data analytics play in creating value from the perspective of after-sales?
2. How can data analytics be utilized to identify key service opportunities during and after internal Capex-to-Opex handovers?

1.2 Scope and restrictions

The scope of the thesis will be set to view international B2B-companies that produce high quality precision products and parts that are meant to be serviced over time. The companies applicable in the study, that act as an original equipment manufacturer (OEM), should also provide after-sales services for their products. The thesis will examine these companies' after-sales business from a data-driven perspective. It will also explore their after-sales value creation models and their compatibility with data analysis tools. The study will be limited to align with the case company's business interests regarding both the theoretical and empirical

sections. The thesis will not place focus on advance rising data trends like artificial intelligence (AI), machine learning (ML) or digital twins due to their complex nature. Regardless, the thesis does not overlook the potential related to these advanced models when reviewing future trends.

1.3 Structure and methodology

The thesis is structured into four distinct sections that progressively delve into more specific topics as the text advances, visualized in figure 2. The first section of the thesis provides the reader with a clear background of its goals and reviews the research questions, as done above. The second section consists of a literature review that begins with a comprehensive theoretical overlook of value chains and value creation within after-sales followed by a review of how data analytics can be utilized in after-sales. The literature review is concluded with the review of sales data analysis as a strategic driver of value creation. The third section of the thesis consists of insight into a case companies internal handover process and their data analytics utilization within this process. In this section the thesis will also be reviewing a data analysis tool that will be created as a result of the empirical part of the thesis. Finally, the thesis will review and discuss the implications of its findings and their effects on future research.

The thesis applies a mixed methods approach to its research. The research methods will include a literature review, practical sales data analysis based on the case company's operational sales data, and interviews from professionals involved in the case company's processes. The literature review aims to provide a theoretical foundation by exploring existing research on data-driven value creation and after-sales business models. The sales data analysis will enable an empirical investigation into patterns, trends, and the effectiveness of data-driven strategies. The interviews will continue to offer qualitative insights into industry practices along with the challenges and opportunities for key stakeholders to utilize the insights provided by the data analytics tool. By combining these three methods the thesis aims to provide a comprehensive view into data-driven value creation from the after-sales perspective of international manufacturing companies.

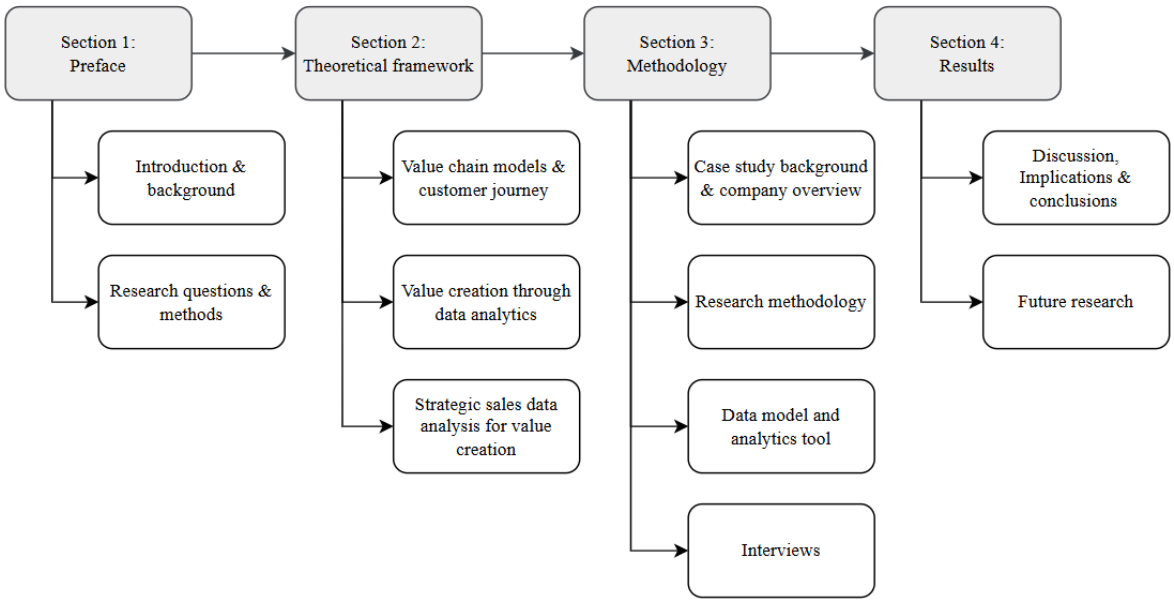

Figure 2: Structure of the thesis.

The thesis employed the ethical and responsible use of generative artificial intelligence tools, such as ChatGPT and Microsoft Copilot, to support its development. These tools assisted in refining ideas, revision of materials used, and enhancing both the language and structure of the thesis. To ensure academic integrity, all facts and sources were individually verified for accuracy and credibility from their original sources.

2 Value chains and customer journeys in after-sales

Value and the process of creating value can be understood, perceived, and interpreted through different lenses and in numerous ways. Each individual, organization or facet most likely has a unique way of valuing products and services. Price, delivery time, and quality are most likely aspects that most customers consider almost always but how they give emphasis on them varies. At the same time the company can derive value from something that does not provide equal value for the customer. For example, when data is collected from an advanced piece of machinery the company gains important knowledge they can use in multiple instances like R&D, predictive analytics, and operational efficiency. At the same time the customer does not directly benefit from this even though the company can improve based on the data collected, benefitting the customer in the long-term.

The academic world does not have a common consensus about the definition of value and value creation within business. As a concept 'value' is infamously hard to define as it is used in multiple different instances and from different perspectives. Simultaneously, the concept of value can be identified as a subjective construct as something of immense value for one party can be viewed as waste by another. The project management institute defines business value as, *"the net quantifiable benefit derived from a business endeavour. The benefit may be tangible, intangible or both. In business analysis, business value is considered the return, in the form of elements such as time, money, goods or intangibles in return of something exchanged"* (Project Management Institute, 2017). The thesis will use the previously discussed definition from here on.

2.1 Value chains and value creation models

To help companies review their value chains Michael Porter created the first value chain analysis model in 1985, illustrated in figure 3. He initially described a value chain as the sequence of activities a business undertakes to deliver valuable goods and services to the end customer. (Porter, 1985) When viewing a firm's value chain and value creation one should look at the firm on a business unit level as this allows for a comprehensive overview of the company's operations without drowning out the smaller details. (Porter, 2001) In a

company’s value chain its products pass through a series of activities that add value to it. During this the product gains more added value as it passes through the value chain compared to the sum of added value of the single activities in the chain. (Porter, 1985)

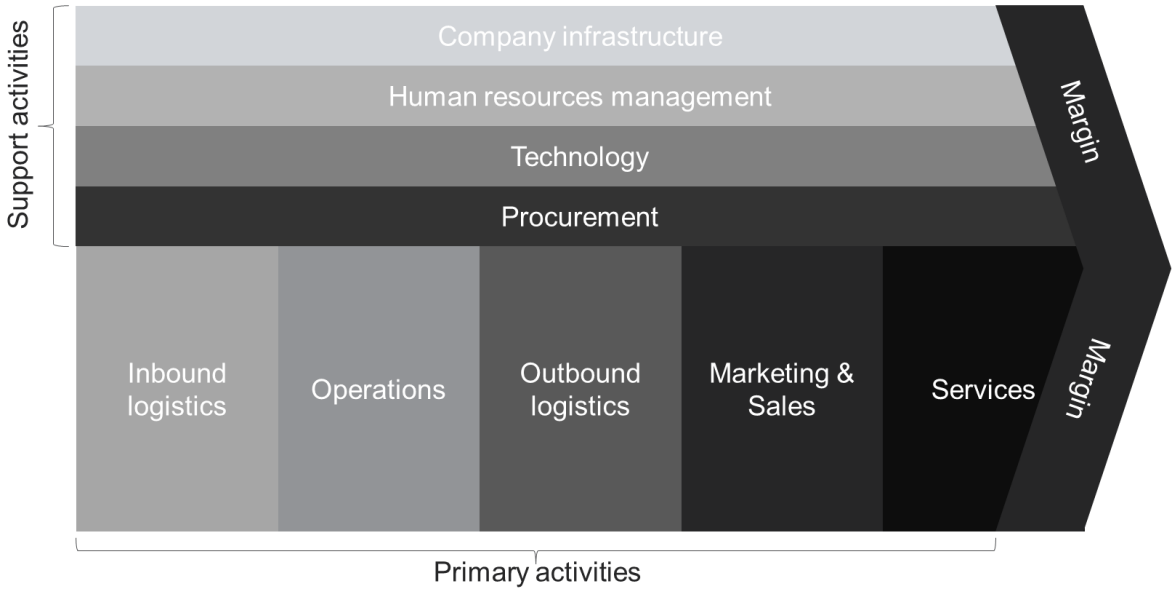

Figure 3: Porter's value chain model. (Porter, 1985)

Porter’s value chain analysis model was the first of many to come, providing a way of viewing the different stages of value creation to help identify the possibility of cost reduction or differentiation (Porter, 2001). In the past 40 years many academically and practically oriented individuals have explored the subject from different angles creating, for example, the global value chain (GVC) analysis and value stream mapping (VSM) models. The different models cater for different needs and viewpoints. When comparing Porters model to the GVC we can distinguish a difference in the way the model views companies in its operational environment. Porter takes a firm-centric view and evaluates the company’s operations to identify their core competences and helps to maximize competitive edge in these sectors. In contrast, the GVC model examines a firm's operational network, focusing on various segments and its relationships with other companies within that network. This allows a more internationally holistic view as it gives insight in the whole industry and its stature. (Chalaby, 2019) This is why the GVC model is commonly used to view multinational companies with operative functions spread across the world. Moreover, the VSM model takes a heavy focus in lean thinking and thus is mostly oriented towards the

physical supply chain of the company (Dadashnejad & Valmohammadi, 2019). This being one of the biggest differences in VSM and Porters model is that VSM does not take into account the support functions like IT or HR, but only focusing on the efficiency of processes directly linked to the delivery of the product. The key difference between the different value chain models have been highlighted in table 1.

Table 1: Key differences of the different value chain models

Category	Porter's Value Chain Model (Porter. 1985)	Global Value Chain Model (Chalaby, 2019)	Value Stream Mapping Model (Dadashnejad & Valmohammadi, 2019)
Focus	Firm-centric view, focuses on internal value creation	Industry-wide perspective, focuses on global production and value distribution	Operational efficiency, focuses on lean processes and waste reduction
Scope	Company-level analysis	Cross-border and multi-company analysis	Process-level analysis
Key Components	Primary & support activities (e.g., inbound logistics, operations, marketing, HR, IT)	Governance structures, upgrading pathways, industry networks	Material and information flows, value-adding vs. non-value-adding activities
Application	Competitive strategy, cost advantage, differentiation	Understanding multinational operations, global trade, and economic development	Improving production efficiency and supply chain management
Limitations	Does not emphasize global networks or supply chain complexity	Difficult to apply at the firm level, complex interactions between firms	Does not consider support functions like IT or HR, mainly physical processes

As the development of information and communications technology has become more and more rapid the need for a way to view the digital value chain has arisen. Miao (2021) defines the digital (economic) value chain as the integration of a company's traditional value chain with the digital economy, creating a system driven primarily by digital elements such as digital models, technology, and data. When comparing to the traditional value chain models, one major difference is the dimensionality of these value chains. Porters traditional model

operates in a linear flow where the value is added to the product as it progresses through the company's different processes. (Porter, 2001). At the same time a digital value chain operates as a continuous and dynamic process that brings value to the whole digital industry chain. This promotes the value for both information flow within the company but also improves the operational entities. For example, Amazon's after-sales support uses data-analytics to realize the value of customer feedback and product returns which can be utilized in multiple different operational and digital business sectors (Kandemirli, 2018) Here the digital value chain is utilized to create operational value based on data.

In addition to traditional and digital value chains, the value creation process can also be examined through the customer journey. This represents the interactions between the customer and the supplying company throughout various stages of their relationship. In an industrial B2B setting understanding the customers' needs and end goals is crucial as this improves the customer engagement. This leads to improved satisfaction and fosters long-term relationships (Hamilton & Price, 2019). Halvorsrud, Kvale, and Følstad (2016) emphasize that customer journeys serve not only to understand the customer's perspective but also to uncover valuable insights into their overall experience. Their review of the literature reveals a consistent portrayal of customer journeys as tools for both adopting the customer's viewpoint and gaining a deeper understanding of their experiences. This is why the examination of customer journeys has increased its interest among both academics but especially practitioners as they aim to improve competitiveness. Despite academics having identified the potential the research related into customer journey management still remains narrow. More specifically the B2B customer journey can be considered under studied as existing literature views are both with little coverage or from niche scoping. (Purmonen, Jaakkola & Terho, 2023)

The B2B customer journey can be divided into three phases the pre-purchase, purchase, and post-purchase phases (Purmonen et al. 2023). All of these contain their important touchpoints that which need to be attended to with a comprehensive approach to managing them. This is called the company's Customer Journey Management Capability (CJMC). It refers to the company's ability to strategically utilize each phase and manage customer interactions in every step of the customer journey ensuring consistency and value creation. This can be seen in each phase of the B2B customer journey and can further be divided into the following four touchpoints: (Homburg & Tischer, 2023)

1. Value anchoring – The degree to which the company aims to create value in each touchpoint in a strategically aligned customer proposition (Homburg et al. 2023). To ensure that maximal value anchoring is created companies can utilize both internal and external market research and data. By focusing on specific customer segments and reviewing distinct key aspects of the market segment the company can aim to answer the needs of these customers better. (Lemon & Verhoef, 2016) For example, data analytics can be used as a part of a proactive maintenance strategy, anchoring value through service delivery (Gandhi, 2023).
2. Consistency – The number and spacing of touchpoints in the customer journey from the customer point-of-view. Consistency issues can easily be highlighted with data analysis of customer feedback, interaction history or customer retention rate developments. Gartner (2024) expect that 80% of B2B sales interactions will happen digitally by 2025, so data from these touchpoints should be widely available. A similar trend can be noticed in other parts of the customer journey making them longer and more diverse (Homburg et al. 2023).
3. Internal integration – The level of effort put into integration in both online and offline channels to deliver smooth transitions in the customer journey (Homburg et al. 2023). Even though one of the most important milestones for a company is closing a sales project, the customer will remain loyal and create value in the long term if they are professionally taken care of. This is why everyone along the customer journey needs to be equipped with the most important information from the Customer Relationship managements (CRM) system as only knowledgeable employees can act as needed. (Woelke, 2023)
4. Individual control – how the companies individuals monitor the value creation within each touchpoint, specifically value delivered from a customer's viewpoint. (Homburg et al. 2023) A necessary requirement of understanding and managing customer experience is the ability to measure it. This should be monitored both empirically by individuals but also numerically throughout the touchpoints. These can be done, for example, through sentiment analysis or other emerging techniques of evaluating touchpoint interactions. (Lemon et al. 2016)

As the concept of CJMC aligns closely with the structure of the B2B customer journey, companies should place notable emphasis on strategically managing it if they are looking to create value and customer engagement through the purchase process. As illustrated in figure 4, each phase can be linked to critical touchpoints. By reviewing both CJMC and the different phases of the B2B customer journey, both individually and in relation to each other, companies can assess their success during these key touchpoints and evaluate the experience customers receive as they move through the process. A key enabler of this continuous assessment is the internal feedback loop, which plays a crucial role in refining both CJMC and the purchase process.

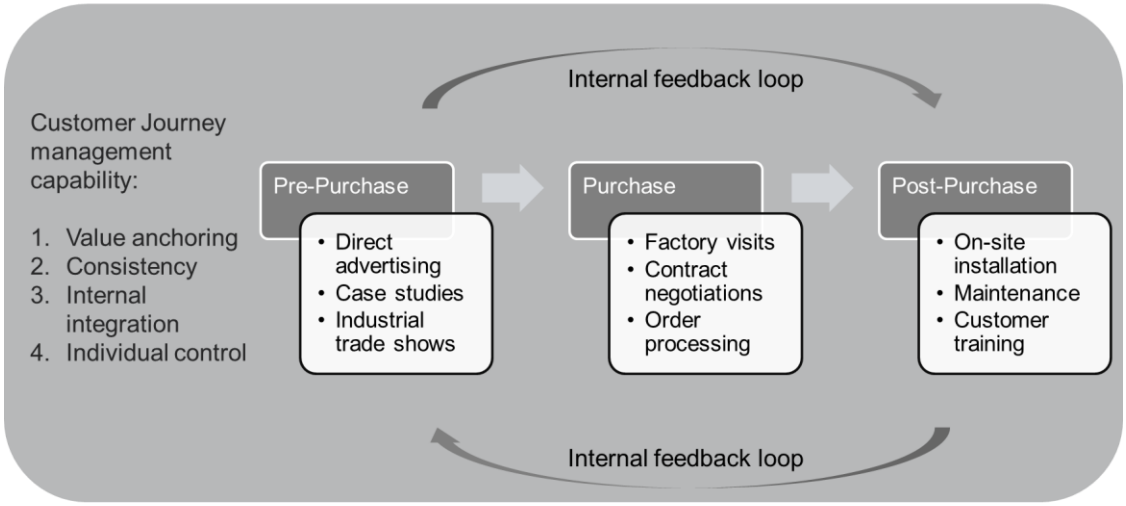

Figure 4: Customer journey management capability in relation with the traditional customer journey (synthesized from, Homburg et al. 2023; Purmonen et al. 2023)

2.2 After-sales business models

A company's business model describes the way it creates, delivers, and gains value within its operations. A business model is built from multiple different business segments, such as strategy and stakeholder relations, that combined form the model. In a traditional production-oriented company this business model has been viewed through the form of a stream of transactions usually closely following the supply chain of the company. In this mostly linear value chain, it is easy to assign responsible parties of the value enhancement process. (Kans

& Ingwald, 2016) Horenbeek, Ostaeyen and Lilian (2012) argue that the shift in product marketing from traditional to functional has increased the importance of well-organized maintenance services for equipment manufacturers. In traditional product marketing, the assumption is made that, when the customer buys equipment they use it responsibly and maintenance it as required. Functional marketing on the other hand views the purchase more as a functionality than an asset. This development has been fuelled also by internal developments within the industry to provide more comprehensive product-service solutions and industrial services. The change has happened in the past two decades and is currently increasing as we can see, when looking at company's like Kone and ThyssenKrupp and how they have been able to develop their services and so improve their revenue substantially. When integrating after-sales into a company's operations, it is crucial to incorporate this aspect into the company's overall strategy. Simply expanding services is unlikely to create a lasting competitive advantage or significantly improve financial performance. (Kohtamäki, Hakala, Partanen, Parida, Wincent, 2015)

It can be noted that each company has its own approach to providing after-sales services, however this thesis will examine the following commonly identified models: *Service contract, Predictive maintenance, Performance-Based* and *Third-party* models. To further understand the important differences between these business models we must review them individually. These models can be identified to consist of important touch points between the customer and the OEM throughout the products life cycle and not just additions to the original sale. The key differences of these after-sales service models have can be found in table 2. On top of these models' company's offer different kinds of warranty policies that serve as guarantees of the product quality. Generally, it establishes the liability among the seller and buyer if the product does not perform at a satisfactory level (Kohtamäki et al. 2015).

Once a warranty period is extended beyond its standard coverage, either by length or scope, it becomes an example of a *service contract*. The contract acts in both a protectional and informational role as it protects the customer from repair/replacement costs and informs them about product reliability. (Murthy, Solem, Roren, 2004) The value created from this relationship is mutual as the customer gains added reliability, more predictable maintenance costs, and reduced equipment down time. Similarly, it fosters a long-term customer relationship ensuring both a consistent revenue stream and access to important data on their

product performance for the company providing the equipment and service. By being able to offer pro-active support and reliability, these services also reduce the attractiveness of switching to an alternative service provider (Baines, Lightfoot, Benedettini, Kay & Roy, 2009). Strategically this model requires investments in the operational facilities, technology and training of staff to ensure high and consistent quality of service (Murthy, Atrens & Eccleston, 2002). Creating a working environment that accepts only high-quality actions is essential in maintaining the service level agreed upon between the company and customer. The costs affiliated with creating constant improvement and obtaining a high reputation in service quality with clients should be heavily considered by the company as unexpected failures can be pricey. Company's need to internalize that their production process is no longer part of a black box system where the client can see only the end product, but their operations should reflect credibility and trust within all business sectors. (Brax & Jonsson, 2009.)

Predictive maintenance can serve as a standalone after-sales support model or be integrated with other service methods, making it a key example of servitizing manufacturing. Servitization can be defined as a strategic choice for an organization to shift its capabilities and processes from selling products to offering integrated bundles of products and/or services that deliver value in use (Baines et al. 2009). This shifts the maintenance focus from the customer to the manufacturing company as the OEM aims to monitor and forecast potential failures before they occur. We can see companies like ABB providing this kind of support services with their sensor, which collects data from the device it's connected to and analyses it to create a report for the maintenance engineers (ABB, 2024). The model emphasises a proactive rather than reactive stance to service improving machine health, reduce unpredicted down time, reducing labour costs, and optimizing maintenance scheduling (Lee, Kao, & Yang, 2014). This both provides the OEM with feedback on customer needs and enables the R&D team to take initiative for further improvements (Grubic, 2014). By allowing both flexibility to the customer and providing the OEM with valuable information about their products in the field a mutually beneficial relationship is created. Furthermore, as the relationship continues it builds trust towards the OEM's data analysis capabilities making it less appealing to change service providers and so fostering longer customer relationships (Porter & Heppelmann, 2015). Strategically the service models require the company to have both tangible and intangible assets to support this data

centric business model. For the tangible infrastructure like sensors to provide value they need to be complemented by intangible assets like knowledgeable employees and existing data analysis methods. This also requires the company to change their strategy on topics like data governance and other IT security issues as if these matters are not met with the utmost care, it will sooner or later likely reflect in lost customers. (Bokrantz, Skoogh, Berlin, Wuest & Stahre, 2020)

Performance based servicing, also called as the "power by the hour" model, is an approach towards providing after-sales support and logistics. At its core, the model centres on delivering performance outcomes rather than individual components, repairs, tools, or data. The emphasis is placed on ensuring a predetermined level of availability that aligns with the customer's objectives. A fundamental element of this approach is the clearly defined contract between the manufacturer and the customer, which sets specific performance targets. Notably, service providers retain the autonomy to determine how these targets are met, applying their expertise to devise the most effective solutions (Kim, Cohen & Netessine, 2007). In other words, while the contract outlines what the equipment must achieve, the service provider decides how those outcomes are delivered (Macfarlan & Mansir, 2004). The model also demands a change in mindset regarding value creation. As Lewitt (1972) notes, a classic example of this is that the customer does not really want to buy a drill, but they want a hole in the wall. The value is not necessarily in the physical equipment but in the needs they fulfil. Moreover, Gordon (2001) has stated that aligning both the customers and the company's objectives has the possibility of large cost efficiencies. Aligning these objectives may be challenging as the client company almost always has to co-create or co-produce value within the process. In the previously discussed hole-drill example the servicing company cannot deliver the value of a serviced tool to make holes if the client company does not know how to use the drill. This requires the providing company to focus more on the customers delivery scape and shift both support and operational functions mindset towards delivering benefits for the customer, instead of individually focusing on their activities. (Ng, Roger & Yip, 2009) The strategy of the servicing company should focus on long-term performance and assisting the customer to take comprehensive advantage of their tangible or intangible value creation process. (Kumar & Markeset, 2007)

Another business model for managing after-sales services involves outsourcing specific aspects of the operation to third-party providers. When viewing different parties in the model

we can clearly establish three different parts. The first party is the OEM of the equipment, and the second party is the receiver of the goods. The third-party acts as a middleman, an enabler, who does not take credit for the product but who is used to provide it to the end customer. Functions like transport, maintenance, and information services are operational after-sales functions that commonly can be outsourced to specified partners. (Hertz & Alfredsson, 2003) This model of service focuses heavily on value created by reducing costs while trying to have minimal effect on quality to the end-customer. By reducing the services the OEM provides, and placing a heavier focus on the company's core business functions, it can aim to lower its operational costs without lowering its level of service.

The use of external service providers in certain aspects of the after-sales process can lead to improvements, as such providers typically prioritize ongoing innovation in their specialized fields of operation. Value is also created through risk mitigation, as the service provider typically assumes responsibility for any risks that arise within their processes. (Bryson, Sundbo, Fuglsang & Daniels, 2020) However, this does not rid the manufacture of risk or responsibility as the company must also take strategic action when outsourcing functions. The outsourcing company should be very clear and concise on what functions they should or can outsource and which partners can they trust to support their value creation within the after-sales process. Key word being "partner", as the new company in the value chain needs to be viewed as a business partner not only a service provider or a means to reduce costs. The interaction and governance between the companies should be actively up kept maintaining value creation to all stakeholders involved. (Artunian, 2006)

Table 2: Key differences of the different after-sales models

Category	Service Contract Model	Predictive Maintenance Model	Performance -Based Model	Third-Party Model
Focus	Extended warranties and long-term service agreements	Proactive monitoring and forecasting of equipment failures	Focuses on delivering outcomes rather than individual services	Outsourcing of after-sales services to external partners
Key Characteristics	Provides protection and reliability for customers	Uses IoT sensors and data analytics to predict maintenance needs	Contracts specify performance goals rather than service inputs	Common in logistics, maintenance, and customer support
Value Proposition	Ensures predictable maintenance costs and long-term relationships	Reduces downtime, improves efficiency, and optimizes maintenance schedules	Aligns customer and provider objectives to create cost efficiencies	Reduces costs while maintaining service quality
Challenges	Requires investment in training, facilities, and quality control	Requires both tangible (sensors) and intangible (data expertise) investments	Requires high flexibility and co-creation of value with customers	Risk of reduced control and dependency on service providers
Strategic Considerations	Focuses on building trust and minimizing customer churn	Shifts focus to data governance and IT security as key priorities	Encourages innovation in service delivery and contract management	Requires strong partnership governance and clear service agreements

3 Maximizing value creation through data analytics in after-sales

With industrial B2B companies aiming to extend customer relationships to excel in today's competitive business environment, after-sales has become a critical sector for most businesses. In the meanwhile, after-sales like every other sector, has grown the amount of data they are exposed to and have available. Leveraging this available data can help companies to gain valuable insight and improve their services and customer satisfaction. According to a study conducted by McKinsey, companies that are able to utilize this data are reporting above-market growth with increased earnings before interest, tax, and amortization (EBITDA) of 15 to 25 percent. (Böringer, Dierks, Huber & Spillecke, 2022) By effectively applying data analytics to their after-sales strategies, companies can enhance their competitive position in the market, increase customer retention, and improve their long-term value creation.

3.1 Understanding the strategic value of data analytics in after-sales

Runkler (2016) describes data analytics as the use of computer systems to process and analyse large volumes of data in order to support decision-making. He also talks about the way it has evolved to become a very interdisciplinary field which combines multiple different aspects and techniques from other scientific study methods such as AI, pattern recognition and statistics. Data analysis commonly distinguishes four different phases: data preparation, modelling, analysis, and postprocessing. Each of these phases consist of multiple different actions such as data collection, cleaning, visualization, and interpretation.

When looking at Runkler's definition we must also note that data analytics and data-driven decision-making has taken major steps within the last years. This can also be seen in how companies have changed their strategic operation models giving larger emphasis on services and after-sales sectors within their business models. While a large portion of the focus regarding data analytics revolves around optimizing manufacturing and operational excellence, the analysis of sales data simultaneously provides valuable insight into market trends, revenue growth opportunities, and customer behaviour. For example, by analysing customer purchase patterns companies can aim to identify future trends and hidden customer

preferences that can be utilized in the future (Chen, Chiang & Storey, 2012). Even though this requires well allocated resources from the company, it is also an important way of creating and capturing value from the data that is available (Jelassi & Martinez-Lopez, 2020).

3.1.1 Data analysis in industrial manufacturing

Understanding that as achieving or evaluating a business goal is usually the main reason for the use of data analysis tools, it is important to note the strengths and limitations of the data set on hand. Historically data is not originally collected to perform the analysis but for some other reason such as invoicing or item tracking. Similarly, it is important to note that not all data sources are as reliable or as widely available as others. (Provost & Fawcett, 2013) In an industrial manufacturing setting the data is usually collected through tracking systems like ERP, CRM and IoT, but also feedback surveys, and other qualitative methods can be used (Davenport, Haeeis & Abney, 2017). Because of how the data is collected it usually isn't naturally in the right formatting or clean (Provost et al. 2013). When talking about "dirty data" practitioners refer to data that contains outliers, missing values, or values that are not possible, such as negative time. Dirty data can also be messy due to problems with data structuring or data types.

According to a study conducted by CrowdFlower, which surveyed about 80 data scientists, up to 80% of time spent on data analysis consists of collecting and cleaning the data. At the same time 76% of the people surveyed reported that data preparation is the least interesting part of their job. (Press, 2016) The steps commonly taken to cleaning data are outlier detection, data deduplication, data transformation, and rule-based cleaning (Ilyas & Chu, 2019) The user also plays a critical role in the data collection process due to the inherent risk of generating inaccurate or misleading data. It is essential to emphasize that human errors are unavoidable as long as people are involved in data input. In most cases, the human element cannot be entirely eliminated from the equation. Even a single error, such as mislabelling or inputting incorrect information, can skew an entire data model in the wrong direction. For this reason, standardized processes must be implemented to minimize the impact of human errors and ensure greater data accuracy. (Brachard & Pace, 2011) This will also help minimize the workload related to data cleaning and preparation. Professionals

doing this data transformation should also be aware of areas where the data is commonly input by humans to catch possible issues in the data at an early phase of the data analysis process.

After collecting, processing, and cleaning the data so that it can be used for the analysis the data modelling phase begins. The goal of the modelling phase is to recognise a pattern or model within the data that can later be applied for further use like forecasting or trend predictions. The model represents a reality created to serve a specific purpose. For example, a map is a model of the physical world that has been created to serve a certain purpose that leaves out the unwanted details. (Provost & Fawcett, 2013) This model then helps its users to make decisions based on the information available. Fitting the data in different model types and visualizing it can be split into three levels, which have been visualized in figure 5. On the first level the data can be viewed in a chart, table or dashboard that present layered or statistically relevant data allowing it to be visualized from multiple different perspectives. The second level of data modelling is used to create predictive models using statistics, simulations, or through AI techniques. The third level of modelling is reserved for optimization models that aim to find the ideal solution to a problem, while considering the pre-established requirements. Generative AI can be identified as a fitting example of this type of modelling. (Liberatore & Luo, 2010)

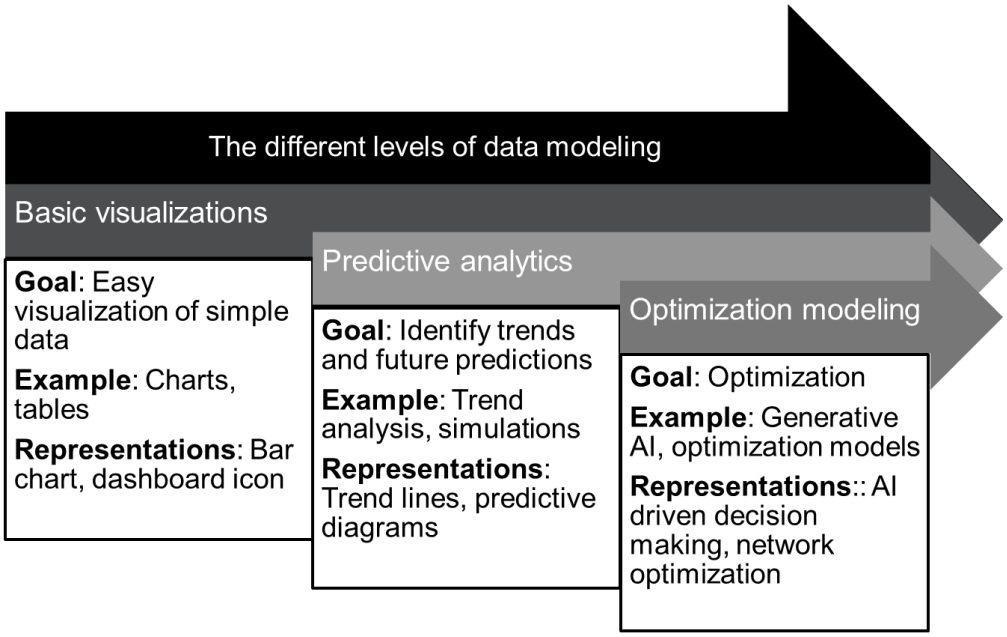

Figure 5: The different levels of data modeling. (Liberatore et al. 2010)

The analysis phase offers a wide variety of methods, which can be chosen based on the tools and expertise available, the quality and nature of the data, and the specific goals of the analysis. For industrial manufacturing data, descriptive and diagnostic, prescriptive and predictive, and anomaly detection analysis are typically the most suitable approaches. Throughout these analysis methods two main themes can be spotted: data as a source of statistical analysis and the aim of improving decision-making (Habel, Alavi & Heinitz, 2023). Descriptive and diagnostic analysis tools both view verifiable historical data and aim to answer questions through that. Descriptive data analysis methods focus on understanding "what happened" in an organization's processes. To gain a holistic view, using multiple different data sets can help in creating comparisons. For example, when looking at a company's economics, viewing metrics like year-over-year changes in pricing or revenue generated per customer could be viewed through descriptive data analysis. (Sharma, A. K., Sharma, D. M., Purohit, Rout, Sharma, S. A., Jeyanthi, Choudhury, Hack-Polay, Singh & Abujar, 2022) Diagnostic analytics on the other hand aims to view "why" something happened. It is commonly used in succession with predictive analytics further applying statistical techniques of finding the root cause of the phenomena. (Sharma, Chourdhury & Toe, 2022.) An important aspect to note, when performing diagnostic data analysis, is the difference between correlation and causation, as even though a correlation between two elements can be found it does not always prove causation. An example of diagnostic analytics could be backtracking the growth in demand for a certain product in a specific market area to trends that are enforced by news affecting the area or other locational factors. (Cote, 2021)

Once the company decides still to progress from descriptive and diagnostic tools that view historical data the next natural step will be prescriptive and predictive data analysis. Predictive analytics views historical data and attempts to give insights into "What could happen" in the future. This can be done through statistical models that view correlations and build on statistical significance. (Habel et al. 2023) This insight is then used to help decision-making and to leverage the identified potential regarding customer identification or shifts in markets (Sharma et al. 2022). Predictive analytics then further aims to build on this and seeks to answer "What can or should be done" to the prediction made on the previous level. This information can then be utilized in any business decision from product launch timings to resource allocation. For example, Lenovo was able to reduce their warranty costs by

approximately 15% after they utilized predictive analytics to better understand the claims they were receiving. Predictive analytics has gained a stronger foothold within businesses as data has become more available, the calculation power of computers has become more accessible, and the need for a competitive edge has steadily increased. (Roy, Srivastava, Jat & Karaca, 2022)

Analysis methods can also be considered to support multiple different approaches as in this case anomaly detection can be utilized for descriptive, diagnostic, and predictive analytics depending on its use case. Anomaly detection is something that humans have been doing forever as noticing something happening that is out of the ordinary and connecting it to a change can come naturally. Goldstein & Uchida (2016, p. 1) define anomaly detection as just this, "*the process of identifying unexpected items or events in datasets, which differ from the norm.*" This has multiple application possibilities from fraud detection to equipment failure indication. The models are based on predictions from historical data of a process that has the primary assumption that the normal behaviour is stable. Models can also be created around cyclic processes or around major long-term trends. (Mehrotra, Mohan & Huang, 2017) Anomaly detection can also be used alongside each of the previously discussed analysis techniques to improve data quality and to review non-typical trends.

Data visualization plays a critical role on how well the insights from the data can be comprehended and utilized in decision-making. Eberhark (2023) defines it as a visual representation of information or ideas, created to effectively convey a message or content and enhance the audience's understanding. A large array of tools can be used to convey the message from qualitative diagrams to quantitative ones. Three key principles of data visualization include clarity and simplicity, accuracy and integrity, and aligning the visual with the data while considering human perception. Widmay (2020) emphasizes the need of prioritizing the message behind the visualization even before creating it. He proposes that visuals should almost always remain as concise as possible and be backed up by a caption which provides as much detail as necessary. The message of the visual should be clear from the start so that it can easily be written down and conveyed through the caption. Visualizations on their own can be insufficient as they are part of a bigger picture. The visual should add to the text and vice versa. (Unwin, 2020) The second important aspect in data visualization is the data quality and integrity. The saying, "garbage in garbage out" applies to this section exceptionally well. An undetected data quality issue can considerably affect

a company regardless of the organization size. For example, an analysis based on poor-quality data can result in misinformed business decisions, inaccurate budgeting, and ultimately financial losses. (Wibisono, Sammon & Ciara, 2024). Similar issues can arise if an incorrect data set is used, or the scope used in selecting the data set is biased. As important as ensuring data quality is choosing the right visualization form to support the data. Different data sets need to be illustrated differently to reflect the truth and by selecting an incorrect diagram or legend the data set can be skewed or disintegrated. This can be also a result of incorrect software usage as different data sets have different needs. This is especially notable with geometric visualizations as humans naturally associate different shapes with certain values. (Midway, 2020) For example, people naturally view a circle, like a pie chart, with it adding up to 100% but this is not always the case. Similarly, one has to consider cultural differences and other human factors when aiming to create accurate visualizations. Due to different social environments and the heterogeneity of people in these environments one must accept that not all signs and colours are interpreted unanimously. This should be considered when thinking about the visualization as, for example, Western cultures read left-to-right while Asian cultures can either read from right-to-left or top-down. (Schaap, 2012)

Finally, the postprocessing phase of data analytics focuses on utilizing the data and insights gained from the analysis. This can be done through applying the insights to existing strategic frameworks, such as a balance score card, that utilize business metrics to evaluate business development. Key performance indicators (KPIs) are often a natural part of these tools, aiming to measure the potential improvements resulting from the implementation of a new procedure. As KPIs are the indicator focusing on the most critical aspects related to the company's success they give a good overview of does the change add value and effectively align it with organizational goals. KPIs also measure the impact of data-driven insights on strategic and operational performance, making more tangible performance measures. In an industrial B2B manufacturing setting KPIs could, for example, include measurements like production efficiency, downtime reduction, cost savings, or gains in customer satisfaction. According to Davenport et al. (2017), these indicators assist firms in determining if the adjustments the company has made are producing the intended results and guarantee ongoing alignment with corporate goals. As previously discussed, these KPIs need to be clearly visualized, accessible and used in the appropriate way as frequent monitoring allows them to be integrated into the company's strategy and allows the stakeholders to act on possible

trends or anomalies. (Grover, Chiang, Liang & Zhang, 2018) For some company's this change might require changes in organizational culture as a data-driven mindset is not always a given. A study conducted by Kiron, Kirk & Ferguson (2012) found a strong correlation between the ability to leverage analytics for innovation and gaining a sustainable competitive advantage, highlighting the importance of such a mindset for companies aiming to progress into this direction. Figure 6 visualizes an example structure of an analytical process, placing focus on the transforming of analytical insights to business applications. The top of the figure represents the analytical process, progressing from data collection to advanced analytics, while the bottom highlights its practical implementation in business operations.

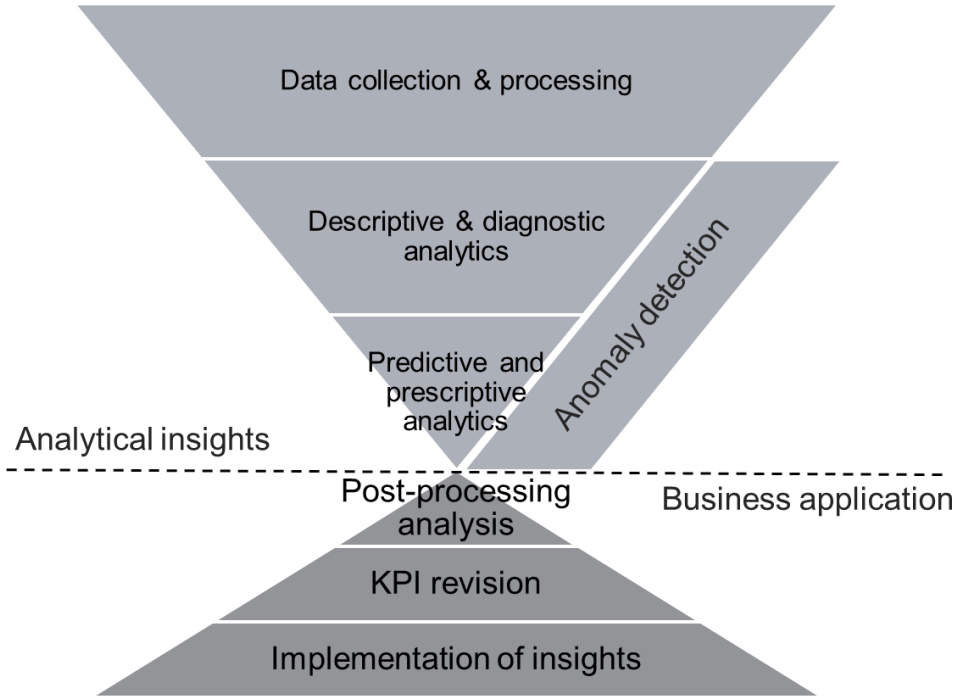

Figure 6: The different phase of data analysis commonly used in industrial manufacturing.

3.1.2 Visualizations as an aid for decision makers

As discussed above, the role of how visualizations are used as support to the data analysis plays a key role on what is emphasized and how well the potential value of the data can be captured. As a part of decision-making, it is important to note that the visual does not always

convey the same information. When multiple different stakeholders, from diverse functions, view a graph they will all receive the same information, but most likely draw different conclusions depending on their viewpoint. This will both facilitate communication and collaboration within the different functions but also allows them to make the connection between their outputs. (Kirk, 2019) This can allow the companies to identify, locate, and work on the underlying reasons behind issues.

Visual models also take advantage of humans' natural cognitive abilities aiming to simplify and draw attention to areas with most importance (Cairo, 2016) For example, graphs have been shown to attract more attention when looking at risk communication when comparing the same data to texts paired with tables. Graphs have also been associated with more precise assessments and decision-making. Simultaneously, the visuals provide a way of appealing to the viewers visual working memory, which has been shown benefits of enhancing comprehension leading to improved judgement effectiveness and efficiency (Eberhard, 2023). This ability to simplify and compact the key information allows the involved stakeholders to reduce their cognitive load and aid in improved decision-making (Few, 2012).

In addition to the above, visualizations also contain the ability to provide insights on the future through predictive models which showcase trends or patterns based on historical data. These models can be utilized to predict future demand, or other customer behaviour traits if done correctly. This information can then be used for functions like strategic planning, resource allocation or risk management tools. (Rangasamy, Rajamohan, Janarhanan, & Manu, 2023) This enables the company to make proactive strategic decisions rather than reacting to market events. The ability to measure and match internal performance with external needs can be crucial to a company's success especially in cyclic events or products. This alignment enables firms to effectively respond to market fluctuations while maintaining competitiveness. (Jalilian, 2018)

Visualization models can also be customized based on the industry the company operates in to highlight the unique requirements of these industries. Various industries rely on industry specific visualization techniques to collect and convey the insights relevant to their objectives and operational goals. For example, a heatmap is a popular visualization tool used to display matrix-like data, highlighting patterns shared by specific rows and columns,

making it especially useful in identifying trends and correlations (Gu, 2022). In industrial sales heatmaps can be used to identify and highlight difference in sales areas for better resource allocation. Heatmaps allow the viewer to gain a better understanding of spatial data when comparing to data clusters on a chart. It also allows the map to be tailored to user requirements, as users generally prefer simpler maps. Heat maps are also perceived as easy to use and offer relatively quick interpretation compared to other models. (Słomska-Przech; Panecki & Pokojski, 2021)

3.1.3 Best practices and pitfalls

Being able to utilize data analytics accurately is a major asset for any company. However, to achieve the benefits the data must be utilized correctly and so it is crucial that the people creating these different applications are aware of the best practices and common pitfalls that are involved in the data analytics process. To ensure that the data analysis is both impactful and reliable, organizations should focus on implementing these three key best practices that guide the process. Firstly, defining clear objectives that are in line with the company's business goals for the analysis. Creating these clear measurable values that can act either as a target line or as a benchmark is key as it will be the main driver regarding the analysis. Secondly, ensuring the data quality is good and properly governed. Maintaining a high level in data quality is essential for reliable analytics which can be achieved by implementing existing frameworks like top-down or bottom-up models. The models form a base for how data governance decision flow throughout the organization. (IBM, 2024a; Gartner. 2024) Lastly, companies should invest in the proper analysis tools and talent. Having the required infrastructure coupled with an office culture driven by analytics and knowledge sharing is equally as important as the other previously mentioned two. Without the proper tools no amount of planning or data governance will facilitate proper data analysis. (Misbah, 2023)

Having established the key best practices for successful data analytics, it is equally important to recognize and address the common pitfalls related to the topic. Understanding these challenges allows the organizations to proactively mitigate risks involved and grasp a maximal amount of potential value. Naturally these pitfalls are partial opposites of the best practices as unclear motives, and the use of poor-quality data are most common challenges. This usually creates misleading insights and provides the decision-maker with an unclear

situation where they either have the wrong information or have been provided with information that does not solve their issue. (Littley, 2012) Similar issues can be caused when incompatible data sets are combined unknowingly. This is something both good data governance and knowledgeable staff can aim to address. (Gartner, 2024; Misbah, 2023) A more recent phenomenon is over fitting data as this problem has increased as machine learning algorithms and AI's have been introduced. Overfitting is caused when the data set is too close to the training data used to program the model resulting in inaccurate modelling predications that differ from the training data, tainting the model. Similarly, the opposite of underfitting can happen when enough data is not being used to train the model, and the model is not able to determine reliable relationships between input and output variables. (IBM, 2024b) Even though these types of errors are more related to more advanced analysis methods, these aspects can also be seen in more traditional analysis models in situations where too much or too little data is being used in the analysis resulting in decision-making, based on untrue insights. Being able to identify these common pitfalls does not make the person immune to them but allows them to alert others or make changes when noticing them.

3.2 Value of data in the after-sales business

Data can be used in multiple ways and as a part of multiple different areas of the after-sales process to create value. By utilizing data analytics, companies can focus their efforts into transitioning their operating models from reactive to proactive, while simultaneously improving customer experiences and optimizing product life cycles. This proactive approach can be utilized to establish a lasting competitive advantage by developing a service that systematically positions the company as the preferred supplier. (Brehmer, Rehme, Guenzi & Geiger, 2009). This will further ensure operational continuity combined with growing trust and customer loyalty. The advantages of data analytics in creating continuous improvement have been visualized in figure 7. Wamba et al. (2017) expect data analytics to have a major impact in value creation processes on an industry wide level. The authors consider data analytics a crucial enabler for manufacturing companies aiming to develop functions, such as asset and business process monitoring, and business transformation. This capability will help the company continuously enhance after-sales services and better align with customer needs. Zhang et al. (2020) take the concept further by proposing that customers should play an active role in the data analytics process. They suggest transitioning

from viewing customers merely as passive data providers to engaging them as active participants. By involving customers directly in the analytics process, their study demonstrated significant improvements in customer relationships and enhanced performance of new products.

Predictive analytics has also become a major asset in after-sales by enabling companies to forecast customer needs and segment different customers with better accuracy. A prominent way of applying predictive analytics in customer segmentation is to identify groups of customers that could directly benefit from tailored sales strategies (Hofacker, Golgeci, Pillai, & Gligor, 2020). Creating a categorization for different customer groups enables the company to align resources with their interests, retain key customers, and identify potential repeat customers for strategic targeting. An example of this is being able to target cross-selling and upselling opportunities at the correct time based on customer insights into purchasing patterns and preferences. This approach can both boost the customer view of the company but also improve revenue. (Wedel & Kannan, 2016) A proactive sales strategy can help reach customers before they identify an acute need and so reduce the risk of customer churn in the long-term. Another proactive stance to after-sales is to review warranty claims. By analysing the data related to the warranty claim companies can continuously improve their entire process and refine their product design (Kamble, Gunasekaran, & Gawankar, 2018). This can even help improve brand reputation regarding possible failures and lower warranty costs. Simultaneously, the involvement of the customer as part of the warranty data collection will help build better transparency and trust with the client. In some situations, customer loyalty can even be higher after a professionally handled warranty claim, than without the warranty issue to begin with. When the interaction regarding the claim is actively managed, and the company and client establish a shared, aligned perspective on the severity of the situation customer satisfaction can improve. This phenomenon is called the service-paradox. (Hübner, Wagner & Kurpjuweit, 2018).

When reviewing the effects of data usage on business we can also note the financial and operational efficiency advantages as the correlation between improved customer management skills and sales growth is clear. Sales growth through data analytics can happen through identifying potential service gaps, processing customer information, and creating a general overview of the customer. Data analytics and an analytic culture within the company have both been identified to have a positive effect on monetary metrics such as return on

investment (ROI), profitability, and sales growth. (Hallikainen, Savimäki & Laukkanen, 2020) Even so, Akter et al. place great emphasis on strategic alignment of data analytics capabilities with the company's business goals. The study notes that companies that are able to pinpoint their analytical need to achieve their strategical goal are able to grow their market position in the long run. A study involving over 2000 professionals in 100 countries from 25 different industries highlights this as 87% of respondents expressed the need to improve their organizations level of analytics management. These findings can be supported when looking at evidence of "born-through-analytics companies" such as Facebook. (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016)

When looking at improving the visibility of unrealized sales potential companies should commonly review their customer segmentation again and aim to utilize data analytics in re-evaluating these segments. By reviewing historical sales data companies can aim to highlight possible sales gaps by comparing actual and calculated potentials in specific segments or market areas (Wedel et al. 2016) The models can also be, for example, decision trees or regression models that review how or what aspects affect sales or how have the best sales cases been realized. Providing strategic insights on what should be the company's focus areas to reach their goals (Hofacker et al. 2020). An interesting analysis method regarding B2B after-sales is performing a "market basket" -analysis, which is a data-driven pattern recognition technique that aims to identify trends in customer purchase behaviour and frequency. It can be used, for instance, to identify which products are commonly purchased together or which product combos can be indicators of upcoming customer churn. (Silvers, 2012) The methods discussed earlier, such as predictive analytics methods, can further help the companies to expand and evaluate their insight from the market basket analysis.

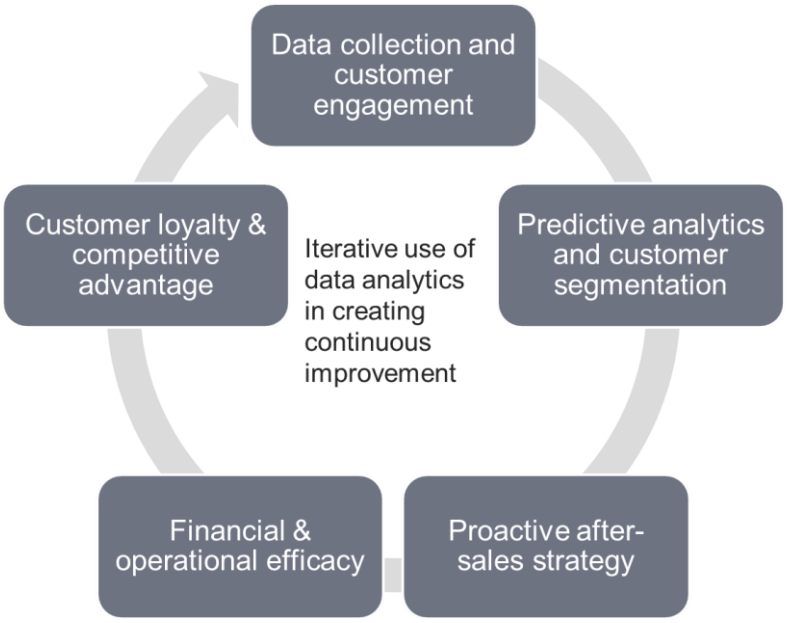

Figure 7: Iterative use to data analytics. By continuously improving after-sales processes with data-driven insights, companies can establish a sustainable competitive advantage and maximize customer lifetime value.

3.3 Optimizing internal project handovers: capex-to-opex

Internal project handovers, such as the transition between the original project teams and the operational teams are critical in ensuring operational continuity and mitigating disruptions. In a B2B manufacturing company an example of this kind of handover could be between the original project teams that are delivering the project for the customer and the teams responsible of after-sales and services after the original project has been completed. In this scenario the original project is commonly considered as a capex project from the customer viewpoint as they are investing into new infrastructure, and the after-sales and services provided after the commissioning of the project are considered as mandatory opex's as it is part of upkeeping the existing infrastructure and maintaining operational functionality. Common best practices of ensuring the smooth handovers include standardized and structured processes, comprehensive documentation, and open communication between all stakeholders involved.

A standardized framework will help with process flow and ensure that all the necessary information is passed on to the next responsible. Marques, La Falce, Marques and De Muylder (2019) emphasize that a structured approach to information sharing, supported by

internal commitment to the process, enhances the knowledge maturity, meaning the level a company utilizes the available data, within the projects it conducts. The framework should include a schedule of responsibilities, a description of the relevant documents related to the project, a list of the stakeholders that are involved with the project, and key action points that need to be checked as part of the handover process. (Cartlidge, 2020) In addition to this the active stakeholders involved should critically evaluate the process and discuss should something be added to the framework. Effective documentation and the utilization of appropriate tools are pivotal in ensuring seamless internal handovers within organizations. The documentation should involve all the necessary information about the project such as key contacts, project descriptions and any unexpected difficulties that have arisen. (Miller & Oliver, 2015) A study conducted by Kwok, Clapham, White, Austin, and Calder (2018) reviewed the internal handover process of medical patients before and after a standardized checklist was implemented to the handover and found out that the likelihood of a mistake caused by a communication error dropped by 22 percent with average patient processing time rising only 13 seconds. Even though this process is not directly compatible with industrial project handovers, it demonstrates well how standardized processes, and proper documentation can have an effect of the likelihood of success, with little to no negative effect on resource use. As previously stated, the active communication and involvement of all stakeholders in an early phase of the process plays a vital role in the ensuring clarity and responsibilities (Marques et al. 2019). Digital tools like collaboration platforms and cloud-based systems can be used to improve stakeholder accessibility and involvement. This transparency also allows the stakeholders to access the information in real time which can be vital.

Internal project handovers between different teams, including capex-to-opex handovers, involve challenges due to different priorities between the teams involved. The challenges can be related to misaligned objectives between teams, insufficient early engagement of stakeholders, or inadequate knowledge transfer. This has been illustrated in figure 8. Hide (2016) notes that commonly capex teams are prioritizing that the project is delivered on time and within budget, focusing on short-term goals. In contrast, Opex teams prioritize long-term goals, such as operational efficiency and maintaining profitability. These siloed goals can cause teams not to reach their full potential or even harm the project.

The different drivers can also cause tension between teams further damaging the dynamics between the parties involved. This tension can further be reflected to other stakeholders and cause uncertainties regarding the process of the project and the company. Uncertainties can also be caused by poor internal communication between stakeholders reflecting in disengagement, further increasing the likely hood of dissatisfaction after the project is finalized. (Davis, MacDonald, & White, 2010) The involvement of all stakeholders has also been shown to lower both expense types so improving both predictability and profitability, while simultaneously improving customer satisfaction. (Ho, Tan, Yang, Zdaniuk, & Schwegler, 2019)

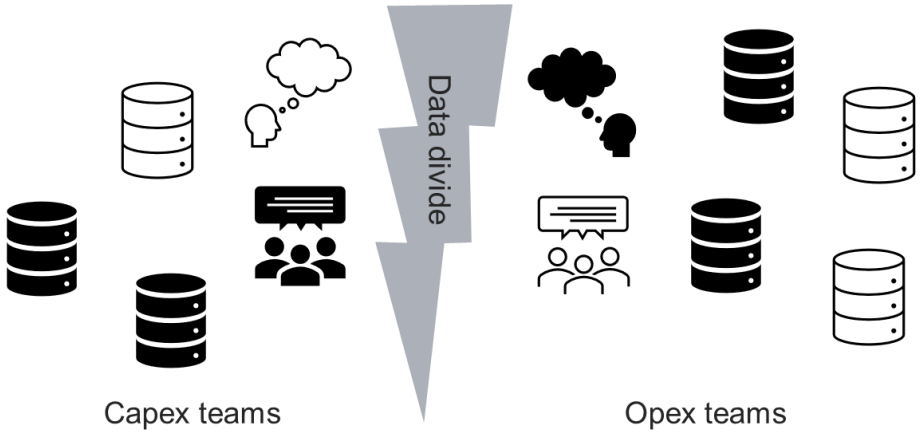

Figure 8: A data divide between the capex and opex teams because of operating under different premises, knowledge, and goals.

Data analytics can be utilized to help smoothen project handovers and mitigate reoccurring risks by providing an improved basis for informed decision-making, enhance knowledge transfers and promote transparency between teams. A key benefit of data analytics in project handovers is the ability to standardize and compile the relevant information for parties involved ensuring both credibility and comprehensiveness to the customer (Marques et al. 2019). It also allows teams to monitor and identify possible upcoming issues providing them the possibility of being proactive about the situation. Up-to-date dashboards and other collaborative platforms allow the teams to monitor the projects progress, address possible issues, and contribute to the decision-making (Ho et al. 2019). This transparency can reduce uncertainties related to the project and strengthen stakeholder confidence towards the

company as they are able to proactively deal with issues (Davis et al. 2010). This can also help solve internal misalignment and bridge the gap between short-term deliverables and long-term goals of the company closer together. This can foster major improvements both in financial profitability and the customers view on the company's ability to handle their project. Finally, as Kerzner (2017) discusses, data analytics allow the monitoring of the project with the use of KPIs, with metrics that are used to define and monitor the project success. Well-defined KPIs can allow the company to highlight trends, such as is the project going to be ready in time. However, it is also important to note that the KPI's cannot be utilized to answer the question, "what needs to be done in order to improve". By selecting and monitoring the right KPIs, a company can focus on measurable metrics that enable teams to effectively manage the project while ensuring a smoother handover. (Kerner, 2017) By combining high quality data, a knowledgeable staff, and standardized ways of working the company can aim to gain the most value out of the data available to them.

4 Strategic sales data analysis for long-term value creation in after-sales

When looking at customer generated data, sales data is one of the most prominent and extensive sources that can be utilized for strategic value creation and decision-making. Well managed and collected data can be used to create various different analysis and drive insights into areas such as customer management strategies, the experience delivery for stakeholders involved, and financial management (Williams, 2014). In the after-sales sector, data usage can be particularly valuable when analysing purchasing patterns, customer needs, and optimizing operational efficiency. In today's data-driven environment these topics can be considered as essential in obtaining growth and preserving competitiveness.

4.1 Driving competitive advantage through after-sales data analytics

The role of after-sales in maintaining sustainable growth and a competitive advantage is crucial for today's manufacturing companies. As businesses shift their focus towards fostering longer customer relationships, after-sales services have become a key component for their strategic approach. This can be seen when looking at major manufacturing companies' annual reports and more specifically the revenues of different functions. For example, in 2022 Kone was able to generate an equal amount of revenue in new appliances, and services sold to their existing installed base (Kone, 2022). One should also note that most commonly after-sales retain a higher profit margin than equipment sales as direct costs involved are significantly smaller.

To measure and enhance their performance, companies must focus on KPIs that align with their strategic goals. These KPIs will naturally differ depending on company functions but nevertheless, customer satisfaction is in the centre of all when aiming to create and preserve customer relationships. Williams (2014) raises the point that businesses can achieve sustainable growth, in both financial metrics and in active customer base retention by utilizing customer data to improve the purchasing experience. Metrics such as Net Promoter Score (NPS) and customer retention rates are crucial when looking at how clients view the company and how willing they are to stay with it in the future. High levels of customer

satisfaction in individual touch points lead to long-term loyalty and repeat customers which directly contribute to revenue growth. When looking at KPIs that are focused on financial and operational efficiency Gaiardelli et al. 2007 highlight the importance of service efficiency regarding both topics. Service efficiency metrics like mean time to repair (MTTR) and first-time fix rate (FTFR) can be used to evaluate operation performance. Both KPIs take a customer centric view on internal service efficiency, aiming to keep customer down-time to a minimum. The authors emphasise that the operational efficiency has also financial effects as fewer follow-up visits reduce operational costs. MTTR can also be used as an internal benchmark between service units as insights into resource utilization and workforce productivity. Both metrics can also be directly linked to customer satisfaction. (Gaiardelli, Saccani & Songini, 2007) Understanding the link between operational efficiency, financial metrics, and customer satisfaction can be considered instrumental in enhancing revenue streams and utilizing the available customer data. (Legnani & Cavalieri, 2010)

Creating a data-driven after-sales function that uses data analytics and metrics to monitor both their internal performance and external market activity allows the company to gain a deep understanding of its strengths and improvement areas. It also allows the company to gain actionable insights into behaviours, trends, and preferences it would not be able to otherwise utilise. This allows the companies to gain a long-term advantage as it allows it to better personalize services and optimize their offerings to exceed expectations. For example, being able to utilize data analytics in identifying customers that are at risk of changing service providers allows the company to take a proactive stance to the situation instead of reacting to it when the customer is about to leave. (Ijomah, Idemudia, Eyo-Udo & Anjorin, 2024) In these situations, metrics such as customer lifetime value (CLV) plays a key role in identifying, comparing and prioritizing high value customers' needs and preferences. By allocating resources effectively to answer these needs companies can aim to retain their loyalty and let go of unprofitable customers. (Dogan, Hiziroglu, Pisirgen & Seymen, 2024) By tracking CLVs companies can also aim to review their after-sales strategy and operations with a critical view and adjust them to better align with their intended customers' expectations. This approach enables companies to design tailored loyalty programs and service packages, fostering deeper engagement with key customers while enhancing both revenue predictability and growth.

While data utilization opens a vast number of opportunities for companies, the challenges of being able to realize the potential even partially should also be recognised. These challenges can be broadly categorized into two main types: those related to data and technology, and those stemming from strategic and organizational concerns. One of the largest data-related issues is that processes related to after-sales commonly generate data from multiple different touchpoints such as ERP and CRM systems, service records, and customer meetings. However, the data from these touchpoints is not available throughout the company but it is siloed across departments or business units, effecting how the different units view the customer. Kache & Seuring (2017) note that the IT infrastructure and the accessibility of information provides the company with the framework for future business practices and so they should place emphasis on the hand-over of data between departments. They also note the importance of standardized ways of using the interfaces to ensure a high level of data quality and integrity. This can be challenging due to its multidisciplinary nature mixed with data privacy and compliance regulations such as GDPR, which impose restrictions on data handling and usage. To overcome these challenges, companies should consider investing in new ways of data governance that allow data to be utilized across the company. The systems should prioritize data accuracy, cross-functional accessibility, and security. Academics suggest the use of cloud-base analytics frameworks such as data lakes as one solution to mitigate these issues. They provide scalability, enhanced integration capabilities and possibly even financial advantages while also enabling improved problem solving, decision-making, and performance. (Sun, Ye, Schwarthoff, Rosin, Vakkalagadda, Chang, Ubbara, & Chinthakindi, 2021) This can mean considerable investments as legacy systems can be hindered by technological limitations affectively restricting the use of more powerful analysis models. Future trends, particularly data-heavy models like AI or ML, often highlight this phenomenon. (Bughin, Manyika, Chui, Henke, Saleh, Wiseman, Sethupathy & Guru, 2016)

The second major issue with after-sales companies aiming to utilize data analytics is organizational culture and strategic decisions. Organizational resistance during the change towards a data-driven decision-making culture can pose major issues as employees have grown accustomed to more traditional operation models. Davenport et al. (2017) review that creating a data-driven culture is essential in collecting the benefits of analytics. Companies should empower employees with the necessary tools and training to embrace the new ways

of working as lack of digital skill can be a contributor for resistance. In addition, companies should consider investing in talent for key positions aimed to drive this change. Another challenge organizations have is tying the analytics goals with business objectives, without a clear view on how to do so, resulting in the analysis becoming isolated and failing to deliver measurable insight to the business objectives. (Akter et al. 2016) It can also drive a wedge between different departments as conflicting metrics are implemented causing mismatch. Even when robust data systems and analytics frameworks are in place, companies may struggle to align different teams' objectives, which can create inefficiencies and roadblocks in decision-making. For instance, a sales team may prioritize high volume and revenue growth, aiming to acquire as many customers as possible, while customer service teams focus on delivering high-quality interactions and ensuring customer satisfaction, emphasizing long-term relationships and effective issue resolution. These differing objectives, illustrated in figure 9, can lead to conflicting KPIs that make the processes work against each other in some instances. As technology advances and continues to evolve companies will have to be more and more proactive about embracing change and reviewing their ways of working to ensure they can compete in the data-driven economy (Jegan Joseph Jerome, Sonwaney, Bryde & Graham, 2024).

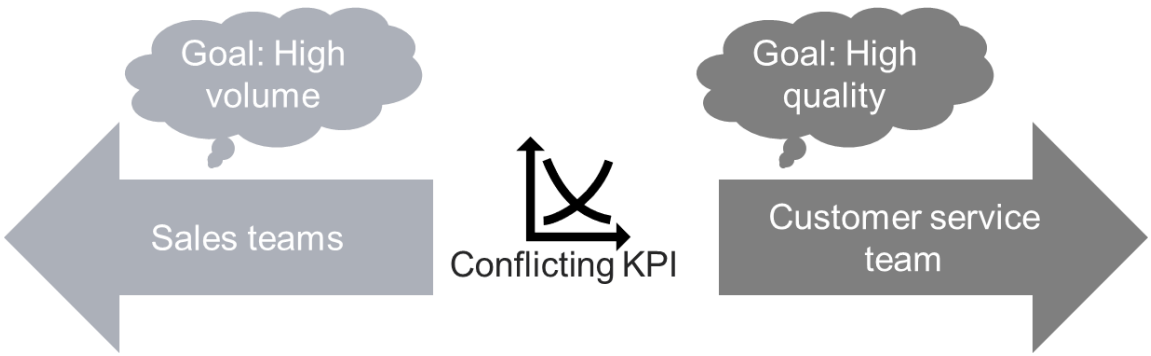

Figure 9: Without shared KPIs, such as Customer Lifetime Value or Net Promoter Score, teams will continue to pursue opposite directions instead of working toward a common goal. Aligning KPIs ensures that both sales growth and customer satisfaction contribute to long-term success.

4.2 Frameworks for integrating analytics into value creation

Multiple previous chapters highlight the transformative possibility of customer segmentation using after-sales data. A numerous number of studies have presented a way of applying different frameworks to improve companies' customer relationship management and increase proactive action. In the recent years both academics and practitioners alike have been able to create new frameworks and upscale older models by applying new technical implementations to existing models. These frameworks include the more recent RFM-ARIMA framework which combines a Recency, Frequency, and Monetary (RFM) analysis with Auto Regressive Integrated Moving Average (ARIMA) modelling, and the more traditional Uplifting model (Londhe & Palwe, 2022; Devriendt, Moldovan & Verbeke, 2018). These models both provide their unique insights in how these predictive analytics can be applied for customer insights and value creation.

Londhe et al. (2022) present the hybrid RFM-ARIMA framework to address two key challenges: identifying churned customers who remain as "noise" in the company's dataset, skewing analysis, and enhancing the accuracy of future growth projections. The authors start with an RFM-analysis that helps categorize customers into four categories, visualized in figure 10: star, disengaged, new, and light while proceeding to place them into a matrix representing current monetary value vertically and future monetary value horizontally. The star customer segment provides high current and future monetary value, as they represent the loyal and frequent buyers who are crucial for long-term success. The disengaged customers hold high current value but lower future potential due to a decline in engagement and purchase frequency. New customers consist of clients who hold large future value but low current value which can be seen in improved engagement and the opportunity to create a long-lasting relationship. Finally, customers in the light segment have a low monetary value and purchase less frequently. After this, customers in the light segment were excluded as noise, as they are more unlikely to have a substantial effect of future sales and are more likely to skew the analysis. Then the statistical forecasting model ARIMA is applied to the remaining data set. ARIMA is a time-series model that works especially well on non-stationary forecasting of time series. The merger of these two concepts provides the company with a more accurate customer-centric view on sales forecasting, a view on customer diversity, and best possible growth opportunities. (Londhe et al. 2022)

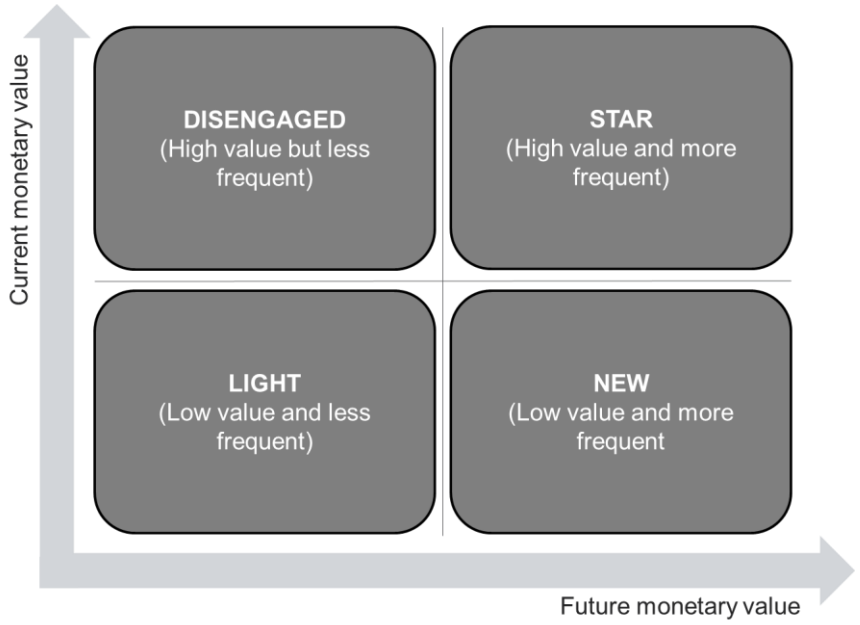

Figure 10: Customer segmentation matrix. (Lounde et al. 2022)

Unlike the previous model Devriendt, Moldovan, and Verbeke (2018) review a different approach that does not necessarily segment customers based on current and future monetary value, but which customers are most likely to respond positively to a targeted marketing action. The model focuses on analysing customer behaviour both with and without company interaction, enabling the organization to identify which customers to target with campaigns, thereby improving resource management and campaign effectiveness. Using an A/B testing approach with a control group (not targeted) and a test group (targeted), this method segments customers into four categories based on their likelihood to make a purchase. The matrix organizes customers vertically by whether they would buy when targeted with an offer and horizontally by whether they would buy regardless of receiving an offer. The four customer segments, visualized in figure 11, are: sure things, lost causes, do-not-disturbs and persuadables. Sure things are customers, also known as the always-buys, that buy regardless of if they are targeted or not, so targeting them does not generate additional returns. Lost causes similarly represent customers who are unlikely to generate significant additional revenue, as they cannot be persuaded to make a purchase even when targeted. The first two segments also uphold hidden additional costs as fixed costs of interacting with the customer are involved. The do-not-disturbs represent a customer segment that the model aims to avoid.

They are customers that don’t respond if not targeted but will respond if done so. The issue is that targeting certain customers with a retention campaign may offend them, leading to their departure and resulting in measurable additional costs. Finally, persuadables are customers that respond only because they were targeted and generate additional revenues because of the sales campaign. This segment of customers are the ones that should be identified and targeted in the uplifting model. (Devriendt et al. 2018)

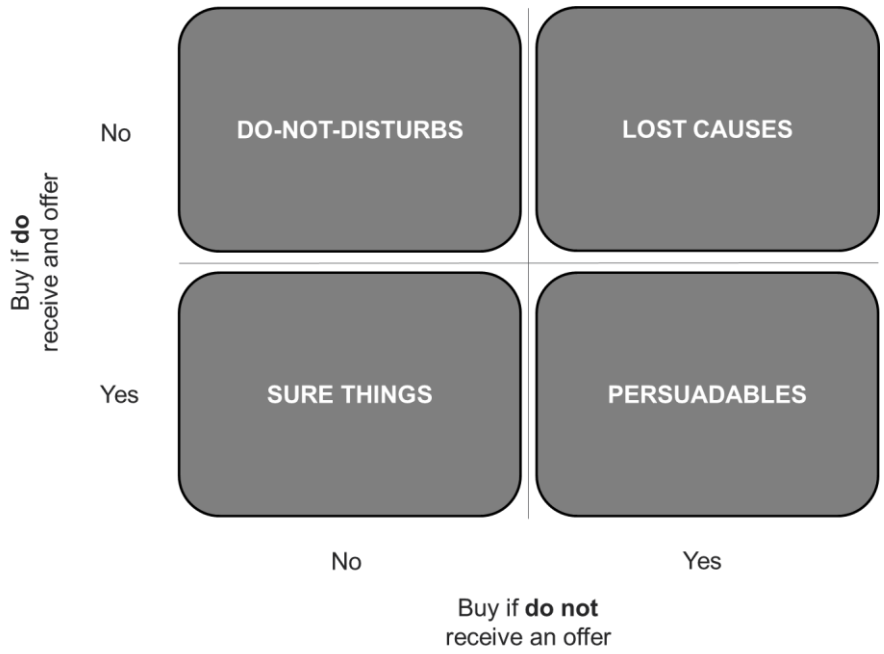

Figure 11: Response and treatment matrix. (Devriendt et al. 2018)

To fully grasp the potential of these data-driven value creation frameworks company’s must shift their focus and support towards a more data-driven culture. Tying strategic elements, technological capacity, and knowledgeable staff together to form a culture that views data as an asset and not just a by-product. By effectively tying data-driven value creation to the company’s strategy it will be forced to evaluate organizational resources also from various stakeholder perspectives allowing them to account for different risks and benefits. As these can vary significantly depending on applications it is crucial to evaluate the different scenarios and systematically assess the targeted use of value creation through data-driven decision models. This will provide the company with the possibility of evaluating the business value, technical readiness, and financial return levels of the different focus areas aiming for maximal ROI and value creation. (Kakuschke, Legner, & Jung, 2025)

An example of tying a company's strategic elements to data-driven operating models is aiming to decrease warranty claims of a manufacturing company by improving the level of information that can be monitored from the product. This shift allows the company to provide new and more valuable services to its clients as it should be able to provide a higher level of reliability for its equipment. As a downside, the company may have to adopt part of the customers manufacturing risks especially if the company aims to provide an output-oriented service guaranteeing a certain performance level. Consequently, data analytics should be viewed as one of the key components of managing these risks. (Stucki, Meierhofer, Gal, & Gallina, 2024). Gouveia, de la Iglesia, Abrantes, & López Rivero (2024) propose that companies would benefit from appointing either an individual or a team dedicated to data governance to oversee the integration and strategic planning ensuring that the data potential is captured to the best extent possible, especially when transitioning into a more data-driven way of operating. The same party should also review and uphold high integrity, security, and ethical standards regarding data management. It is important to note that this type of oversight is crucial when handling data that shapes the customer experience and influences decision-making directly affecting the customer.

When looking at the company's technical capacity, multiple different sources describe it as the backbone that data-driven culture is established on (Kakuschke et al. 2025; Stucki et al. 2024; Gouveia et al., 2024). This capacity is formed from the infrastructure, tools, and systems that are utilized in data collection, analysis, usage, and decision-making combined with the competences and knowledge to capitalize on the available information. To further demonstrate this, a study by Omrani, Rejeb, Maalaoui, Dabic, and Kraus (2024) highlights that the IT infrastructure and the level of innovation within companies are the two most significant drivers of new digital technology adoption. This is something companies should prioritize, as larger gaps with competitors are harder to close, and learning new digital skills becomes increasingly challenging the further behind you start. The modern companies that are able to capitalize on the potential data commonly operate using a combination of cloud-based infrastructure, data lakes and data warehouses that provides them with an agile way of operating combined with the scalability required for continuous growth (Demchenko, Cuadrado-Gallego, Chertov, & Aleksandrova, 2024). Having a solid infrastructure basis is only half of the puzzle as finding and retaining skilled staff can pose difficulties for companies. While technology can help companies to automate data collection and analysis,

the human interpretation and contextualization is the key in making the business decisions. A wide range of skills is required from the data professionals as they must be able to perform the analysis and effectively communicate it to decision-makers often portraying technical concepts to stakeholders with a very different background and set of skills (Omrani et al. 2024). This is also why companies should foster inter-role data literacy to ensure that all level of employees understand the importance of data and its effects of their roles within the company. Data literacy refers to the ability to ask the right questions, understand the insights on the data, and utilize it in making informed decisions. (Fattah, 2024) Fostering a culture where more and more people within the organization are able to process the available information increases the impact of the data-driven insights. Companies that prioritize staff development will be better positioned to leverage their data assets competitively in the long-term.

4.3 Measuring the effects of data utilization and missed out potential

Obtaining a clear and accurate view of the effects of a new data analytics tool or evaluating unrealized sales potential in a B2B manufacturing setting can pose challenges to companies particularly when trying to monetize this value. When looking at issues related to the effective measuring of a tool's effects, they can largely be tied to complex sales and manufacturing processes, lack of visibility in the data, and the influence of external factors that are not consistent. Meanwhile when looking at how to measure lost or missed out sales potential the issues are related to the uncertainty of estimations, what-ifs, and root cause tracking.

The three most prominent causes of the poor measuring of new data analytics tools are not being able to isolate other existing variables from the evaluation, the effect becoming visible with a delay, or the lack of a base line. Schleicher & Baumann (2018) discuss that in complex systems, like industrial manufacturing, evaluating the performance of a system is increasingly difficult as standardizing other effecting elements, such as the economic trend, is not possible. For example, comparing historical data from similar time periods to evaluate an effect can be misleading, as other influencing factors may skew the results entirely. Proving that something is as of result of the new tool and not due to changes in personnel, parallel processes or economic shift can be challenging. This is also due to most benefits

being commonly visible only after a period where the necessary data is collected and processed, and the new tool is adapted by its intended users (Cai & Zhu, 2015; Schleicher et al. 2018). After launching the tool, users may struggle or portray resistance with its use, which may underscore its potential at first (Schleicher et al. 2018). As the impact of data analytics tools can unfold over extended periods, promptly assessing the tool's effectiveness may undermine its real potential. Finally, as companies aim for more and more data-driven decision-making models they utilize the data available to them in new ways creating a lack of baseline in some situations. The baseline period provides a reliable comparison that provides the observers with important knowledge on existing trends and subsequent changes after the implementation of the tool. It helps to demonstrate changes, indicates weather the change is due to the implementation, and that the change is significant. (Hawkins, Sanson-Fisher, Shakeshaft, D'Este & Green, 2007)

To mitigate these issues and to establish an effective way of measuring the impact of data analytics tools, companies must adopt a structured and methodical way of approaching the challenges posed by the complex environment. As reviewed in previous chapters, the importance of creating the KPIs that align with the intended target is key. Fischer (2021) explains similarly that, the importance of following and acting on the measured KPIs once a proper data set has been recorded cannot be understated. He emphasizes that measurements should always lead to a process of improvement. Measurements should be made with proper recordings, recordings should lead to analysis, and analysis should result into actions. Following this way of operating and completing each part with the appropriate level of detail will help the company evaluate both its performance but also the tools it has chosen to apply to the process. When acting based on these insights, companies should consider establishing a control group that allows them to compare the results, similarly as in A/B testing (Quin, Weyns, Galster & Silva, 2024). This allows the company to review the changes made, for example, when launching a data analytics tool, it could be done on market A at first and then compared to the baseline of market B. After applying the tool to both markets the company could test possible future changes in a similar fashion. This also allows the company to consider the long-term changes and possible value adding features such as improved knowledge of the tool and data quality. Regular feedback loops and active quality monitoring can also be established as important factors when looking at the effectiveness of a new data analytics tool. By creating a systematic way of analysing and evaluating the success of

internal data tools, companies can increase their value creation potential and improve their decision-making (Conoscenti, Cardella, Passantino, & Verbert, 2019).

While these methods help companies to assess their data analytics tools and the company's effectiveness to utilize the available data, they don't fully cover how these manufacturing companies can review or estimate the lost or unrealized sales potential. Academically this is a topic that has been cover from an inventory management viewpoint but a focus from the sales or data analytics functions has limited coverage. In today's multichannel markets, customers have a variety of service providers to choose from, giving them greater leverage to negotiate. In this environment, being able to forecast the future demand is not only important for companies so that they can plan their own production, but also to accurately estimate the number of customers that are likely to change to a competitor or walk away from the products entirely. (Subramanian & Harsha, 2019) Understanding how well the company can capture the potential demand is a critical aspect of business planning and the evaluation of competitiveness. Kumar & Petersen (2012) discuss how the challenge of measuring lost, or unrealized sales potential is heavily related to the invisibility of these events. In industrial settings, the sales cycle is often lengthy and influenced by multiple touchpoints, which complicates the identification of specific factors leading to lost sales, this can happen especially during the beginning of these processes, causing the reason for the loss to be mislabelled or not recorded entirely (Grewal, Hulland, Kopalle, & Karahanna, 2020). This not only leads to customer dissatisfaction but also higher risk of customer churn. Not tracking these lost sales opportunities properly can also lead companies to overestimate their customer loyalty and underestimate their potential losses.

When sales tracking is done with high quality, it can be combined with other feedback collected from customers, to form insights combining factors behind lost sales cases. Understanding the root causes why the customers abandon the sales process can be used both to improve in these sectors but also to monetize the value of the loss. Creating a structured approach to data collection on lost cases, can help identify gaps when comparing to competitors, lead time issues or product feature expectations. This customer information can then be reflected towards the company's sales strategy and applied if the company choses to progress into the chosen direction (Homburg, Schäfer, & Schneider, 2012). This could be done, for example, using structured interviews. It can also be interesting for companies to review sales cases using a won-loss analysis model which compares the features of a

successful and unsuccessful sales case aiming to identify purchase patterns. Being able to analyse and single out the major factors effecting the purchase decisions can help the company to identify their losses better and help them take strategic measures to counter these losses (Steenburgh & Ahearne, 2012). In addition, the lost sales categorization provides the company with the prerequisites to estimate their loss through predictive analytics models. The comparison can be done, for example, by calculating the estimated revenue loss per loss type. Ultimately, companies can create estimations only based on historical data as calculating an absolute value of the loss can be done only after the deals have been realized.

5 Case study: international manufacturing company

5.1 Company overview

The study was conducted in collaboration with a Nordic precision parts manufacturing company that operates across various industrial industries. The company focusses heavily on different industrial processes supplying technological equipment, automations solutions, and supportive services. In 2023 the company employed over 19 000 professionals across all 7 habited continents and had a net sales value of around 5 billion euros. The company currently operates as a global market leader in several fields and is striving to improve their market position in multiple others. The thesis was conducted in collaboration with one of five major business lines within the company. It has the capability to create millions of unique configurations of its products to match the customers individual needs and most of the orders coming in for the business line require extensive requirements engineering and documentation.

Naturally, this accumulates a large amount of data that is managed and utilized by both operative, supportive, and administrative personnel daily. The company's long history provides them with a wide range of clients and credibility but also hinders its growth as their data management systems have changed during this time. Legacy systems and versions of these systems consist of multiple unique data sources which pose challenges in utilizing the available data to its fullest.

The company has distinguished the need to improve their after-sales model to be more proactive some while ago and as a part of this project has decided to carry out a study that combines a theoretical review, data analysis, and interviews to improve their after-sales opportunity visibility. The data analysis focused on building a Power BI reporting tool that autonomously summarizes sales projects from the companies CRM under one value based on the projects end country. Before the tool was developed there was no simple method of determining project size or importance due to the fragmented way the projects are created in the CRM. As a cause of this, local after-sales and service units could not prepare and

adequately target these after-sales opportunities causing sales opportunities to either remain undistinguished or untargeted.

5.2 Research methodology

The research deploys a mixed-methods research design integrating qualitative data analytics and semi-structured interviews to form a comprehensive review of value creation through data-driven decision-making in the after-sales processes. This approach ensures a robust basis for analysis as it allows the study to review the success of the data analysis and the value it brings to the processes from a wide range of viewpoints.

More in depth, the research used an explanatory sequential mixed method. A model which first executes the quantitative, the data analytics, inquiry and analysis of the study and then uses the qualitative data, the interviews, to explain and aid in elaborating the results. The name “explanatory” comes from the nature of the study as the quantitative data is later reviewed through the insights that have come up in the qualitative phase of the research. This type of analysis is common in research that has a strong quantitative alignment. (Hafsa, 2019) The method was chosen as the focus of the study was aimed at the data analytics tool from the very beginning.

The explanatory sequential mixed methods -model, visualized in figure 12, consists of five phases aiming to explore both the quantitative and qualitative data combining the strengths of both methodologies. The study begins with a qualitative data collection and analysis phase where to goal is to identify patterns, trends, and relationships. The follow up phase guides the development of the qualitative research with a focus on unclear or surprising results of the quantitative phase. The quantitative data collection can be done, for example through interviews or surveys. After reviewing both the quantitative and qualitative research data and highlighting the connection between the statistical results and the practical insights in the interpretation phase the study can aim to finally reflect on the results. This is a key step in the process as it determines the future actions or recommendations following the study. (Harvard catalyst, 2025)

Figure 12: The empirical part of the thesis followed an explanatory sequential design.

5.3 Data analysis and visualization

The data analysis consisted of a deep dive into data generated by multiple parties of the organization via the company's CRM system and sales operations. The main challenge the tool aims to address is enhancing the visibility and tracking of various sales projects, including their progress and different stages from start to finish. This added visibility allows the after-sales organizations to plan and take better ownership after the projects are finalized. This not only aims to enhance the ability to capture sales potential but also improve the engagement of the customer and so improve service quality. Before this visibility, in the worst-case scenario, information about an after-sales opportunity could be gained when the customer askes for service support after an operational issue.

The data set consists of around 10 different data tables with multiple different relations between each other, all from the same CRM system. In total the data set contains over 800 columns and over 6 million rows of values spread out into the tables. These tables contain sales project data with some having an extensive sales histories spanning over several years. Key variables of the data set include, but are not limited to, market area, sales and operative country details, time frames of project, different sales stages, and both cumulative and non-cumulative order values. Data cleaning involved correcting human error, such as spelling mistakes, creating supportive tables, such as calendars, renaming columns to improve readability, and removing unnecessary values. Each of these steps involved some degree of manual effort, either in reviewing the extent of the issue and addressing it with a DAX script, or by handling the entire process manually from start to finish. Most of the manual work had to be done due to human based errors or processes changing over the years causing anomality's in the data set. Additionally, the sheer volume of data in the report presented challenges, as updating it became highly time-consuming.

After collecting and cleaning the data set a functioning relationship model was created between the tables. This posed challenges as the columns didn't always follow a unified pattern in how the relations should be viewed. The company's CRM system creates sales projects using a cascading waterfall structure meaning that sales opportunities are linked to projects, projects are linked to accounts and so on. This differing level of detail, with some projects having multiple sub-projects and some having none, was one of the main contributors to the visibility issue of the sales projects. This has been visualized below in figure 13.

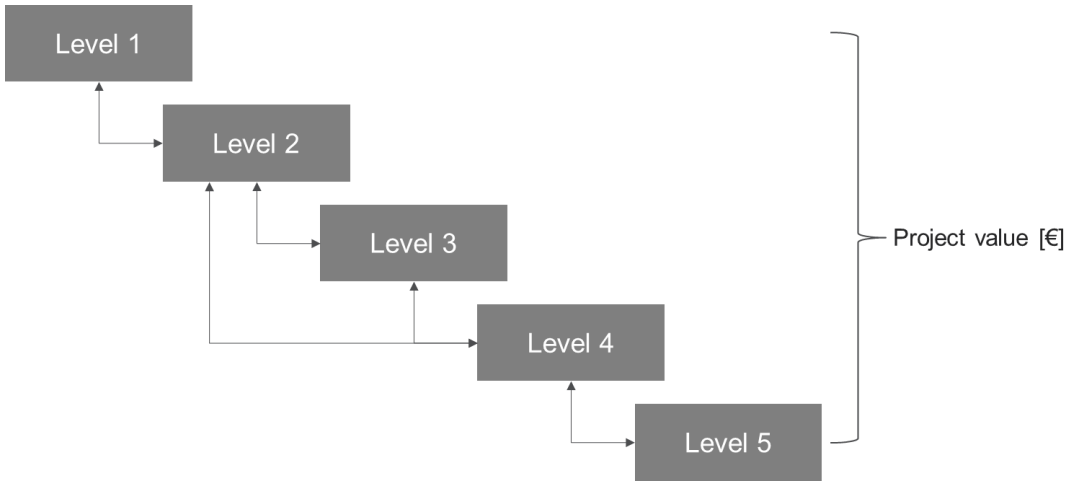

Figure 13: Representation of project data relations. Levels 2-4 could have an unlimited number of sub-levels connected to them

After creating a functioning data schema allowing for all the relations to work properly and link all the needed information on a reliable level. The sales projects were visualized using a Power BI treemap model (figure 14). The visualization was chosen due to its ability to easily combine and compare the sizes of the projects while also stacking the related data tables so that drilling down into related projects is also accessible. Presenting these relationships within a single sales project was crucial in addressing a key issue the tool aims to resolve, which was, providing an easy-to-compare overview of different project sizes. This was combined with a data table that shows the selected projects and allows the user to both easily view the main project details but also access the projects via a direct link to the company's CRM system. By selecting the appropriate filter, such as date, market area or customer the user is now able to view all the related projects and their sales information.

Figure 14: Overview of the data analytics tool that was created as part of the study. Critical or identifying information from the case company's operations has been removed.

5.4 Interviews

Qualitative research acts as an in-depth method of data gathering in a wide range of research opportunities. The insights provided from this research method focuses on participants experiences, perceptions and emotions regarding the subject. When quantitative analysis focuses on numerical values, qualitative interviews take a deep dive in "how" and "why" the subjects behave as they do and so providing explanatory insights into complex phenomena (Sutton & Austin, 2015). A major advantage of semi-structured qualitative interviews is their opportunity to be reactive and flexible to ensure the opportunity of pursuing topics that arise during the interviews. This facilitates a comprehensive review of the subject and captures possible new interest areas or viewpoints. (Gill, Stewart, Treasure & Chadwick, 2008) This also allows the participants the opportunity to review their own experiences and motives behind their actions. This can be seen especially valuable in subjective experiences and the meanings the interviewees assign to them. Keeping this in mind the effects of trust and influence between the interviewer and the interviewee should be noted when collecting data through qualitative interviews. (Ryan, Coughlan & Cronin, 2009)

The interviews review the data analytics tool and the capex-to-opex handover process through-out the different process steps from project sales to service and after-sales. During the interviews professionals on different levels of the organization express their opinions and insights regarding the current status of the process, their initial views of the data tool, and the future development of these topics. To gain a maximal understanding of the relevance of the tool and its possible development areas the tool was reviewed by interviewees that were both familiar and unfamiliar with it and its possible use cases. The hypothesis, which proved to be correct, suggested that opinions vary based on the interviewees' roles. By interviewing individuals across a wide range of positions, a holistic view of the process and its future developments both in terms of workflow and the data tool was achieved.

The interviews followed a semi-structured model. This was chosen to create comparability between interviews without having to compromise flexibility or the possibility of additional questions when interesting topics come up. The interviews were conducted using Microsoft Teams which allowed the interviews to be both recorded and transcribed using the built-in tools, which allowed the interviews to flow more naturally. Teams also allowed the interviews to contain a wider range of professionals as multiple of the interviewees operate in locations around the globe. The interviewees where knowledgeable of the recording and transcription of the meeting. In addition to Teams, the interviewer made highlighted notes on the most interesting parts of the interview using a pen and paper. The interview questions were provided to the interviewees in advance, alongside with an initial overview description of the data tool for those that were unfamiliar with it. An overview of the participants that where interviewed can be found in table 3. Interview body and questions can be found in annex 1.

Table 3: Overview of interviews conducted

Interview #	**Role**	**Role in handover**	**Date**	**Time**
1	Manager	Services	27/01/2025	36min 57s
2	Director	After-sales	28/01/2025	42min 56s
3	Manager	Business development	29/01/2025	35min 04s
4	Manager	Sales	29/01/2025	33min 15s
5	Manager	Business development	31/01/2025	48min 48s
6	Head of	After-sales	03/02/2025	52min 53s
7	Director	Business development	04/02/2025	44min 53s
8	Director	Sales	06/02/2025	53min 21s
9	Manager	After-sales	06/02/2025	37min 23s

5.5 Key findings

5.5.1 Handover process

The interviews had two focus areas: the capex-to-opex handover process and the data tool that was built as part of the study. By reviewing both, the interviews were able to determine where the tool could be useful and how it could be incorporated into the current process. At the same time, the interviews highlighted key development areas within the process. During the course of the interviews, it became clear that no unified approach to completing the capex-to-opex handover was documented or systematically followed within the company. Instead, various market areas and countries had developed their own ways of operating, often leading to inconsistencies. In many cases, the practice appeared to be informal and ad hoc rather than a structured and systematic process. Multiple interviewees, regardless of their position within the organization, emphasized this as a critical challenge.

Interviewee #3: In some situations, the handover process is not governed or monitored in any way from the business unit perspective, so no official process has been established to provide support for the handling organization.

Interviewee #4: …the process works in our market area, but we too have some newcomers who are still not that familiar with this kind of "shadow organization" that passes on the required information as there is no clear process on how to do so. […] But the communication works as a result of this shadow organization that has been formed as a result of experiences and long terms of employment.

One of the key factors contributing to the fragmentation of the process is the company's long history, coupled with variations in operating cultures across different regions. Additionally, the lack of systematic unification following M&A deals and natural expansions has further reinforced inconsistencies. As a result, ownership of the handover process remains unclear, with no clearly assigned responsibilities. Without a designated party overseeing it, the process continues to be fragmented, lacking a unified framework to guide its execution.

Interviewee #6: There's so much variation between the different internal organisations as every country has its own little nuances and ways of working with the customers. I would prefer a more unified process. [...] Although there is a set outline (in most cases) *of instructions that have been distributed, people have their own way of interpreting them.*

Another factor that kept repeating in the interviews was the identified potential and the perceived willingness to shift the after-sales and services operation model towards a more proactive way of operating, but the absence of clear management on how to do so hinders the process. The lack of training and routine regarding a proactive handover process with stakeholders involved, both in local and global teams, lowers the perceived importance of a well completed proactive handover. Even though it became clear in the interviews that major improvements with this subject have been made across the past years. It still remains a hinderance of value creation both internally, with necessary information not being handed over, and externally, with customers not receiving the best possible support for their equipment.

Directly related to this is a prevailing sense of uncertainty, often exacerbated by the overwhelming volume of reports and the multitude of tools available to operational teams. This naturally causes resistance to new tools and changes in the ways of working when they are implemented into use. The resistance can then turn into, once again a new way of working of partially adopting the new system but still continuing to use the old methods on the side.

However, as one interviewee pointed out, the root issue may not be the sheer number of reports but rather a reluctance to change ingrained habits. This highlights the need for structured change management and targeted training initiatives to support a smoother transition toward proactive service operations.

Interviewee #2: I know we have too many Power BI's, that we have too many reports. This is something that many countries claim, "Now I'm lost, which Power BI should I look at".

Interviewee #6: ...I don't think that actually, the amount of reports is the problem. Just people's mindset. Still stuck in an old way of working and using the old tools or using old styles.

5.5.2 Data tool

The interviews also assessed the role of the data tool in addressing visibility gaps in the capex-to-opex transition. When looking at the data tool the interviewees shared a positive view of the value and visibility it provides for both the people directly related with the handover process and people in higher management positions. The tool has provided new visibility that was previously lacking, particularly benefiting mid-to-small projects and smaller local organizations where support structures or operation models are less defined. The advantage was sawn as greater for smaller projects and organizations as the larger organizations and projects are commonly more equipped with more resources and/or better support. In some cases, the interviewees reviewed also that the tool can act as an eye opener for some and provide them with a better incentive to shift their operation model toward a more proactive one.

Interviewee #4: The smaller the country organization is the bigger help this will be has they will not be able to focus on everything to grasp an overview on what will be landing"

Interviewee #5: I think we can all agree that the tool is relevant, and I'm surprised that this hasn't been done before. [...] This could help us sell the idea of long-term planning to the salespeople responsible as we can show the data and what could be available for them.

A primary concern raised by many interviewees is the challenge of implementing the tool amidst the extensive array of existing systems, reports, and data sources combined with the local variance amongst working styles. The abundance of information combined with multiple different ways of working can cause the tool to become overlooked or lost within the multitude of available reports. This can potentially be a significant impactor on the effectiveness of its implementation and hinder the potential benefits the tool could offer. The interviewees noted that the tool has the potential to foster a more proactive approach in service and after-sales operations, but this shift depends on broader organizational buy-in.

Interviewee #3: I think the tool is perfect, but without what I just said (the process requires work, time, and commitment from management to make the change to a more proactive model), *answering questions seven and eight, it doesn't have relevancy for the handover process.*

Interview #2: This is a good tool as it is focused on a particular topic, which is to understand to potential. [...] If something is missing directly in the power BI, if I'm interested to find this information I will find this information. It will take me one hour, two hours maybe. Maybe I will ask somebody to help me, and it will take three days. But I will get this information. I will get this data. I do not see the major problem to be the data available in the tool, it's a good tool, but how to teach people to use that tool and how to convert it for their plans?

Even though the tool contains sales project data spanning over a decade, its optimal functionality is observed in projects initiated in recent years and for projects that have been planned to be completed in the future. Interviewees highlighted this as a key advantage, as the tool effectively supports a majority of sales projects while also providing a basis for refining and developing how both local units and management reviews the after-sales support and services. Being able to view the projects in your market area in an easily comparable way so that you can gain an understanding of the project size and scope will help planning and prioritization. It also helps to highlight the time frame the projects will take place in and so allow the organizations to take pre-emptive measures so that they can plan and allocate resources to meet the projected support needs before they are realized.

Interviewee #6: So, for me, yeah, it's definitely relevant to our business. It's relevant to sales. It can be used for, I would have said all service business and future service business for one of a better description.

Interviewee #5: The problem here is that if a project is landing and scheduled for 2026 currently our planning process doesn't extend to this time period. As we are currently thinking somewhat narrowly at the moment. […] This provides good reflections on how our time frame is far too short.

5.5.3 Future development

The future development of the tool was discussed at the end of each interview, and this was the area where most difference arose based on the function and position of the interviewee in the organization. In contrast, when discussing the process itself, interviewees demonstrated greater alignment in their views, emphasizing the need for a more unified and documented approach. Improved process structure would enhance both information flow and the clarity of responsibilities across all stakeholders. Among the various aspects discussed, the most consistently valued improvement was the enhancement of internal communication between all parties involved in the project as early as possible.

Interviewee #8: One major thing is that having a single global process on, how to deliver data and how it (the process) *operates. It's important as the company is operating globally. [...] It all comes down to communication, if we are currently struggling with selling the value of the installed base in some instances, how can we get this* (the tool) *through to everyone involved. And that's why it* (the process) *should be carved into stone and clear for all.*

When looking at the tool itself, the development ideas where heavily tied to the positions of the interviewees, with the connection being that interviewees in the same organization, wished for similar functionalities. Most of the new functionalities that were spoken about were very specific and would hinder the universality of the tool and specify it more towards only that organization. The only similar idea that came from more than one organization was that the report should be visible in the CRM system to minimize the number of individual systems in use and to help the integration process as there would be less new features to take in.

Interview #4: It (the report) *should be imported directly into the CRM system. [...] Whenever it* (the information) *stays at the Power BI level, no matter how good the tool is, there is a significant risk that it will be difficult to implement. Once you use a report only once or twice here and there, you forget it even exists.*

Conversations also arose in some instances about does the tool require future development and will it add value. As previously discussed, the multiple data sources and reports available can be experienced as overwhelming. This is also true when looking at the complexity of different data sources. So, by adding information to the report the readability and relevance of the data tool may be negatively affected as the most important values could be overlooked or otherwise not prioritized in the intended way.

Interviewee #3: From my perspective, the tool already fulfils its function. So, by adding things, they need to be absolutely necessary. So, it doesn't, you know, take focus away from the function we already have.

6 Discussion

6.1 Interpretation of findings

The findings from the empirical section of the study, including both the data analysis tool and the interviews that where conducted based on it, strongly suggest that data analytics have great potential to improve the value creation of after-sales and so benefit both internal and external stakeholders. This effectiveness, however, is greatly contingent on the robustness of the internal business processes the data analytics tools are designed to support. This can be seen when looking at the interviews reviewing the case company's capex-to-opex handover process and the tool that has been built to support it by improving after-sales opportunity recognition. To fully be able to grasp the potential of both the tool in question and other data-driven decision-making methods the company need to improve their internal handover process. With structured, high-quality efforts from the entire organization, the process could be established to both support internal business organizations and the customer in a more proactive way. This would further allow the company to implement new ways of utilizing the data available and to improve after-sales yield.

The academical theory supports these findings as Porter's value chain models and its subsequent applications emphasize that value is created through a sequence of independent activities that together create a greater positive effect than when viewed individually (Porter, 1985). In the company's case, the potential value available from the data tool is dependent on multiple different occurring activities around it. If critical activities within the sequence, such as sales data input, are inefficient, then the overall value potential that is created by the data analytics tool is diminished. The same can be said about value creation and utilization in the capex-to-opex handovers. If the process is handled inefficiently with various ways of working, i.e. the operation models don't follow a structure, the value of generated in the sequence is lower than its potential. In this scenario the data analytics tool cannot systematically support the handover process as it cannot be implemented into a value adding sequence. This is particularly relevant when looking at the role of predictive analytics tools and proactive operating models in after-sales such as performance-based servicing and

predictive maintenance as they rely heavily on efficient information transfers between teams and data-driven decision-making.

The empirical study further reinforces the reviewed theory on the customer journey management capability, as noted by Homburg et al. (2023). They highlight internal integration, the number of resources allocated to ensure seamless transitions in the customer journey through integration across both online and offline channels, as a key touchpoint effecting the customer journey. A fragmented handover process reduces the internal integration and consistently hinders the company's ability to provide comprehensive after-sales experiences and create value in comparison to their full potential. In a worst-case scenario, the customer will start to replace the installed base with competitors' equipment from the moment it has been installed. In comparison, a company that is able to ensure a systematic way of operations is more likely able to leverage data analytics on a larger scale and ensure proactive stakeholder engagement driving improve capitalized service opportunities. The tool eases the process of knowledge transfer, facilitates a smoother capex-to-opex handover and incentivizes its users to apply a proactive after-sales mindset to their ways-of-working.

6.2 Implications for the after-sales

The key implication of this research is that while data analytics is a valuable enabler of after-sales optimization, it is not a standalone solution. This is also supported by theory as Kohtamäki et al. (2015) note that simply expanding services, without proper governance, is unlikely to create a lasting competitive advantage or improve the financial performance significantly. One could even argue that the empirics suggest that without proper governance the implementation of data analytics can negatively affect the company's operations and finances. This underlines that a company's effectiveness of analytics depends on the organizations ability to integrate it into their existing processes and how well these implementations are later governed. The most critical area affected by this is the proactive utilization of internal knowledge. The theory suggests that data-driven decision-making can help companies to proactively address possible equipment failures, optimize maintenance schedules, and target customers at the optimal moment with customized sales packages (Lee et al. 2014; Wedel et al. 2016). However, the empirical findings suggest that this potential is

commonly not fully realized due to crucial data points becoming lost, misinterpreted, or unacted upon during the process. This further leads to after-sales opportunities to not be valued on the level they should be or even the loss of internal knowledge. Crubic (2014) emphasises the importance of organizational alignment in the utilization of internal knowledge and the servitization of after-sales, which further supports the importance of internal cohesion in information transfers.

The company's ability to effectively manage and act upon customer data is directly linked to its long-term revenue growth and competitive advantage (Popovič, Hackney, Tassabehji & Castelli, 2021). The case study suggests that while the data collected and managed by the company is, on some level, acted upon. These directly linked action could be drastically improved to ensure that the company does not leave business opportunities untargeted. The challenge remains that while the opportunities for after-sales improvements exist, they require structured and consistent efforts to be effectively realized. The tool should be understood to be used as a means to ensure that all opportunities are captured. The case company's 'low-hanging fruit' of after-sales business opportunities are considered as such due to their abundance rather than their ease of attainment.

6.3 Recommendations on future action

To fully start leveraging the potential provided by data analytics in after-sales the company must place focus on standardizing and documenting the capex-to-opex handover process so that it becomes unified regardless of stakeholders involved. Establishing clear guidelines and responsibilities and ensuring that all relevant stakeholders have access to the tools and information necessary will help improve both internal communication and cross functional collaboration. This can be reinforced by theory as Marques et al. (2019) emphasize the correlation between an organization's knowledge maturity, meaning the level a company is able to utilize the available data, with structured approaches to shared information and internal commitment to the process.

Alongside this, the company should evaluate its technological readiness, meaning both the hardware and software capabilities but also its employee's skills to utilize the data tools in an efficient manner and data literacy skills. Having the appropriate knowledge of which tools

to use at what point and how to utilize them should help with the employees overwhelming feeling of reports and tools at hand, as noted by multiple interviewees. Prior research by Davenport et al. (2017) also underscores the importance on continuous learning in creating a data-driven culture within the company. This could be further incentivized by evaluating existing performance metrics so that they place emphasis on the effective utilization of the chosen tools, aiming to integrate data-driven insights into different workflows. A study by Akter et al. (2016) further supports this as it argues the companies that are able to link their analytics with their business strategies are better positioned to sustain a competitive advantage over its competitors.

Given the extensive nature of these recommendations, successful implementation will require strong leadership and cross-functional coordination. These changes will affect a wide range of functions, different market areas, business units and existing operations, which requires the engagement and commitment of top management for these changes to be solidified. Effective data utilization will not only enhance internal decision-making and efficiency but also lead to an improved range of tailored and proactive engagement with external stakeholders. If successful, the company will be able to grow its value creation through data analytics and improve the realized yield generated by after-sales while simultaneously improving its data analytics capabilities.

As a final note for both future research and the companies applying data analytics to their customer data, the revision of ethical and legal concerns must be noted. As the thesis reviews the use of predictive analytics within proactive after-sales models the companies doing so are obligated to review their use of the data with the customers. For example, when a company A sells a device to company B and as part of that device, an IoT sensor collects data from the main product and its functionalities the questions of “Who owns the data and how can it be utilized for further analysis?” arises. In one sense value can be created symbiotically if the manufacturing company gets to analyse the data as then they can both improve their products based on it and provide predictive maintenance for the end customers. On the other hand, as the data is part of the end customers operations, they might have concerns to keep their operation data for internal use only. This is a subject that will be ever more prominent when more advanced data modelling tools, such as AI, will be incorporated into the operations of both the manufacturing company and its customers. When applying

their own adaptations of the subject companies will also have to note the difference between market areas as legislation will most likely differ.

6.4 Limitations of the study

While the research provides valuable insights into leveraging data analytics for value creation in the after-sales business, it is important to note that the study acknowledges several limitations that may affect both the results and their generalizability for wider market contexts or industries. One main limitation of the study is that, while the literature review can be applied to more on a general level, both it but especially the case review was conducted with a heavy focus on only one specific company and their operations, which limits external validity and generalization. During the course of the interviews no trust issues or influence of the interviewer over the interviewees was detected.

The second main limitation of the study was, that as it used sales data from only one company the possible biases within the data may affect the results of the data tool. The development on this tool also relied heavily on historical data which may not accurately predict future trends, for example, if the data is inconsistent or is tainted via human errors in data input. The technical limitations related to the data analytics tool that was developed should be noted. The integration of the tool into active use was not thoroughly tested and most likely will present potential challenges in the real-world, as previously noted.

The study also notes its constraints related to the use of more traditional data analytics tools as singling out AI and ML models may limit the potential for deeper predictive analytics insights and the implementation of more data-driven strategies. Also, the tool was built with the company's current organisational chart, operational activities, and IT infrastructure in mind, and changes to these may affect the tool's functionality and relevance. Future research involving broader industry contexts and more advanced analytics methodologies could address these limitations and enhance the study’s contributions.

7 Conclusion

7.1 Summary of key findings

The study reviewed how data analytics can be leveraged in value creation in after-sales within a B2B manufacturing context. The theoretical frameworks reviewed in the study create a comprehensive argument that predictive analytics, the establishment of clear value chains, and customer journey management are essential items in todays after-sales operations. These elements can be considered crucial as they facilitate improvement in customer satisfaction, enhance operational efficiency, and boost revenue growth. Predictive analytics both shifts the business toward a more proactive operation model, but also allows the company to anticipate service demands, reduce downtime, and help target customers at the opportune sales moment. Clear value chains ensure a streamlined workflow, which can systematically help identify areas of improvement or cost reductions. Customer journey management provides an improved environment for customer engagement leading to more accurate service tailoring based on customer needs raising customer retention rates. While the theory highlights a wide range of use cases for data analytics tools for after-sales business cases, the empirical findings reveal that this potential cannot always be fully realized as this is heavily dependent on existing internal process structures and operation models. Both sections call attention to the company's technical readiness and data literacy as it acts as a prerequisite for achieving meaningful improvements for the implementations of new data tools.

As the study progressed it aimed to answer the main research questions to provide the reader with a holistic view of value creation, different after-sales business models, and how data analytics can be applied to creating symbiotic benefits within a company. The first research question of the study was:

> "What role can data analytics play in creating value from the perspective of after-sales?"

Data analytics plays an exceedingly growing role in the value creation process in the after-sales business by providing companies with new insights into market information, improving

operational efficiency, and driving revenue growth. As companies continue to invest into their digital transformation and implement data-driven strategies their analytics capabilities will become increasingly critical in maintaining competitive advantages. This will most likely be even more relevant in the future as the race for AI and ML models implementations continue to grow. The second research question of the study was:

> "How can data analytics be utilized to identify key service opportunities during and after internal Capex-to-Opex handovers?"

Data analytics can be utilized in identifying key service opportunities during and after the internal capex-to-opex handover process in multiple ways such as customer segmentation, market analysis, and internal process optimization. As a part of this study a data analytics tool was created to support after-sales opportunity recognition based on previously realized sales projects. The tool is built on a thorough examination of existing data sources, followed by data standardization, modelling, and analysis, culminating in a treemap model that provides users with a comprehensive overview of all relevant projects and their statuses. This aims to provide improved visibility and incentivize the responsible after-sales units involved to provide support to other internal and external stakeholders, and to actively pursue a more proactive after-sales strategy.

While data analytics bring massive value potential and can act as a major driver of business growth, it is important to note that it is not a standalone solution but acts in a supportive manor. This supportive aspect can especially be seen in decision-making as data analytics can help the company gain an improved overview through data analytics, but the analysis itself cannot solve existing issues. For companies to be able to fully grasp the potential of data analytics it must be actively implemented into the core of the business, so that each functions support the analytics process so that the analytics can later support them.

7.2 Contributions to theory and practice

The study extends existing research by combining a comprehensive theoretical review of value creation and after-sales business models with a practical perspective through an empirical case study of a manufacturing company. It provides a practical perspective on how data analytics can be applied to project sales data to improve an international B2B

manufacturing company's after-sales opportunity visibility. This was a gap in the existing theoretical literature as previous studies had not placed emphasis on the after-sales perspective of international manufacturing companies. This was also true when looking at existing literature reviewing company's data-driven decision-making as a part of their servitization strategies. For the case company, the study provides a fully functional data analytics tool that was specifically built and customized for their needs, a deep dive into their existing capex-to-opex handovers containing multiple different viewpoints within the organization, and concrete recommendations regarding the future development of their operations.

7.3 Future research directions

Future research should consider evaluating the case companies process after the chosen improvements have been successfully implemented. By doing so an interesting comparison could be reviewed of how much value creation was captured through the changes and how does the improved process facilitate data-driven decision-making within itself. This could also be examined from multiple other perspectives such as customer retention or after-sales yield growth. It may also be lucrative for future studies to review multiple different companies operating in a similar setting. The comparative nature of the study would allow future researchers to further enrich our understanding of the best practices of leveraging data analytics in after-sales.

As the analytics capabilities within companies grow, another subject that would be interesting to study would be the utilization of future data-driven tools like AI, machine learning and digital twins. As this is a subject that continues to draw both attention and investments towards itself the potential effects on business drivers must be noted. By addressing these areas, future studies can continue to build our understanding and provide new innovative ways to utilize data analytics in manufacturing and servicing industries.

Regarding the development of the data tool that was provided for the company, it may be interesting to add additional layers of information so that it can be utilized on multiple different levels of the organization. Adding the number of devices involved in the original sales project could help after-sales gain a more comprehensive view of the possible after-

sales value of the project. This could be even more lucrative in a situation where a connection between the data tool and the existing installed base data would be established as the tool could indicate the percentual growth of the client's site before and after the capital project has been delivered. When reviewing future development ideas, the company should keep in mind that the tool was built maintaining a simplistic style to keep all available data relevant and easy to interpret to avoid it becoming overcrowded with information.

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Appendix

Appendix 1 – Interview body:

Introduction and agenda

Background

1. What is your role and responsibilities at the company?
2. How long have you been in this position?
3. How do you take part in the Capex-Opex handover process?

Current state of the Capex-Opex handover process

4. Please describe the Capex-Opex handover process from your point of view?
5. How do you ensure that all the necessary information is passed to the people who require it? What tools do you use to do so?
6. What currently works well in the process?
7. What is the biggest challenge in the process from your point of view?
8. What needs to be done to fix this challenge?

Tool demo if needed.

Issues related to the handover process

9. What is your overall impression on the handover tool and its relevancy?
10. How could you use it to improve your way of working with the handover?
11. Is there a value/visual that you find especially useful?

Future development ideas

12. What future improvements would you require from the tool?
13. In an ideal dream world: How would you develop the current process?