Ilmari Aatola

DIGITALIZING DEMAND FORECASTING IN INDUSTRIAL SERVICES

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Faculty of Management and Business
Associate Professor Tuomas Korhonen
Professor Teemu Laine
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ABSTRACT

Ilmari Aatola: Digitalizing demand forecasting in industrial services
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Modern manufacturing companies adopt servitization strategies to capture revenue from after-sales services, referred to as industrial services. Despite the expected benefits and recurring revenues from industrial services, practical difficulties in implementing servitization strategies lead to challenges in maintaining profitability and flexibility of the organization. One of the main challenges from an operational perspective is the intermittent demand pattern of industrial services, which makes demand forecasting extremely complicated. While forecasting methods and digital support systems have developed over the years, there have been limited advancements in practice.

This thesis approaches the phenomenon by conducting interventionist research in collaboration with an industrial service organization. The main objective of the thesis is to develop an understanding of how digitalization could enhance forecasting practices in the context of industrial services. As sales and operations planning (S&OP) has been commonly used for facilitating integrated demand and supply planning within manufacturing companies, its feasibility for industrial service organizations is examined in this thesis. The study begins with a literature review to establish a theoretical foundation for the thesis. The findings from the literature review were utilized to generate relevant interview questions for a current state analysis. After gaining an understanding of the literature and the case organization, an initial framework for digitalizing demand forecasting was created. The framework was used as an intervention, and further focus groups were organized to evaluate and refine the proposed framework.

The study reveals that the advancements in forecasting practices in the literature are often unrealized due to practical challenges, such as data collection limitations or the complexity of the service offering. This research managed to identify how digital tools can enhance forecasting industrial services providing a realistic framework for digitalizing forecasting practices. While previous literature has focused on forecasting methods based on historical sales data or installed base information, this study highlights the importance of incorporating more future-oriented data, such as information from quotations and sales pipeline, for short-term demand forecasting. Additionally, the study identifies machine learning applications as a promising avenue for managing the complex datasets typical for industrial service portfolios.

The findings also confirm that successful digitalization of demand forecasting requires not only technological tools but also a well-defined process and a shared internal understanding of that process, consistent with existing literature. The S&OP process was identified to be suitable for industrial service organizations, particularly when their service portfolio is transitioning from reactive services towards more proactive services. The framework proposes the S&OP process to be implemented, as in addition to contributing to forecasting accuracy, it enables better alignment between demand and operations planning.

This thesis contributes to the existing demand forecasting literature by demonstrating how digital tools can be utilized in the industrial services sector, providing direction and a foundation for future studies. Future research is needed to evaluate the proposed framework in a real-world setting. In general, digital solutions for forecasting require more research with actual data.

Keywords: Demand forecasting, industrial services, sales and operations planning, S&OP

TIIVISTELMÄ

Ilmari Aatola: Kysynnän ennustamisen digitalisoiminen teollisessa palveluliiketoiminnassa
Diplomityö
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Modernit valmistavan teollisuuden yritykset panostavat palvelullistamisen strategioihin realisoidakseen jälkimarkkinapalveluista saatavia lisätuottoja. Vaikka teollisten palveluiden odotetaan tuovan hyötyjä esimerkiksi toistuvien tulovirtojen myötä, kyseisten strategioiden käytännön toteutukseen liittyy haasteita, jotka vaikeuttavat organisaation kannattavuuden ja joustavuuden ylläpitämistä. Yksi keskeisimmistä operatiivisista haasteista on teollisille palveluille tyypillinen epäsäännöllinen kysyntä, mikä tekee kysynnän ennustamisesta haastavaa. Vaikka ennustamisen menetelmät ja digitaaliset järjestelmät ovat kehittyneet vuosien aikana paljon, niiden käytännön soveltamisessa on edistytty vain rajallisesti.

Tässä diplomityössä lähestytään edellä esiteltyä ilmiötä interventionistisella tutkimuksella, joka toteutetaan yhteistyössä teollisen palveluliiketoiminnan case-organisaation kanssa. Tutkimuksen päätavoitteena on luoda ymmärrystä siitä, miten digitalisaatio voisi parantaa ennustamiskäytäntöjä teollisten palveluiden kontekstissa. Myynnin ja toiminnan suunnittelua (engl. Sales and operations planning, S&OP) on yleisesti käytetty kysynnän ja tarjonnan suunnitteluun valmistavan teollisuuden yrityksissä, ja tässä tutkimuksessa sen soveltuvuutta tarkastellaan teollisen palveluliiketoiminnan näkökulmasta. Tutkimus alkaa kirjallisuuskatsauksella, joka luo teoreettisen perustan tutkimukselle. Kirjallisuuskatsauksen tuloksia hyödynnettiin nykytilatutkimuksen haastattelukysymyksien luomisessa. Kun työn teoreettiseen taustaan ja caseorganisaation nykytilaan oli tutustuttu, luotiin alustava viitekehys kysynnän ennustamisen digitalisoimiseksi. Tätä viitekehystä käytettiin tutkimuksen interventiona, ja sen arvioimiseksi sekä edelleen kehittämiseksi järjestettiin fokusryhmätilaisuuksia työn toisessa empiirisessä osiossa.

Tutkimus osoittaa, että kirjallisuuden luoma kehitys ennustamisen menetelmissä jää usein toteutumatta käytännön haasteiden, kuten tarvittavan datan keräämisen tai palvelutarjonnan monimutkaisuuden vuoksi. Tässä tutkimuksessa onnistuttiin tunnistamaan, miten digitaaliset työkalut voivat parantaa teollisten palveluiden ennustamista luomalla realistisen viitekehyksen ennustamiskäytäntöjen digitalisoimiselle. Vaikka aiempi kirjallisuus on keskittynyt ennustamisen malleihin, jotka perustuvat historiadataan tai asennetun laitekannan dataan, tämä tutkimus korostaa tulevaisuudennäkymiin perustuvien tietolähteiden, kuten tarjouskannan ja myyntiputken, merkitystä lyhyen aikavälin kysynnän ennustamisessa. Lisäksi tutkimus tunnistaa koneoppimisen soveltamisen lupaavaksi tulevaisuuden ratkaisuksi ennustamisen kehittämiseksi.

Tulosten perusteella kysynnän ennustamisen onnistunut digitalisoiminen vaatii teknologisten työkalujen lisäksi selkeästi määritellyn prosessin ja yhteisen ymmärryksen tästä prosessista, mikä on linjassa aiemman kirjallisuuden kanssa. S&OP-prosessi todettiin soveltuvaksi teolliselle palveluorganisaatiolle erityisesti silloin, kun palveluportfolio siirtyy reaktiivisista palveluista kohti proaktiivisia, suunnitelmallisen elementin omaavia, palveluita.

Tämä tutkimus luo kontribuution olemassa olevaan kysynnän ennustamista käsittelevään kirjallisuuteen osoittamalla, miten digitaalisia työkaluja voidaan hyödyntää teollisten palveluiden kontekstissa, tarjoten suuntaviivoja ja perustan tuleville tutkimuksille. Jatkotutkimusta tarvitaan esitetyn viitekehyksen arvioimiseksi todellisissa käyttötilanteissa. Yleisesti ottaen digitaaliset ennustamisen ratkaisut vaativat enemmän tutkimusta realistista dataa käyttäen.

Avainsanat: Kysynnän ennustaminen, teolliset palvelut, myynnin ja toiminnan suunnittelu

USE OF AI IN THESIS

I have utilised AI tools in my thesis:

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☒ Yes

The AI tools utilised in my thesis and their purposes are described below:

Names and versions of AI tools: Microsoft Editor (Word), Microsoft Teams (Transcription), ChatGPT-4o, Grammarly, DeepL

Purpose of using AI tools: AI tools have been applied for proofreading, translation, and developing structures of sentences. In addition, AI was used for transcription of interviews.

Sections where AI tools were used: Data collection: Transcription; Handwriting of the thesis: Abstract, Introduction, Literature review, Research methodology, Results, Discussion.

I acknowledge that I am fully responsible for the entire content of my thesis, including the parts generated by AI, and accept accountability for any violations of ethical standards in publications.

PREFACE

I would like to express my gratitude to the case company for providing me with this opportunity. My sincere thanks go to the members of the steering committee, Laura, Mika, Mikko, and Tuomas, for their encouragement and insightful discussions, which were invaluable throughout this process. I am also deeply grateful to my university thesis advisor, Tuomas, whose guidance and inspiration enriched my research journey in countless ways.

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Finally, I want to thank my friends and family for their unconditional support and for the positive distractions that provided much-needed balance during the writing process.

Helsinki, 29 October 2024 (6/17)

Ilmari Aatola

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LIST OF ABBREVIATIONS

AI	Artificial intelligence
ARIMA	Autoregressive integrated moving average
CRM	Customer relationship management
DSI	Demand and supply integration
ERP	Enterprise resource planning
ETO	Engineer-To-Order
FSS	Forecasting support system
FVA	Forecasting value added
IBI	Installed base information
IBP	Integrated business planning
IVR	Interventionist research
LSU	Local sales unit
MA	Management accounting
ML	Machine learning
MTO	Make-To-Order
MTS	Make-To-Stock
SBA	Syntetos-Boylan approximation
SSC	Services supporting the customer's actions
SSP	Services supporting the supplier's product
SSU	Service supply unit
S&OP	Sales and operations planning
TSB	Teunter-Syntetos-Babai

1. INTRODUCTION

1.1 Background of the research

Servitization has gained significant interest in operations management research, as manufacturing companies seek to shift their businesses from product-based manufacturing toward providing value-added services (Baines & Lightfoot, 2013; Kamal et al., 2020; Brax et al., 2021). Product-service business models are essential for modern manufacturing companies to sustain competitiveness, as service offerings are generating more revenue for manufacturers compared to product-based offerings. Despite the expected benefits of servitization, researchers express concerns regarding the practical difficulties associated with implementing the servitization strategy, known as the servitization paradox (Kamal et al., 2020). Brax et al. (2019) identify two paradoxes in the relationship between servitization and company performance: the financial paradox, where profitability may not be maintained due to high investment in service development, and the organizational paradox, where increasing services can lead to rigidity and unsuccessful organization changes.

Demand forecasting has a central role in any supply chain company, as operational decisions related to logistics, purchasing, inventory control, production planning, and cash-flow management depend on forecasts (Fildes & Goodwin, 2021). After-sales service providers, particularly, face the challenging task of forecasting due to fluctuating characteristics of demand patterns. Industrial services typically contribute to extending the lifetime of industrial equipment, often referred to as the installed base (Van Der Auweraer et al., 2019), and this thesis focuses on demand forecasting of base and intermediate services related to the installed base. The cost-availability trade-off is emphasized, particularly, in the context of product-related industrial services, as they balance between inventory holding costs and equipment downtime costs (Pinçe et al., 2021).

There is an ongoing debate on how digitalization can enhance management accounting (MA) practices (Quattrone, 2016; Rikhardsson & Yigitbasioglu, 2018; Moll & Yigitbasioglu, 2019; Korhonen et al., 2021; Tiitola et al., 2024). In the context of servitization, digitalization facilitates not only enhanced preventive maintenance but also more effective and efficient value creation and capture by leveraging various software components. On the other hand, servitization can facilitate value capture of digital solutions, since for instance, remote monitoring service technologies require service contracts. (Kohtamäki et al., 2019) In addition, new technologies in data analytics enable more accurate demand forecasting, as modern algorithms can process and analyze large datasets and learn about the relationships of various actors (Seyedan & Mafakheri, 2020). This thesis addresses the digitalization of demand forecasting practices to contribute to the servitization literature from an MA perspective.

The sales and operations planning (S&OP) process is often used to balance customer demand and supply capabilities in manufacturing companies (Tavares Thomé et al., 2012; Tuomikangas & Kaipia, 2014). The S&OP process has been found to improve forecasting accuracy, as well as the performance of other operational measures, such as inventory level and capacity utilization, ultimately leading to improved financial and competitive performance (Wagner et al., 2014). While the interest in S&OP has been increasing during the 21st century (Kreuter et al., 2022; Tavares Thomé et al., 2012; Tuomikangas & Kaipia, 2014; Vereecke et al., 2018), there is a lack of research on how S&OP design is affected by the context (Kristensen & Jonsson, 2018). As manufacturing companies are transitioning from base services toward more advanced services including increasingly preventive elements (Kohtamäki et al., 2019), this research on designing and implementing S&OP in the context of industrial services is timely.

1.2 Research objectives and scope

Various academic fields provide diverse perspectives on how services in manufacturing are conceptualized, setting the foundation for defining the scope of this thesis. In marketing and strategic management literature, many manufacturing-related service taxonomies are related to the dichotomy of services supporting the supplier's products (SSPs) and services supporting the customer's actions (SSCs). After-sales services, such as product repair and maintenance complementing physical products are considered as SSPs, whereas process-oriented offerings not linked to specific products, such as R&D services, are considered as SSCs. (Raddats et al., 2019) Within the operations management literature, services in manufacturing are classified differently. For example, Baines and Lightfoot (2013) provide a taxonomy of base services (e.g., installation and spare part provision), intermediate services (e.g., maintenance and technical support), and advanced services (e.g., performance-based contracts and pay-per-use agreements). Each service category delivers different outcomes for customers. Base services contribute to product provision, intermediate services are focused on the maintenance of product condition, whereas advanced services are delivered through the performance of the product (Baines & Lightfoot, 2013). Different service categories and their formation on top of each other are presented in Figure 1. This thesis focuses on forecasting the demand of product-related services in categories of base services and intermediate services.

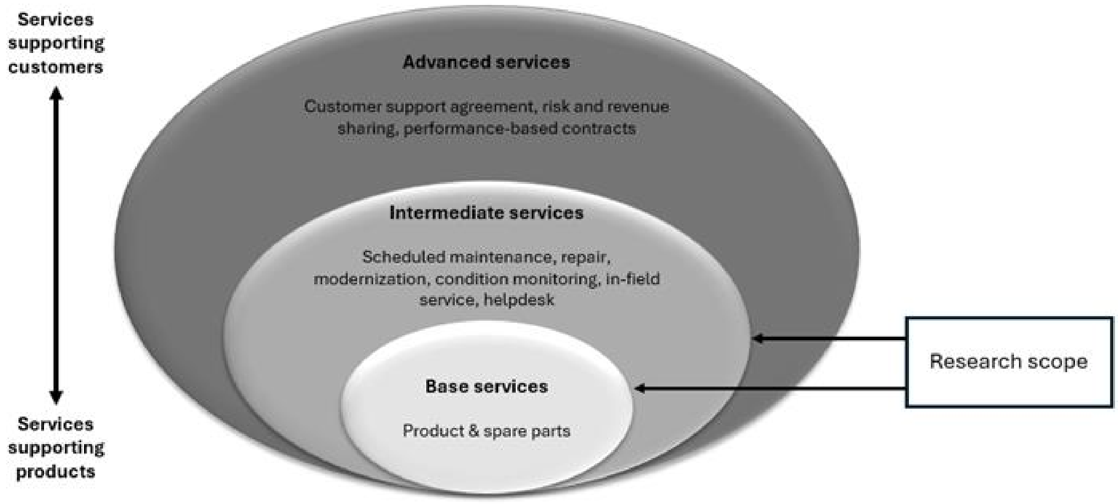

Figure 1: Types of services of a manufacturer according to Baines & Lightfoot (2013, p.68) and the research scope

The forecasting of industrial services has not been extensively studied, as shown in Table 1. However, as a subcategory of industrial services, spare parts forecasting has been widely studied, with most research focusing on intermittent demand forecasting methods. Recently, installed base forecasting has received increasing attention in the industrial service literature, though these studies have also been mainly within the context of spare parts. This thesis aims to contribute to the limited research on forecasting industrial services while drawing on existing studies related to spare parts forecasting. Since intermediate services are built upon base services, the literature on spare parts is relevant to the broader scope of the thesis.

Although this thesis focuses on forecasting industrial services, it is reasonable to consider general developments and challenges in forecasting practices. While forecasting methods and supporting tools have developed significantly in the last decades, improvements in demand planning practices have been limited (Armstrong et al., 2015). Various technology companies offer computer-based statistical forecasting systems for their customers to utilize modern algorithms for accurate forecasting. However, forecasting support systems (FSSs) have not been optimally exploited, and forecasting experts tend to overrun system forecasts with their judgment (Fildes & Goodwin, 2021). Vereecke et al. (2018) argued that demand planning processes are not comprehensively understood within companies, and particularly organizational factors are neglected.

The objective of this thesis is to explore how digitalization can enhance forecasting practices in industrial services while addressing the gap between advancements in the general forecasting literature and their translation into practical developments. To achieve this, the study employs prescriptive theorizing, a method aimed to improve the often-cited lack of practical relevance in management studies (Hanisch, 2024). In prescriptive theorizing, theories are not only designed to explain observed phenomena but also to offer guidance for solving real-world problems. This approach seeks to deliver guidelines or frameworks for decision-making. This thesis will provide a comprehensive analysis of the forecasting process, involving various forecasting dimensions such as data management, forecasting methods, and organizational factors (Vereecke et al., 2018). Thus, the outcomes of the research aim to guide future research toward a level of maturity that reflects the practical capabilities of industrial organizations. Although the main research question is framed within the context of industrial services, the findings may hold broader relevance:

RQ1: How can the digitalization of forecasting enhance demand forecasting practices in industrial services?

To comprehensively answer the main research question and to involve various dimensions affecting forecasting practices, supporting research questions are necessary. Forecasts in supply chain companies are typically based on historical sales data (Petropoulos et al., 2022). However, accurate forecasting of industrial services requires other data types, such as installed base information (IBI) (Dekker et al., 2013). According to Van der Auweraer et al. (2019), data management practices are not considered in-depth in installed base forecasting literature, and those studies often assume that organizations have access to relevant data. They propose further research on installed base forecasting methods based on real data, where the data collection and analysis have also been done realistically. Stormi et al. (2018) found that applying installed base forecasting methods would improve forecasting practices in industrial services, but the practicability is limited due to challenges in data management. Thus, the second objective of this thesis is to identify data management practices necessary for forecasting industrial services and to establish realistic data requirements for further development of forecasting methods. This objective is approached by reviewing the existing literature and comparing the findings with the practical data collection capabilities of the case organization. The first sub-question is:

SQ1: What kind of data management is needed to support demand forecasting in industrial services?

Forecasting methods are obviously at the core of any forecasting process, and modern FSSs include algorithms for various forecasting practices (Petropoulos et al., 2022). While mathematical analysis of forecasting models is not included in the scope of this thesis, the specific characteristics of forecasting in industrial services are considered to understand the requirements for digitalization. The second sub-question is:

> *SQ2: What kind of characteristics of a demand forecasting model would match the requirements of industrial services?*

While research on S&OP has primarily focused on studying manufacturing companies pursuing Make-To-Stock (MTS) and Make-To-Order (MTO) strategies, there is a lack of research on how S&OP should be designed in different contexts (Kreuter et al., 2022; Kristensen & Jonsson, 2018). Although there is a substantial body of research on S&OP in manufacturing, the literature search revealed that only a few studies have explored S&OP in the context of industrial services. This research, therefore, focuses on how the complexity of the supply chain impacts S&OP design, as one of the overlooked research areas proposed in the literature (Kristensen & Jonsson, 2018). The complexity of the supply chain can arise from various factors, such as uncertainties in supply and demand or process and product complexity, which may exist due to, for example, multiple sales units (Kristensen & Jonsson, 2018). Depending on the level of supply chain complexity, coordination mechanisms need to be adapted, and they have a central role in S&OP (Tuomikangas & Kaipia, 2014). Given that the S&OP process has proven beneficial for enhancing overall operational performance in industrial organizations, it is an attractive research area in the context of industrial services. The third sub-question is:

> *SQ3: How can a systematic S&OP process support demand forecasting in industrial services?*

Forecasting research often focuses on developing mathematical models, whereas achieving the objectives of this study requires a more managerial approach. In this research, forecasting methods at the core of the forecasting process are treated as a “black box” to facilitate the thorough research on dimensions contributing to the forecasting process.

1.3 Structure of the thesis

This thesis approaches the digitalization of demand forecasting in industrial services through theoretical and empirical sections. The theoretical section is conducted with a literature review, and those theory-based findings support the implementation of the empirical part of the research. The literature review presents what previous research has found regarding the context of this thesis, whereas the empirical section critically evaluates and develops these findings in collaboration with the case organization, which meets the criteria of the context.

The literature review develops an understanding of the research phenomenon by addressing all the research questions. First, sub-chapter 2.1, titled Applying digital tools in forecasting, presents how forecasts are typically generated in supply chain companies, involving baseline forecasts and human judgment. Furthermore, the principles in the use of digital tools are first presented in a wider MA context, followed by a deeper review of digital applications for demand forecasting. As the comprehensive literature search presented in Table 1 revealed, there is hardly any literature on S&OP in the context of industrial services. Therefore, sub-chapter 2.2 regarding S&OP is written from the perspective of traditional manufacturing companies, creating a background for implementing an S&OP process in general. However, contextual factors affecting the implementation of S&OP are considered to provide initial direction for examining S&OP in an industrial service organization. The case organization in this research has not implemented a formal S&OP yet, and thus, existing literature regarding maturity models for S&OP transitions is addressed as well. The structure of the thesis is illustrated in Figure 2.

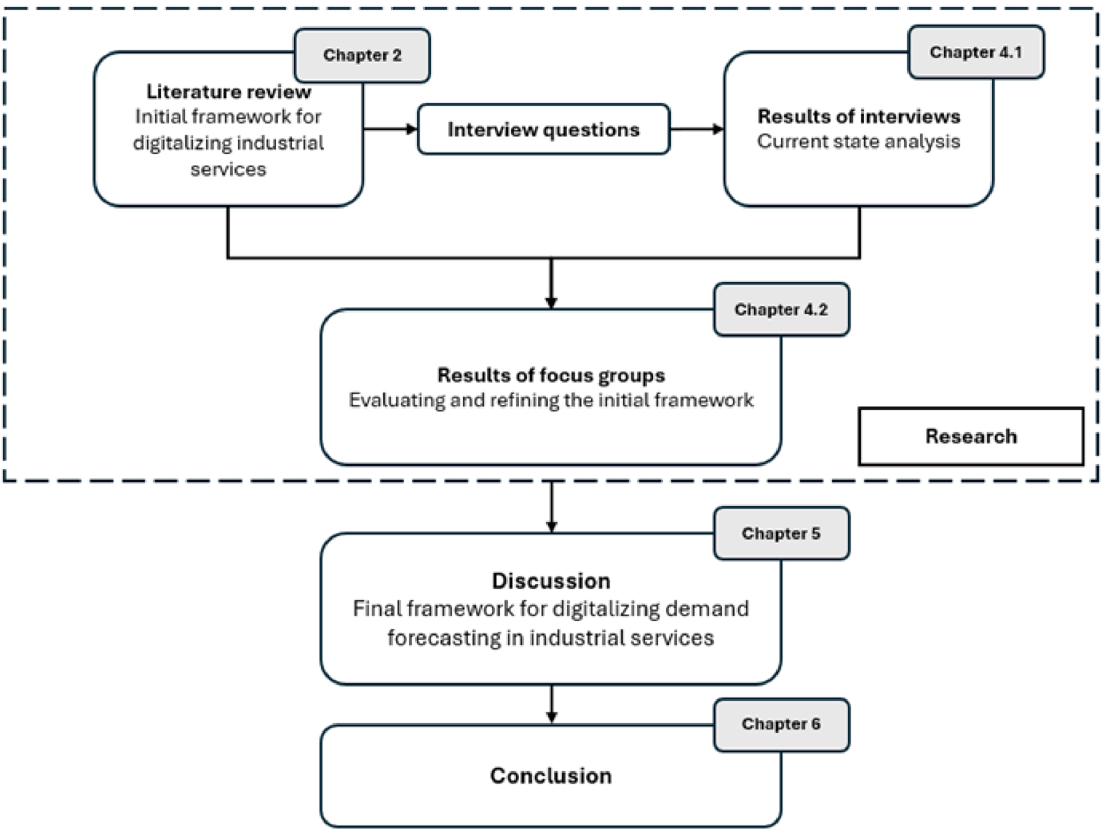

Figure 2: Structure of the thesis

Sub-chapter 2.3, titled Demand forecasting in industrial services, gathers various forecasting practices applied in industrial services. General characteristics of industrial service businesses are introduced to support examining the overall forecasting process from all dimensions. The main forecasting methods for industrial services identified in the literature are presented in relation to SQ1 and SQ2, focusing on data management and the characteristics of the forecasting methods. Finally, the synthesis presented in sub-chapter 2.4 involves the summary of findings from the literature review and the development of an initial framework for digitalizing demand forecasting in industrial services, which will be further examined in the empirical section.

As the research follows interventionist research -strategy, the empirical section consists of two separate phases, the current state analysis (4.1), and the development phase around the intervention (4.2). The methodological choices of the research will be further discussed in Research methodology (Chapter 3). As Figure 2 illustrates, the results of the empirical section will be linked to the existing literature in Discussion (Chapter 5). Finally, contributions to the academic literature and suggestions for future research will be presented in Conclusion (Chapter 6).

1.4 Literature review process

The literature review covers three distinct yet interrelated research fields providing a coherent theoretical foundation for the study. The process of writing the review started with a comprehensive literature search, which was divided into three separate areas of investigation. First, search clauses were developed for each research area starting from broad search clauses with key terms, and refined step by step based on the volume and relevance of the search results. The development of search clauses and results is presented in Table 1.

While the systematic search provided a foundation for the literature review, pearl growing was also used to complement the initial findings. This step helped to capture important articles that might not have appeared in the search results but were still relevant to the context of the thesis. For instance, some articles regarding digital tools were found outside the scope of the predefined search clauses, as they would have required more precise search terms.

The primary database used for the search was Scopus, chosen for its comprehensive collection of peer-reviewed articles. Scopus provided access to high-quality sources, ensuring the research was built on a robust academic foundation. As complementary databases, Andor and Google Scholar were occasionally utilized. These platforms helped to identify additional relevant literature, particularly for niche topics or when certain key studies were not available in Scopus.

Table 1: Literature search clauses and results in Scopus

Digitalization of forecasting	Sales and operations planning	Forecasting industrial services
forecasting AND "supply chain" → 4 170 results	"sales and operations planning" OR "S&OP" → 390 results	forecasting AND "spare parts" → 542 results
forecasting AND "supply chain" AND "data" → 1 922 results	"sales and operations planning" OR "S&OP" AND demand → 167 results	forecasting AND "intermittent demand" → 242 results
forecasting AND "supply chain" AND "support system" → 170 results	"sales and operations planning" OR "S&OP" AND "industrial service" → 1 result	forecasting AND "industrial service" → 10 results
forecasting AND "supply chain" AND analytics → 262 results		forecasting AND "installed base" → 35 results

The thesis primarily focused on including peer-reviewed articles from high-quality publishers. The quality of the publishers was verified through the Finnish Publication Forum, and publishers rated at levels 1 to 3 were emphasized. This system provided a reliable benchmark for evaluating the academic relevance of journals used. In addition to publisher quality, the number of citations was also considered when selecting articles. However, for the section on S&OP, the central literature often came from practitioner papers, as much of the foundational work and models in this area have been developed and documented by industry professionals. These practitioners are recognized as the key contributors to the field, and their papers were included in the thesis to provide practical insights and to complement the academic sources.

2. LITERATURE REVIEW

2.1 Applying digital tools in forecasting

2.1.1 Humans interacting with digital tools

The roles of MA are expected to evolve with the digitalization of the accounting profession, and there is an ongoing debate on what effect will different digital tools have on it (Rikhardsson & Yigitbasioglu, 2018; Moll & Yigitbasioglu, 2019; Korhonen et al., 2021; Tiitola et al., 2024). Some researchers have raised concerns about the transition of digitalizing MA practices by arguing that it might harm decision making or even guide people to make worse decisions faster (Quattrone, 2016; Moll & Yigitbasioglu, 2019). The role of MA will be discussed next to understand what phenomena will be digitalized.

Hall (2010) provides three key insights into the role of MA and the usage of accounting information in managerial work. First, he identifies that managers use accounting information to develop a comprehensive understanding of their work environment rather than only for specific decision-making purposes. This knowledge development role emphasizes the need for accounting information that is easily understandable while still offering a holistic view of organizational performance. Second, Hall highlights that accounting information is just one component of a broader information set that managers rely on, and it serves as a common financial language facilitating communication. Third, Hall points out the importance of verbal communication in tailoring accounting information to suit specific operational issues.

The role of MA has also been identified as a maieutic machine referring to the Socratic method of generating knowledge by answering questions (Busco & Quattrone, 2018; Tiitola et al., 2024). Busco and Quattrone (2018) stated that while recognizing that achieving perfection is practically impossible, maieutic machines rely on the hopes and beliefs of their users to continue asking questions and sustaining the process to find complete answers. Thus, in the context of MA, the purpose of the maieutic machine is to exploit accounting information to question current ways of doing, facilitate communication, and develop new ideas (Busco & Quattrone, 2018). MA should continue its role as a communication facilitator dealing with uncertainties but it is not yet sure, whether this role can be sustained through digitalization, while digital tools are producing more numbers as if they were the truth (Quattrone, 2016).

The fundamental purpose of digital solutions is to collect, process, and analyze data to enhance managerial decision making (Rikhardsson & Yigitbasioglu, 2018). Thus, digitalization could support Hall's (2010) insights above, providing easily understandable information about the whole organization to help managers build an understanding of their work environment. Analytics-driven techniques, however, can increase cognitive load and bias among decision makers (Rikhardsson & Yigitbasioglu, 2018). To address these issues and sustain the conversational (Hall, 2010) or the maieutic (Busco & Quattrone, 2018) role of MA in the context of digitalization, organizations and management accountants need to gain a deeper knowledge of the decision-making process, the nature of the tasks, and the requirements of the users (Rikhardsson & Yigitbasioglu, 2018; Tiitola et al., 2024).

To preserve the maieutic role of MA in the era of digitalization, it is crucial to balance the three identified discourses: computation, judgment, and interaction (Tiitola et al., 2024). The computation discourse views technologies such as artificial intelligence (AI) as a tool to enhance efficiency and accuracy by automating data collection and processing tasks. The judgment discourse emphasizes the irreplaceable value of human oversight, responsibility, and critical thinking in decision-making processes. The interaction discourse advocates for a collaborative approach where AI supports but does not replace human decision makers, ensuring transparency and mutual enhancement.

Each of these discourses, if applied independently, has its disadvantages and potential benefits simultaneously. Relying solely on the computation discourse could lead to a scenario where digital applications are blindly trusted without understanding the purpose of automation, resulting in unexpected outcomes. (Tiitola et al., 2024) This computational approach, however, may contribute efficiently to the implementation of digital applications. On the other hand, difficulties in identifying processes for increasing automation (Korhonen et al., 2021), combined with the uncertainty about the integration of digital tools into decision-making (Quattrone, 2016), can be a harmful situation. In contrast, an exclusive focus on the judgment discourse might slow the adoption of beneficial technologies, keeping organizations inefficient and preventing them from leveraging advanced analytical capabilities (Tiitola et al., 2024).

Lastly, emphasizing the interaction discourse could lead the focus to the outcomes of MA digitalization giving less attention to the decision-making process itself (Tiitola et al., 2024). According to Rikhardsson and Yigitbasioglu (2018), digitalized data-driven decision making prioritizes identifying stable patterns in data to guide actions, with less emphasis on understanding the underlying reasons. For instance, if consistent buying behavior patterns are observed, a company can plan its sales strategies around these patterns without examining the causes (Rikhardsson & Yigitbasioglu, 2018). In other words, organizations might treat advanced digital applications as so-called black-boxes, without understanding the calculation logic in the background (Moll & Yigitbasioglu, 2019; Tiitola et al., 2024). The role of management accountants should then be to critically evaluate what digital tools, such as AI-based tools, propose, and even a closer collaboration with the information technology experts is advisable (Moll & Yigitbasioglu, 2019). In conclusion, a balanced approach that integrates these discourses is essential to maintain the maieutic role of MA, ensuring that digital tools enhance, rather than replace, the critical human elements of questioning, debate, and continuous improvement (Tiitola et al., 2024).

2.1.2 Basics of business forecasting

The theory of forecasting stems from the premise that past and current knowledge can be used to predict future events (Petropoulos et al., 2022). According to Armstrong (2001), forecasting is needed when decision makers are uncertain about the future or when future events cannot be controlled. Forecasting is applied in many fields such as business, politics, and weather forecasting, and thus, different forecasting methods serve different needs (Armstrong, 2001). The long history of forecasting research enables sophistically tailored forecasts for many purposes (Petropoulos et al., 2022). Forecasting is often confused with planning, although they are different terms, as forecasts can be used to predict the outcomes of various plans (Armstrong, 2001).

Armstrong (2001) modeled forecasting as a systematic process with formal procedures. The forecasting process includes both quantitative elements, such as data and modeling, and human involvement, either in the creation of forecasts or in their application to decision making (Petropoulos et al., 2022). The six main phases of the forecasting process are presented in Figure 3, providing a general framework adaptable to the specific requirements of different organizations.

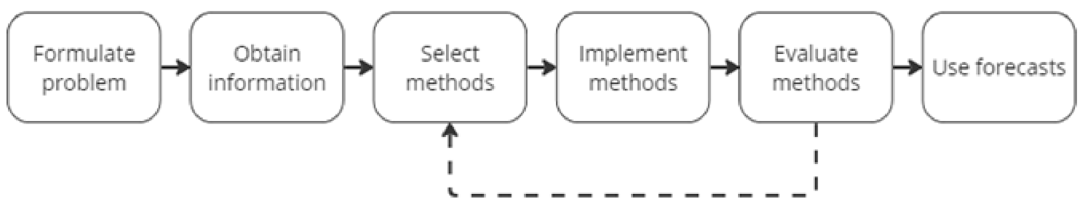

Figure 3: Forecasting process according to Armstrong (2001)

Formulating the problem involves identifying the problem, setting objectives, and evaluating, whether the future events regarding the problem can even be forecasted. The next phase is obtaining information, which involves the identification, collection, and preparation of data. Although it is recommended to follow theory in identifying relevant data, organizations might need to seek alternative data sources due to special circumstances. (Armstrong, 2001) In an ideal situation, all relevant information and variables could be obtained for forecasts, which should be the target (Armstrong et al., 2015). Fildes et al. (2009) found similarly that more effective use of the available information, such as market intelligence, improves the accuracy of forecasting. On the other hand, it is important to exclude all uncertain variables from possibly damaging the accuracy and validity of forecasts (Armstrong et al., 2015).

The selection of methods should be guided by empirical evidence if relevant research for the given context exists. The selection process can be simplified by decomposing the situation into more manageable components and matching appropriate methods to these components. For example, additive decomposition means creating forecasts separately for different segments, such as product families, and then adding them together to form an overall forecast. (Armstrong et al., 2015)

Petropoulos et al. (2022) emphasize the importance of the fifth phase, in which the chosen forecasting method is assessed to determine its effectiveness. Armstrong (2001) implies that in practice, it is often difficult to evaluate the quality and reliability of a single forecast. However, decision makers can determine whether the forecasting process is appropriate for the identified problem (Armstrong, 2001). Forecasting methods and their accuracies can be evaluated by benchmarking other methods, using error metrics, or testing statistically (Petropoulos et al., 2022). In the forecasting process, the connection from the evaluation phase back to selecting methods implies that the process is iterative, ensuring the identification of the most suitable forecasting method for varying needs. This iterative development is important, as the effectiveness of a forecasting method may not be immediately apparent, leading companies to continue employing an unsuitable forecasting approach even for long periods (Fildes & Goodwin, 2021).

2.1.3 Creating a baseline forecast

The most commonly used approach for forecasting demand to support supply chain planning involves utilizing statistical software that employs a basic univariate forecasting technique, like exponential smoothing, to generate a baseline forecast (Fildes et al., 2009). Demand forecasts are typically created using quantitative techniques, based on statistical and machine learning (ML) modeling, and qualitative techniques, which rely on expert judgment and past experience (Petropoulos et al., 2022). Quantitative forecasting includes extrapolative models (Fildes, 1979) and econometric models (Fildes, 1985) with a long history of research. ML techniques have additionally become an option for quantitative forecasting (Carbonneau et al., 2008). On the other hand, qualitative techniques, such as judgmental forecasting, use expert judgment alone to make forecasts based on advance demand information or practical intuition (Petropoulos et al., 2022). The creation of forecasts in supply chain companies is illustrated in Figure 4. It shows how baseline forecasts can be generated either by quantitative or qualitative methods. Baseline forecast will consequently be adjusted judgmentally to form the final forecast, and these judgmental adjustments will be discussed in the next sub-chapter.

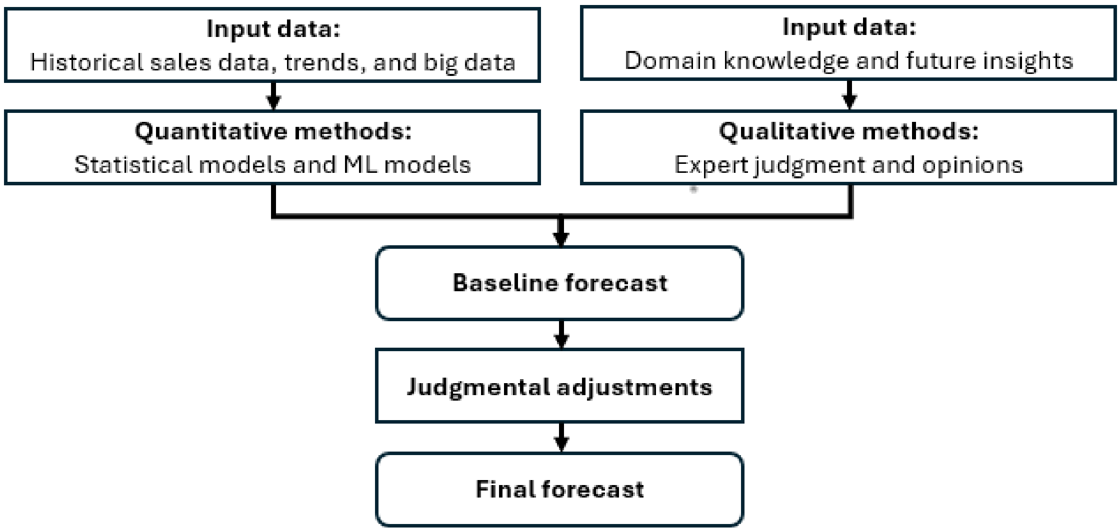

Figure 4: Creation of a forecast in supply chain companies

The quality and availability of data influence the selection of the forecasting method (Hofmann & Rutschmann, 2018). Quantitative time-series methods require information on historical sales data, seasonal influences, and an understanding of trend development. The necessary data for qualitative methods, on the other hand, include expert opinions, domain knowledge, and qualitative insights, such as customer preferences, price promotions, and special events. Researchers have recognized general best practices regarding data usage, such as using the longest possible time-series, and gathering all relevant data available (Armstrong et al., 2015). Meanwhile, companies face challenges related to data scarcity and quality issues (Hofmann & Rutschmann, 2018). There remains a gap in best practices for data usage in forecasting, particularly in clarifying which data elements are most impactful. Establishing clearer guidelines on the optimal data types and sources of data could enhance consistency across various contexts.

Research on forecasting with big data has been increasing over the last two decades (Hofmann & Rutschmann, 2018; Seyedan & Mafakheri, 2020). For demand forecasting purposes in a supply chain context, big data analytics have shown promising results in improving forecasting efficiency and accuracy (Hofmann & Rutschmann, 2018; Seyedan & Mafakheri, 2020), when the right match between big data analytics tools and forecasting methods is found (Hofmann & Rutschmann, 2018). Big data analytics can enhance forecasting methods to overcome typical challenges, such as data availability and quality (Hofmann & Rutschmann, 2018). Still, it is important to remember that high-quality data is crucial for the success of predictive analytics, as accurate and complete data ensures that the predictions are reliable (Hazen et al., 2014).

The supply chain produces a wide variety of data throughout the value creation process, which can be utilized for forecasting purposes and other analytics (Hazen et al., 2014). Analyzing large datasets can enable the forecasting of customer behavior trends, market dynamics, and pricing patterns, thereby assisting organizations in adapting to competitive environments (Seyedan & Mafakheri, 2020). Due to the high volume, high variety, and high velocity characteristics of big data (Seyedan & Mafakheri, 2020), advanced techniques involving ML are often needed for processing and utilizing it (Hofmann & Rutschmann, 2018; Petropoulos et al., 2022; Seyedan & Mafakheri, 2020). While integrating various data sources for demand forecasting is achievable, it requires data-related capabilities from the organization, which are the expertise of data scientists, a suitable technological infrastructure, and technology investments (Hofmann & Rutschmann, 2018).

Extrapolative forecasting involves constructing a quantitative forecast of future values by extending historical time-series data. Commonly known extrapolative models are moving average, exponential smoothing, and autoregressive integrated moving average (ARIMA) (Fildes, 1979). Exponential smoothing is still an important model for many companies, despite the many advances in the forecasting field, as it provides a simple and cost-effective way for forecasting and benchmarking forecasting systems (Boone et al., 2019; Petropoulos et al., 2022). Exponential smoothing calculates a weighted average of past values, placing more weight to recent data points and gradually less to older ones further back in time (Petropoulos et al., 2022). ARIMA models are more complex to create but they can better capture business cycles from time-series datasets, while still smoothing errors with a moving average component (Fildes, 1979).

Econometric models are complex to build and a modeling strategy is recommended to be followed when building them (Fildes, 1985). They are multivariate models (Fildes, 1985) where causal variables should be chosen based on relevant theory (Armstrong, 2001). Variables for sales-oriented models can include factors such as price, income, and competition (Fildes, 1985). Thus, causal variables enable involving external variables in time-series data, and econometric models can be used to predict broader issues compared to extrapolative models (Fildes, 1979).

Aamer et al. (2020) state that ML algorithms learn from past data and can generate predictive models based on pre-designed algorithms. In demand forecasting in the supply chain, the most commonly used ML algorithms include neural networks, artificial networks, support vector machines, and support vector regression (Aamer et al., 2020). Feizebadi (2022) argued that ML-based forecasting methods should improve forecasting accuracy and supply chain performance. Carbonneau et al. (2008) concluded that ML techniques provide more accurate forecasts when compared to the simplest traditional forecasting models, including trend and moving average models. Linear regression, on the other hand, was not found to be significantly worse than ML models in their research. Aamer et al. (2020) propose similarly that ML algorithms could provide more accurate forecasts and computational cost-savings compared to traditional forecasting models.

Makridakis et al. (2020) are more skeptical regarding the improved accuracy of ML models in comparison to statistical models because often studies have compared them to inappropriate benchmarks. Furthermore, they highlight the results of time-series studies where ML models have been less accurate than statistical models. ML models are more vulnerable to excessive variance, whereas statistical models are more vulnerable to bias. Statistical models thrive when forecasting individual time-series or large collections of heterogeneous time-series data, whereas ML models are better for large collections of homogeneous data. (Makridakis et al., 2020) Feizebadi (2022) propose a model where these vulnerabilities are avoided by combining statistical and ML approaches.

2.1.4 Judgmental adjustments

Forecasting should be an objective process based on facts but the human factor exposes it to the effect of organizational politics and personal agendas (Petropoulos et al., 2022). As mentioned in the previous sub-chapter, many organizations create their forecasts on top of a statistical forecast (often generated by forecasting software), which is then reviewed and adjusted by responsible people, such as planners, analysts, and executives (Armstrong, 2001; Petropoulos et al., 2022; Trapero et al., 2013). This exercise is called judgmental adjustment where baseline statistical forecasts are modified with human judgment. Figure 5 illustrates, how this commonly used method is applied in the forecasting process.

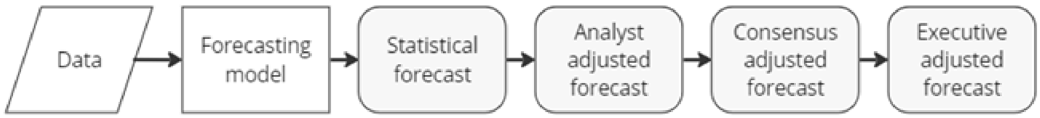

Figure 5: Forecasting process with judgmental adjustments according to Petropoulos et al. (2022)

Judgmental adjustments are used during the planning process to include the planner's knowledge or expectations of upcoming exceptional circumstances in the planning horizon (Fildes et al., 2009). Although judgmental adjustments with up-to-date knowledge can improve forecasting accuracy, they can often be biased resulting in harming the accuracy (Armstrong, 2001). These biases can occur due to optimism, financial and other incentives, lack of consistency, and political manipulation (Armstrong, 2001; Armstrong et al., 2015). In other words, each human adjustment directs the forecast toward their interests, which may not support an accurate, unbiased forecast (Petropoulos et al., 2022). Judgmental adjustments should only be used when the additional information (e.g., a forthcoming new product launch) is not included in the statistical baseline forecast, the information is reliable, and bias can be avoided (Goodwin & Fildes, 1999).

Baecke et al. (2017) analyze the act of judgmental adjustments from four perspectives: how the direction of adjustments, the size of adjustments, the volatility of the data series, and the periodicity of the products impact the forecast accuracy. Downward adjustments have generally proven to be more beneficial than upward adjustments (Fildes et al., 2009; Franses & Legerstee, 2009). According to Fildes et al. (2009), a possible explanation is that upward adjustments often stem from the forecaster's over-optimism and wishful thinking, whereas downward adjustments are made only when there is reliable evidence suggesting a potential downturn in sales.

The relationship between the size of adjustment and forecast accuracy has also been found, with research indicating that big adjustments typically improve forecasts, whereas small adjustments should be avoided (Fildes et al., 2009) Fildes et al. (2009) explain this partly by the finding that forecasters make small adjustments to show that they are working on their assignment and to feel being in control of the forecasting process. Large adjustments are usually made when there is reliable information available indicating bigger changes, which are not yet incorporated in the statistical forecast. Trapero et al. (2013) found judgmental adjustments to be possibly beneficial before future promotions if those adjustments are not overly large. Fildes et al. (2009) found large adjustments to be harmful to forecasting accuracy when making downward adjustments. Thus, it can be concluded that both small and excessively large adjustments are more likely to be damaging to the forecasting accuracy (Baecke et al., 2017).

Volatile market conditions cause challenges for forecasting models, as the models typically lack the ability to deal with exceptional events (Goodwin & Fildes, 1999). These events are difficult for computerized models because there is not much historical information available to predict them in the data set (Baecke et al., 2017). Goodwin and Fildes (1999) found that particularly in these situations where data series is volatile due to an exceptional event, human judgment can improve the accuracy of forecasts. Sanders and Ritzman (1992) found similarly that human judgment outperformed statistical models in the situations mentioned above. It is important to notice, however, that sometimes data series is volatile due to random noise, instead of true trends (Baecke et al., 2017). In low-volatility data series, when there are no promotions or other exceptional events, human judgment will more likely damage the accuracy of forecasts (Sanders & Ritzman, 1992).

The fourth factor potentially impacting forecasting accuracy that Baecke et al. (2017) studied, is product periodicity. They examined this by comparing weekly forecasted products (high periodicity) to monthly forecasted products (low periodicity). Weekly products were forecasted more accurately, and thus, high periodicity can improve forecasting accuracy. This is explained by the increased familiarity of weekly products among people responsible for forecasting. (Baecke et al., 2017) Supporting this conclusion, Edmundson et al. (1988) found in their study that better product knowledge significantly improved the accuracy of forecasts. General business knowledge did not show a measurable impact on forecasting accuracy, suggesting that specific product knowledge is most valuable.

Removing consistent bias can improve forecasting accuracy (Fildes et al., 2009). In an integrative judgment approach (Baecke et al., 2017), the historical human judgment forecast is added to the forecasting model as a predictive variable. The model evaluates whether the variable has added value in the past, and determines, whether human judgments will be counted in the future (Baecke et al., 2017). Petropoulos et al. (2022) addressed a similar controlling system, Forecast Value Added (FVA) analysis, which has faced increasing popularity among practitioners. The purpose of this analysis is to identify whether single activities in the forecasting process contribute to the accuracy or fail to improve it (Petropoulos et al., 2022). In conclusion, these practices help identify the effect of human adjustments in forecasting accuracy. Organizations can then investigate reasons behind those results, and possibly reduce identified bias from future forecasts.

2.1.5 Demand forecasting systems

In a typical use-case scenario, in the supply chain company context, forecasting support systems (FSSs) gather necessary the necessary data to generate forecasts, provide visualizations and summarize statistics for the user, facilitate data pre-processing, and then produce forecasts that can be adjusted based on user preferences (Petropoulos et al., 2022). Fildes and Goodwin (2013) imply that most commercial software tools include robust statistical forecasting algorithms capable of processing large datasets. However, these FSSs typically offer limited opportunities for judgmental overrides, providing minimal support for decisions on when and how to intervene (Fildes & Goodwin, 2013).

FSSs should be capable of: 1) developing precise, efficient, and automated statistical forecasting methods, 2) enabling users to seamlessly integrate their judgment, 3) allowing users to monitor and engage with the entire forecasting process, and 4) being customizable to fit the specific context of the company (Petropoulos et al., 2022). In conclusion, although software for statistical forecasting is already well advanced, there is still a need for improvements, particularly, for facilitating judgmental adjustments within FSSs.

Applying even advanced FSSs may not ensure more efficient and accurate forecasting, particularly, if organizational factors are not considered (Fildes & Goodwin, 2021). Fildes and Goodwin (2021) found in their case study that the case company used a statistical model that was not suitable for their product characteristics, and additionally adjusted the baseline forecast which required significant hours of expert meetings. However, the organization considered the advanced system to work well, and they did not necessitate any changes for it. Hence, the organization was emphasizing the interaction discourse (Tiitola et al., 2024), the advanced system was at least partially a black box (Moll & Yigitbasioglu, 2019), and no one was maieutically questioning its functioning (Busco & Quattrone, 2018).

As a result of their case study introduced above, Fildes and Goodwin (2021) proposed that an FSS will be acceptable as long as it provides an opportunity to adjust statistical forecasts easily and is perceived as beneficial to all human actors. In their case company, middle managers and forecasters were satisfied, because they felt to be in charge of the adjustable system and were unwilling to learn how to use a new one. Executives, on the other hand, did not want more costs from purchasing a new system or to face resistance from middle managers. Furthermore, no indication of the inefficiencies of the current process existed, since the effects of judgmental adjustments were not evaluated.

2.2 Sales and operations planning

Sales and operations planning (S&OP) is a business process for balancing customer demand and supply capabilities within a company by aligning perceptions from different functions to develop a coherent set of plans (Tavares Thomé et al., 2012; Tuomikangas & Kaipia, 2014). S&OP integrates this horizontal alignment, meaning cross-functional demand and supply plans, with vertical alignment, where corporate strategy is bridged to operational activities (Grimson & Pyke, 2007; Tuomikangas & Kaipia, 2014). The planning horizon commonly varies from 3 to 18 months, and S&OP is mostly considered to be at a tactical level of the planning hierarchy (Tavares Thomé et al., 2012). The process and its components are relatively straightforward to understand but a successful implementation of the S&OP process can be highly challenging due to the diverse and evolving needs (Grimson & Pyke, 2007; Wagner et al., 2014). Kreuter et al. (2022) found that existing academic research has still not reached a common understanding regarding the implementation of S&OP, and the current empirical evidence is fragmented.

Other relevant terms that are linked closely to S&OP are integrated business planning (IBP) and demand and supply integration (DSI) (Kristensen & Jonsson, 2018). IBP is a phenomenon primarily used by practitioners and consultancies, and most IBP studies are published in practitioners' journals, consultancy reports, or online blogs (Kristensen & Jonsson, 2018; Schlegel et al., 2021). They explain that IBP is an advanced and mature form of S&OP where the finance function is also integrated fully into the process, and customers and suppliers are involved. The planning horizon in IBP is typically longer because the process has more emphasis on strategic decisions and profitability (Schlegel et al., 2021). Kristensen and Jonsson (2018) found that the literature on DSI primarily addresses the same principles as recognized in the S&OP literature. Esper et al. (2010) define DSI as an integration of demand-side and supply-side processes, which then leads to a balance between market demand and supply capabilities. DSI is a strategic approach creating customer value by leveraging knowledge management regarding market information and business intelligence (Esper et al., 2010). In conclusion, IBP is an advanced form of S&OP, whereas DSI is an alternative framework for S&OP with similar principles.

S&OP is usually implemented as a five-step process including data gathering, demand and supply planning, pre-S&OP meeting, and finally an executive meeting to accept and confirm decisions (Wallace & Stahl, 2008). The five-step S&OP process is illustrated in Figure 6 with short descriptions of each step. The first three steps of the process, data gathering, demand planning, and supply planning, are preparatory phases for the pre-

S&OP meeting where those prepared plans are adjusted and the final consensus plan created (Lapide, 2005).

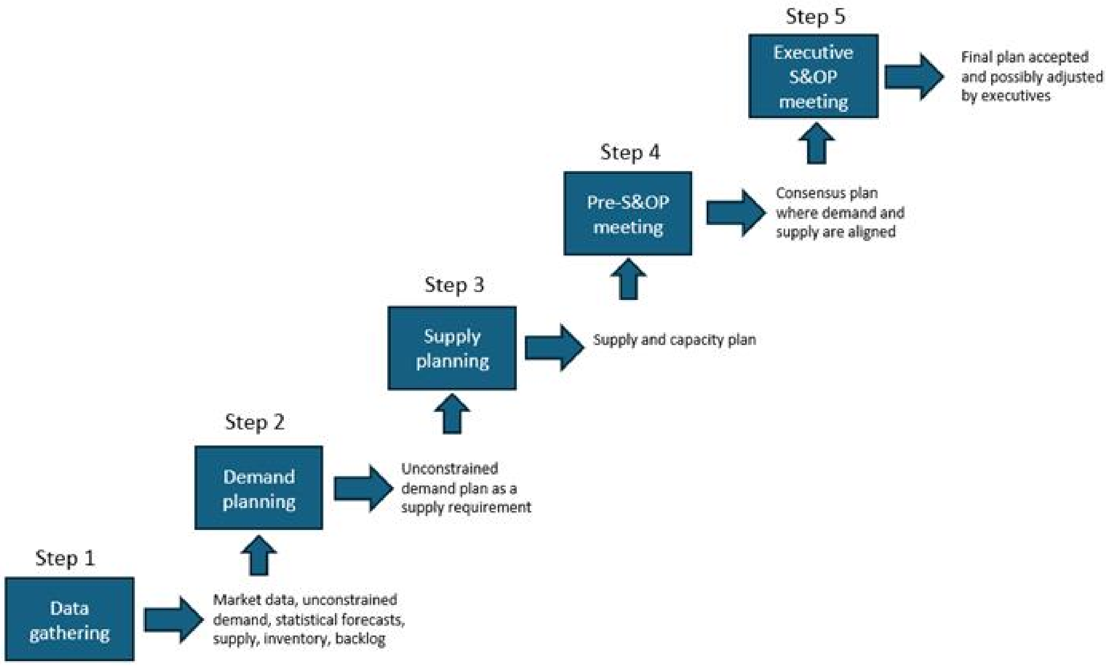

Figure 6: Monthly S&OP process detailing each step and their outcomes according to Wallace & Stahl (2008)

Defining an S&OP team to run and take care of the process is recommended to commit cross-functional participants to the process and its meetings (Tavares Thomé et al., 2012). Lapide (2005) highlights collaboration through meetings and structured meeting agendas as the most important factors of the S&OP process. Literature on DSI emphasizes the importance of cross-functional collaboration as well, to integrate demand and supply successfully and to ensure that each function works towards common goals (Esper et al., 2010; Jüttner et al., 2007). The S&OP team should be empowered by the participation of top management, which also contributes to building trust and confidence in the organization (Tavares Thomé et al., 2012). However, the team lead, and thus, the person responsible for the process is preferably not a high-level executive, because their role is to be a facilitator rather than a strong opinion leader (Lapide, 2005).

One of the main research streams in S&OP is the contextualization of S&OP designs (Kreuter et al., 2022). S&OP design refers to the structure of the process is the systems used. Kristensen and Jonsson (2018) point out that while the typical five-step process may be applicable in most organizations, its implementation ultimately depends on the specific context. The context factors that are identified to be affecting S&OP design are industry, dynamic complexity, detail complexity, and organizational characteristics (Kristensen & Jonsson, 2018). These four factors are discussed next through relevant examples.

The effect of the industry context factor is illustrated in Olhager and Johansson's (2012) study where they researched how to translate a design used in capacity and planning strategies in a manufacturing context to an industrial service context. Due to varying characteristics of manufacturing and service operations, capacity and planning strategies should be designed separately for each, unless they share the same operations facilities (Olhager & Johansson, 2012). According to Ivert et al. (2015), dynamic complexity, focusing on the effects of uncertainties in supply and demand, leads companies to operate on different planning levels. For example, in the context of uncertain and dynamic planning environments, organizations may respond by conducting their tactical planning at a stock-keeping unit level (Ivert et al., 2015).

Kristensen and Jonsson (2018) imply that detail complexity, referring to process and product complexity, causes adjustments in S&OP processes. Large companies, with typically more complex processes, have solved this by dividing their S&OP process into multiple processes. For instance, a company with multiple sales and market units may find it beneficial to implement a demand planning sub-process that connects distributors and their customers. The benefits of using advanced digital systems for S&OP in companies with high detail complexity are dispersed, as there is a risk of making the process even more deep and complex. (Kristensen & Jonsson, 2018)

2.2.1 Sales and operations planning development

Multiple authors have conducted maturity models for assessing and developing S&OP in organizations (Grimson & Pyke, 2007; Wagner et al., 2014). These models introduced in the literature have not found a common understanding and they differ in terms of process components, objectives, prioritization, and maturity levels (Wagner et al., 2014). Furthermore, they are not considered holistic enough for utilizing them in practice as such (Tavares Thomé et al., 2012). Thus, they can be applied as supporting models in developing S&OP processes. Depending on the organizational characteristics (e.g., number of suppliers, customers, and demand patterns), each organization should recognize its own level of sufficient maturity to respond to its needs (Vereecke et al., 2018; Wagner et al., 2014).

Reaching even the first stages of S&OP maturity models, organizations are often required to change their business processes and company culture to, for example, enable managers with different kinds of incentives to work towards common goals (Grimson & Pyke, 2007). According to Danese et al. (2018) transitions on lower maturity levels are less complex and such companies can apply serial sequence transitions. In practice, this means starting the transition from the perspective of people and organization and addressing other dimensions individually (Danese et al., 2018). Grimson and Pyke (2007) suggest starting to implement S&OP with a chosen pilot product family that is considered simple in terms of S&OP and forecasting. However, this product family should be strategically important for the business to make the management commit to the pilot (Grimson & Pyke, 2007). Danese et al. (2018) note that as organizations progress to higher maturity levels, the interdependencies between different dimensions increase, and basic digital tools are probably inadequate to support the improved process. Thus, transitions between higher levels are more complex and the criticality of people and organization dimension increases (Danese et al., 2018).

Thomé et al. (2012) found improved forecasts and better-conducted demand plans to be generally initial drivers for S&OP development. Danese et al. (2018) concluded similarly in their case research, that companies tend to start developing their S&OP from demand-related issues. After initiating improvements in demand planning, companies consider the whole structure of internal planning processes and implement necessary improvements. Finally, the improved processes are aligned and adapted to the external stakeholders and environment (Danese et al., 2018). The next sub-chapter discusses demand planning in the context of S&OP.

2.2.2 Demand planning

Demand planning is the second phase of the general S&OP process recognized in the literature, and its purpose is to conduct a baseline demand forecast for the S&OP process (Grimson & Pyke, 2007). Sodhi and Tangi (2011) define demand planning as a phase of forming a supply requirement, which means a demand forecast adjusted with risks. Instead of considering what the company is capable of producing, the baseline forecast is unconstrained presenting what could be sold to customers (Grimson & Pyke, 2007). Demand uncertainty causes difficulties in demand planning, and companies face the trade-off between unmet demand and excess inventories (Sodhi & Tang, 2011). Thus, the demand planning phase is alongside operations planning a core component of the S&OP process, and it should be well-managed to ensure the quality of the whole S&OP process (Vereecke et al., 2018).

According to Lapide (2005), demand plans and demand planning systems should be chosen so that they can be integrated into supply planning and enterprise resource planning systems. The technology architecture for the S&OP process should support collaboration and enable reviewing and editing plans according to meeting outcomes (Lapide, 2005). After all, the goal of the process is to compose a coherent and consensual set of demand and supply plans (Tavares Thomé et al., 2012). In the early stages of S&OP implementation simple spreadsheets might be sufficient enough and the focus should be on developing the business process and the process organization (Grimson & Pyke, 2007).

The organization is one of the main aspects of successful forecasting, and functional integration and cross-functional commitment are emphasized (Vereecke et al., 2018). Oliva and Watson (2011) similarly found cross-functional integration enhancing the demand planning process. A consensus forecast developed with cross-functional collaboration then contributes to aligning the activities and plans of different functional areas (Danese & Kalchschmidt, 2011). The case company in Oliva and Watson's (2011) study had issues forming a sales forecast trusted by all functions because the sales organization lacked interest in investing in the forecasting process. Instead of aligning incentive plans between different functions, constructive engagement made all functions commit to the process.

Constructive engagement means active participation in cross-functional meetings by relevant stakeholders to effectively collect, validate, and process information for planning purposes. Different functions are motivated to participate because they have the opportunity to defend their own agendas while gaining access to broader knowledge from other functions. (Oliva & Watson, 2011) Moreover, when a forecasting process is proven to be a crucial process in a company for achieving competitive advantage, different functions are more motivated to exploit the common forecast instead of building their own forecasts (Danese & Kalchschmidt, 2011; Oliva & Watson, 2011).

2.3 Demand forecasting in industrial services

2.3.1 Characteristics of industrial service business

The addition of services to the core product portfolio to enhance customer value is commonly known as servitization (Vandermerwe & Rada, 1988). The other closely related term in the literature is service infusion (Raddats et al., 2019). Servitization means transitioning from a product-centric approach to a service-centric approach, whereas service infusion is a process in which the relative importance of service offerings increases in comparison to product offerings (Kowalkowski et al., 2017). The former requires even significant changes in the company's mission and business model. Kamal et al. (2020) found common reasons for servitization in their literature review including expediting product sales, extending relationships with customers, increasing market share, and responding to demands from various stakeholders.

The definition of service, in general, is often described with IHIP-characteristics, which are intangibility (lacks physical presence), heterogeneity (variable and inconsistent), inseparability (simultaneous production and consumption), and perishability (non-storable) (e.g., Shostack, 1977; Moeller, 2010; Blut et al., 2014). These characteristics were identified as differences between services and goods from the perspective of marketing management (Shostack, 1977). However, IHIP-characteristics have been criticized for being insufficient and complex in distinguishing services from goods (Vargo & Lusch, 2004).

Vargo and Lusch (2004) propose that instead of differentiating services and goods, service strategies should focus on understanding their inter-relationship and how they function as an entity. Moeller (2010) acknowledges, that particularly, advancements in technology have made traditional views of IHIP-characteristics less applicable. Despite the criticism, these characteristics can still be valuable, when they are contextualized and applied to certain stages in the service delivery process (Moeller, 2010).

Manufacturers are recognized as being inherently product-centric organizations, and particularly in the manufacturing context, research has replaced the debate about differentiating goods from services by focusing on the inter-relationships between them. The special nature of servitization of manufacturers requires a comprehensive understanding of how products and services can be produced profitably. In the marketing and strategic management literature, services in manufacturing are commonly described as essential complements to physical products, enhancing their sale and usage. (Raddats et al., 2019)

Digital technologies can support servitization through the collection of real-time data from customers (Marcon et al., 2022). Companies are transitioning from remote monitoring services to optimization, control, and, ultimately, autonomous systems, incorporating advanced functionalities driven by artificial intelligence (Kohtamäki et al., 2019). Particularly advanced services require significant support from digital tools enabling responsiveness to action (Baines & Lightfoot, 2013; Raddats et al., 2019). In addition, base and intermediate services benefit from digitalization, as it enables remote monitoring to deliver needed spare parts and maintenance at the right time (Marcon et al., 2022). Thus, in the context of demand forecasting, the digitalization of servitization could enhance these practices by providing accurate and real-time data of the installed base to improve the forecasting process.

Raddats et al. (2019) argue that literature has mostly addressed servitization from a manufacturer-centric perspective and they further propose to take a more interactive perspective with all network actors included to enhance the service business. Particularly, advanced smart solutions require collaboration across the supply chain, as companies need to interact with product-service-software systems of all actors (Kohtamäki et al., 2019). They conclude that implementing digital servitization strategies is limited by the collaboration with other actors and their capabilities.

2.3.2 Demand characteristics in industrial services

This section discusses the demand characteristics of industrial services, focusing on base and intermediate services where the primary concern centers on the demand for spare parts. The three typical demand characteristics of spare parts cause difficulties in forecasting them (Petropoulos et al., 2022; Van Der Auweraer et al., 2019). First, spare parts often have intermittent demand patterns characterized by periods of high demand followed by long periods of little or no demand (Pinçe et al., 2021). When the size of demand is highly variable, the demand pattern is called erratic. In the case where the demand is both intermittent and erratic, it is called lumpy (Van Der Auweraer et al., 2019). Second, the demand is generated by maintenance policies and part failures, and third, spare parts are subject to obsolescence (Petropoulos et al., 2022; Van Der Auweraer et al., 2019). Traditional time-series forecasting methods presented in sub-chapter 2.1.3, such as moving averages or exponential smoothing, typically fail to estimate demand for spare parts accurately (Pinçe et al., 2021).

The classical literature on spare part demand forecasting primarily studies methods for forecasting intermittent demand (Van Der Auweraer et al., 2019). However, most of these studies overlook the fundamental factors driving spare part demand, which originate from the replacement of parts in the installed base of machines, occurring either preventively or due to part failure (Petropoulos et al., 2022; Van Der Auweraer et al., 2019). Thus, after-sales demand is also related to the market demand of products (Dekker et al., 2013).

The primary three sources influencing spare part demand include the size and condition of the installed base, the maintenance policies governing part replacement, and environmental factors affecting part reliability. Maintenance is called corrective, when it occurs upon breakdown, and preventive, when it occurs preventively according to policies on maintenance contracts. (Van Der Auweraer et al., 2019) According to Dekker et al. (2013), the size of the installed base follows the same pattern as the product lifecycle, and it can be illustrated through three different phases: initial phase, mature phase, and end-of-life phase.

During the initial phase of product sales, when the number of units sold and the installed base ramp up, the demand for spare part-related services tends to be relatively low because the products are still new (Kim et al., 2017). As presented in Figure 7, the peak of spare parts demand occurs at the end of the mature phase of the product lifecycle, which is approximately the peak of the installed base size as well. The demand for spare parts occurs with a lag after new product sales. However, early needs for spare parts may appear due to quality issues among new products (Dekker et al., 2013). In the end-of-life phase, the demand for spare parts may continue to rise temporarily before gradually decreasing as more products reach the end of their life (Kim et al., 2017). According to Dekker et al. (2013), the spare parts demand reaches almost zero demand quite early before the last machines are taken out of use. In some cases, the product lifecycle could be shortened, if the value of needed spare parts is relatively high compared to a new-generation product (Dekker et al., 2013).

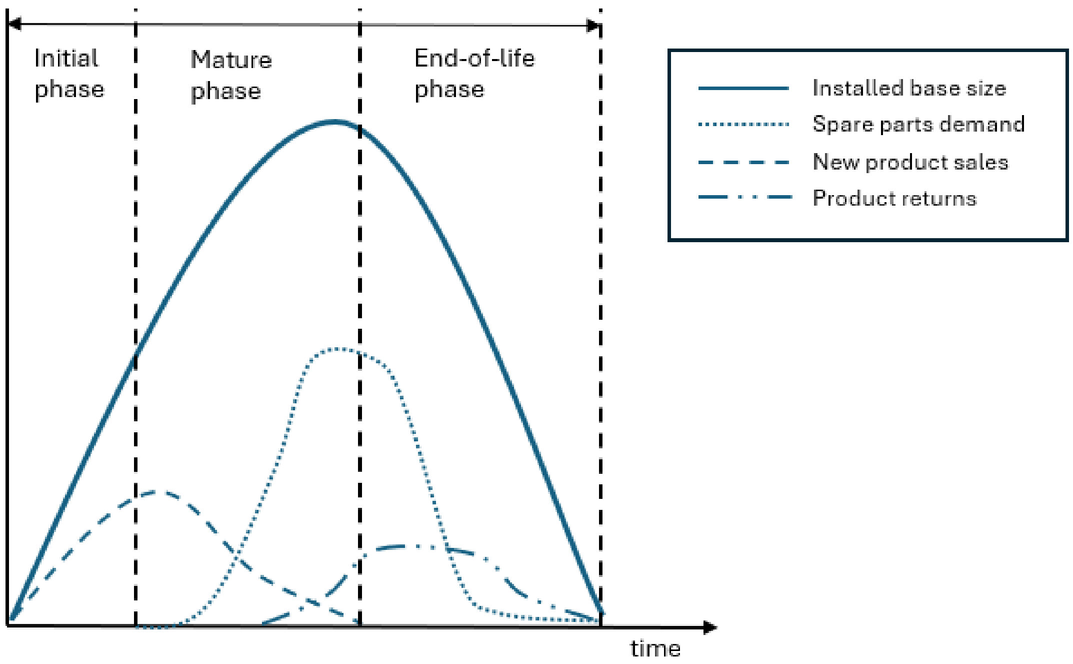

Figure 7: Spare parts demand throughout the product lifecycle according to Dekker et al. (2013)

This sub-chapter discussed the unique demand characteristics that create specific circumstances for forecasting product-related industrial services. These include intermittent demand patterns, maintenance-driven needs, and obsolescence, all of which complicate forecasting accuracy. These characteristics are intrinsically linked to the product lifecycle, as the demand for spare parts evolves alongside the lifecycle stages of the primary product. This understanding sets the foundation for the next chapter, where tailored forecasting methods that incorporate these demand characteristics will be explored.

2.3.3 Forecasting methods for industrial services

This section introduces demand forecasting methods for industrial services, expanding on the traditional quantitative approaches covered in sub-chapter 2.1.3. Figure 8 illustrates how the literature on spare parts forecasting methods is structured. The majority of research is focused on time-series methods for intermittent demand forecasting, but context-based methods, particularly installed base forecasting, are facing increasing interest. (Pinçe et al., 2021) Time-series methods can broadly be divided into parametric and non-parametric methods (Petropoulos et al., 2022; Pinçe et al., 2021). Parametric approaches assume that future demand can be accurately modeled by a statistical distribution with unknown parameters that can be estimated using historical data. In contrast, non-parametric approaches do not assume that the data follows any standard probability distribution. Instead, they use direct methods to evaluate the distributions needed for inventory management (Petropoulos et al., 2022).

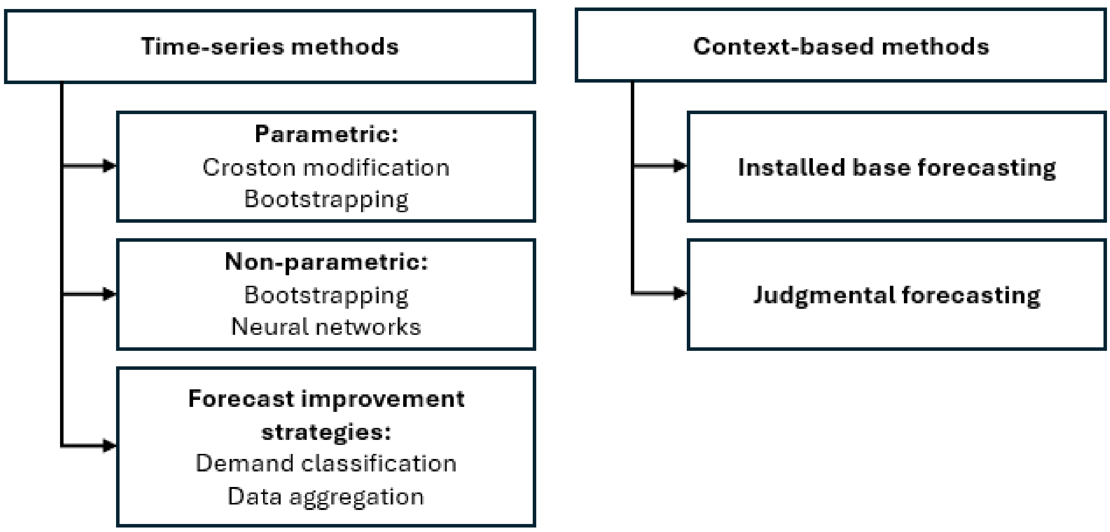

Figure 8: Spare parts forecasting methods according to Pinçe et al. (2021)

Forecast improvement strategies shown in Figure 8 are methods to improve the overall performance of forecasting. Demand classification is used to categorize data as smooth, erratic, lumpy, or intermittent, and suggest the most suitable forecasting method for the defined demand type. Data aggregation methods, on the other hand, aggregate data at various levels and combine different forecasting methods, thus, minimizing the occurrence of zero-demand periods and thereby reducing the variability of forecasts. Selecting the correct level of temporal aggregation is essential, as a level that significantly exceeds or falls short of the lead time duration can lead to inefficiencies. For example, aggregating demand at a monthly level when lead times are measured in days can significantly reduce the effectiveness of temporal aggregation. (Pinçe et al., 2021)

Various forecasting methods have been developed for intermittent demand, as illustrated in Figure 8. However, there are no definitive guidelines on which methods enable the best performances in different circumstances (Pinçe et al., 2021). Intermittent demand forecasting methods stem from the finding that traditional time-series methods fail to generate accurate forecasts with intermittent data (Croston, 1972). Exponential smoothing, for instance, significantly overestimates the actual demand.

A seminal work on intermittent demand forecasting divided the demand into two separate components: demand size and demand occurrence. Subsequently, two separate estimates were formulated with exponential smoothing: one for the inter-demand interval and one for the size of the demand when it occurs. (Croston, 1972) This is commonly known in the literature as Croston’s method, which has become a standard performance benchmark for evaluating spare parts forecasting methods (Petropoulos et al., 2022; Pinçe et al., 2021; Van Der Auweraer et al., 2019).

Another standard method for intermittent demand forecasting is the Syntetos-Boylan approximation (SBA), which is a modification of Croston’s method fixing its bias (Syntetos & Boylan, 2005). Pinçe et al. (2021) argue that SBA has been found to be more accurate in spare parts forecasting than Croston’s method. Nevertheless, Croston's method either outperforms or matches the performance of SBA in inventory metrics, contingent upon the data type (Pinçe et al., 2021).

Teunter et al. (2011) address a problem of Croston’s method and its modifications implying that they are slow to adjust to new demand levels in the case of sudden decreases. They refer particularly to the risk of obsolescence when the installed machines stop operating and no new machines are sold. They propose a new method called Teunter-Syntetos-Babai (TSB), which combines demand size forecasts with demand probability forecasts, instead of demand interval forecasts. Furthermore, TSB updates the demand probability estimate in every period, instead of only after demand occurrence as in Croston’s and SBA, and TSB’s reactions to demand obsolescence are faster. (Teunter et al., 2011)

2.3.4 Installed base information in demand forecasting

Forecasting methods utilizing IBI are mostly causal models with different parameters, which need the identification of explanatory variables (Andersson & Jonsson, 2018; Van Der Auweraer et al., 2019). These methods can be divided into three main groups based on the information used: reliability-based, regression-based, and condition-based (Andersson & Jonsson, 2018). According to Van Der Auweraer et al. (2019), most of the methods apply reliability-based forecasting. Reliability-based methods typically use various data regarding the installed base: the part failure behavior, the current and future size of the installed base, the geographical location, the usage (working conditions), the repair willingness of the customers, and the maintenance policy determined. Regression-based methods, on the other hand, need data on explanatory factors correlated with the demand, for example, the size of the installed base, the part failure behavior, and historical failures. Finally, conditions-based methods require collection and analysis of sensor data to keep track of maintenance activities. (Van Der Auweraer et al., 2019) Different types of IBI that are beneficial for forecasting industrial service products are introduced in Figure 9.

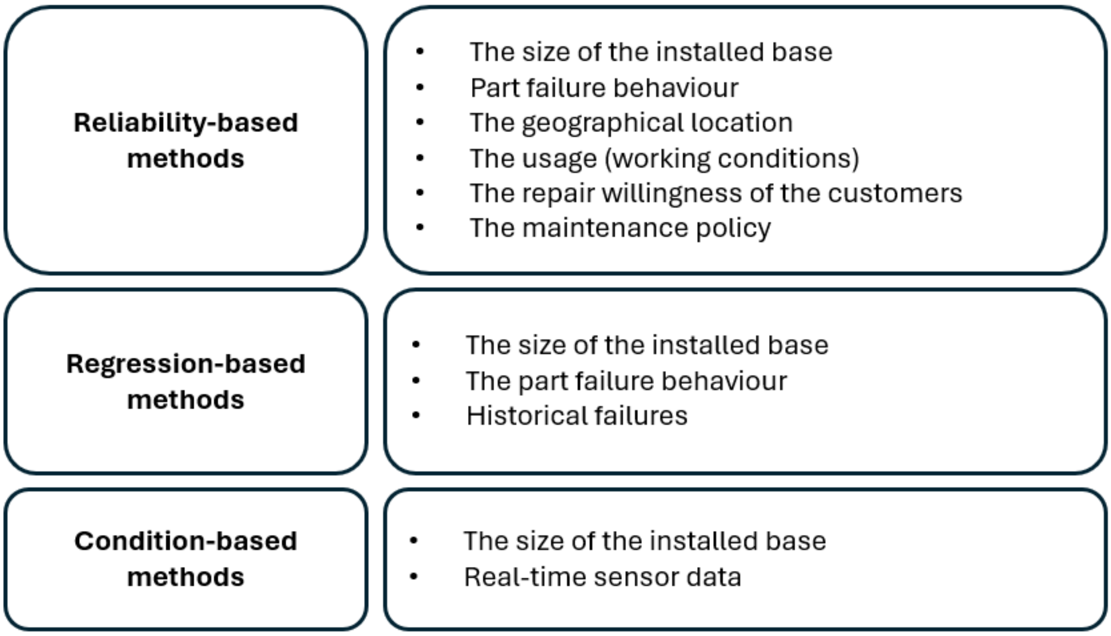

Figure 9: Typical data needs for causal methods for installed base forecasting

Instead of forecasting only with IBI methods, IBI could be combined with more traditional methods, to provide additional information by adjusting baseline forecasts (Andersson & Jonsson, 2018; Van Der Auweraer et al., 2019). Thus, companies could avoid using complex forecasting methods that are required with IBI (Van Der Auweraer et al., 2019).

Collecting IBI can be a major problem for companies (Van Der Auweraer et al., 2019), while up-to-date information is a requirement for utilizing IBI in forecasting (Stormi et al., 2018). Dekker et al. (2013) highlight similarly that the characteristics of the installed base, for example, age and usage, are necessary to make reliable inventory decisions. Particularly, obtaining information on where and how customers are using products can be extremely difficult (Van Der Auweraer et al., 2019). In addition to maintaining IBI, companies must keep track of product information, potential technical improvements, and maintenance history (Dekker et al., 2013).

2.4 Synthesis of the literature review

The literature review explores various aspects of digitalizing demand forecasting practices within the industrial service context, focusing on integrating digital tools and forecasting methods to enhance forecasting accuracy and efficiency. Various findings have been made from different, yet relevant, research streams, and those findings are summarized and synthesized in this section. A summary of the literature review will be presented first in sub-chapter 2.4.1, followed by an introduction of a framework for digitalizing forecasting in industrial services in sub-chapter 2.4.2, which is conducted based on the findings from the literature review.

2.4.1 Summary of the literature review

The transition to digitalized MA and forecasting practices introduces opportunities and challenges. While digital tools can enhance decision-making efficiency, they may also increase cognitive load and risk of bias if not properly integrated with human oversight (Rikhardsson & Yigitbasioglu, 2018). The literature highlights the need to balance computational efficiency with critical human judgment and interaction, ensuring that digital tools complement rather than replace essential human decision-making processes (Busco & Quattrone, 2018; Tiitola et al., 2024).

Forecasting is grounded in the principle that past and present knowledge can inform predictions about future events (Petropoulos et al., 2022), and it is a crucial function in uncertain environments across various sectors such as business, politics, and weather (Armstrong, 2001). Forecasting can be systematically structured as presented in Figure 3, involving phases regarding problem formulation, data collection, method selection, and the use of forecasts, making it a comprehensive yet adaptable process that can be tailored to specific organizational needs.

In supply chain companies, demand forecasting typically begins with a baseline statistical forecast, which is then adjusted based on human judgment (Fildes et al., 2009; Petropoulos et al., 2022). This approach leverages the strengths of both statistical models and human expertise, allowing companies to incorporate up-to-date information and context-specific insights into their forecasts. While forecasting methods have been refined over time and are essential for generating baseline forecasts, they have limitations in practical use due to issues such as low-quality data. Hybrid models that combine statistical approaches with ML have been suggested to mitigate these challenges and improve forecast accuracy (Feizabadi, 2022). The creation of demand forecasts is presented in Figure 4, involving the creation of the baseline forecast through quantitative or qualitative methods. Goodwin and Fildes (1999) notice that the effectiveness of judgmental adjustments on top of baseline forecasts can vary significantly, as they are vulnerable to biases that may reduce forecast accuracy. On the other hand, they are considered beneficial in the context of volatile data series (Goodwin & Fildes, 1999; Sanders & Ritzman, 1992), as often is the case within industrial services.

In the industrial service sector, forecasting is particularly challenging due to the intermittent nature of service product demand, which is influenced by factors like maintenance schedules, part failures, and obsolescence (Pinçe et al., 2021). Traditional time-series methods often fall short in this context, leading to the development of specialized forecasting methods like Croston's method and its derivatives, which are more suitable for handling intermittent demand (Croston, 1972; Syntetos & Boylan, 2005). The integration of IBI into demand forecasts, which includes detailed information about the condition and usage of equipment, has emerged as a valuable approach for improving the accuracy of these forecasts (Van Der Auweraer et al., 2019). However, practical challenges, particularly in data collection, have limited the advancements of IBI-based forecasting.

Forecasting Support Systems (FSSs) are pivotal in automating and enhancing demand forecasting processes. These systems must be robust, user-friendly, and adaptable to specific organizational contexts to facilitate both statistical forecasting and judgmental adjustments (Petropoulos et al., 2022). The quality and availability of data are critical determinants of forecasting accuracy. High-quality, up-to-date, and comprehensive data enable reliable forecasts, with big data analytics showing promise in improving forecast accuracy when matched with appropriate methods (Hazen et al., 2014; Hofmann & Rutschmann, 2018).

Oliva and Watson (2011) highlighted the importance of cross-functional collaboration in forecasting and demand planning. They found that cross-functional integration enhances the demand planning process and contributes to aligning the activities and plans of different functional areas. In addition, Vereecke et al. (2018) emphasized that organization and cross-functional commitment are key factors of successful forecasting, supporting the argument that collaboration across different functions is crucial. The S&OP process could facilitate the collaboration between functions while also integrating demand and supply planning across the organization. Furthermore, it aligns the corporate strategy with operational activities, bridging the gap between high-level goals and day-to-day operations (Grimson & Pyke, 2007; Tuomikangas & Kaipia, 2014).

Although S&OP is well-known, particularly, in traditional manufacturing companies, its implementation can vary widely depending on organizational context, complexity, and industry-specific needs (Grimson & Pyke, 2007; Kristensen & Jonsson, 2018). On top of cross-functional collaboration, effective S&OP requires integrating demand planning systems with broader enterprise resource planning systems, ensuring that the entire planning process is coherent and aligned with organizational objectives (Vereecke et al., 2018). There is a lack of research regarding S&OP implementation and its potential benefits in industrial service companies, and the suitability of the general five-step process will be examined in the empirical section.

2.4.2 An initial framework for digitalizing demand forecasting in industrial services

The initial framework for digitalizing demand forecasting in industrial services, presented in Figure 10, synthesizes key findings from the literature review in a structured form. This facilitates a foundation for a realistic digitalization of demand forecasting, which will be pragmatically examined in the empirical section, and establishes pathways for developing various phases of the forecasting process. The framework is designed to address the unique needs of industrial service businesses, integrating forecasting practices with the S&OP process and involving the supporting role of digital systems. The forecasting process and S&OP process are visualized as distinct yet interrelated streams because forecasting can be done without implementing S&OP, although the two processes are often complementary. As the implementation of S&OP has not received much attention in the industrial service context, it is reasonable to study it as an individual process. The central role of systems is illustrated by their position in the middle of the framework, acting as a link between forecasting and S&OP processes

The forecasting part of the framework follows the forecasting process introduced in Figure 3. All phases are modified and adapted to respond to the needs of industrial service businesses. The first phase is a checkpoint to determine whether a given service product can be effectively forecasted or if alternative planning methods are necessary. The second phase, data collection, presents all relevant data sources that can be utilized in forecasting service products, including historical sales data, knowledge of future events, big data from supply chains, and IBI. Relevant IBI types are introduced in Figure 9. According to the framework, companies can assess whether their organization is capable of collecting and maintaining these data types. Forecasting data sources are consequently linked to specific forecasting methods for which the data can be utilized.

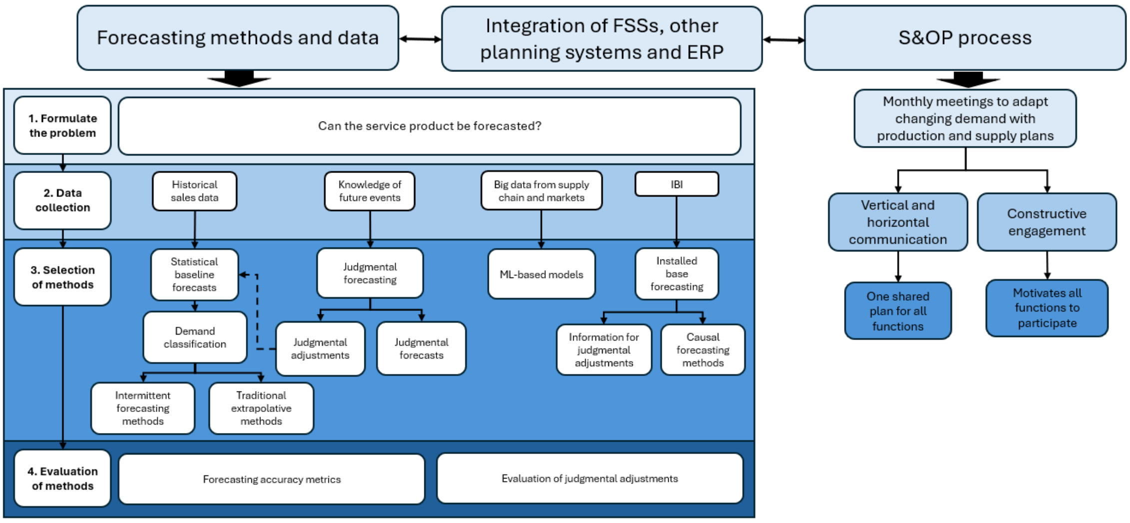

Figure 10: Initial framework for digitalizing demand forecasting in industrial services

In the third phase, the selection of methods, the framework outlines four main streams of forecasting methods for industrial services: statistical baseline forecasting, judgmental adjustments, ML-based models, and installed base forecasting. It is advised to employ multiple methods and combine forecasts to achieve an accurate consensus forecast. When using statistical forecasting methods, the forecaster should classify the demand pattern to determine a suitable forecasting method. In this case, the decision is whether the demand pattern is intermittent or smooth. As identified in the literature review, judgmental adjustments can be used to modify the baseline forecast, integrating human expertise to account for factors that may not be captured by the statistical model alone. Typically, these adjustments are used to refine the statistical baseline forecast, and therefore, they are linked in the framework.

The relationship between big data and ML methods is emphasized, as big data is most effectively processed by ML models, which, in turn, require large datasets to maximize their predictive accuracy (Hofmann & Rutschmann, 2018; Petropoulos et al., 2022; Seyedan & Mafakheri, 2020). Finally, installed base forecasting methods can be used for two different purposes. It can serve as the primary forecasting approach or as additional information to modify the baseline forecast that is conducted using other forecasting methods. Utilizing IBI in a forecasting model often requires advanced causal methods (Andersson & Jonsson, 2018; Van Der Auweraer et al., 2019).

The final phase in the forecasting part of the framework is the evaluation of methods. Forecasting methods and their accuracies can be evaluated by benchmarking with other methods, using error metrics, or testing statistically (Petropoulos et al., 2022). Literature suggests evaluating judgmental adjustments to understand how human intervention impacts forecasting accuracy.

The S&OP process supports forecasting practices and creates a structured platform to align all plans across the organization. While forecasting can exist independently, S&OP serves as a tool for ensuring that demand forecasts are integrated into the broader operational strategy. The framework suggests implementing S&OP as a five-step monthly process, including all the steps introduced in Figure 6. As mentioned already in the summary of the literature review, the S&OP process enables vertical and horizontal communication, which leads to a single, shared consensus plan for all functions, improving transparency (Tavares Thomé et al., 2012; Tuomikangas & Kaipia, 2014).

Central to the framework is the integration of FSSs with other relevant systems, ensuring efficient implementation of forecasting practices and the S&OP process. FSSs should be capable of sharing information with other operational planning systems used for tasks such as capacity and inventory planning (Lapide, 2005). Furthermore, all these systems should be linked to the ERP system. These systems automate data collection, process large datasets, and facilitate real-time updates.

3. RESEARCH METHODOLOGY

The methodological choices of the research will be presented and justified in this chapter. The design is inspired and validated by prior work in the research fields of forecasting and S&OP (Andersson & Jonsson, 2018; Oliva & Watson, 2011; Schlegel et al., 2021). The empirical part of the research begins with a current state analysis of forecasting practices within the case organization. The initial framework for digitalizing demand forecasting in industrial services in Figure 10, created based on the findings from the literature review, will be further evaluated and developed in the second empirical part. Findings from the current state analysis will support the researcher in examining the proposed framework. This chapter begins with an introduction of the case organization, which serves as the site for the empirical part of the research. After the introduction of the case organization, the research design and methodological choices will be discussed in detail, followed by an introduction of the data collection and data analysis procedures employed in the study.

3.1 Case organization

The case organization is a global service supply unit (SSU) based in Finland, operating in the after-market of the electric drives industry. As one of the global market and technology leaders in this sector, the company has strategically separated its entire drives service business unit from its core drives manufacturing operations. Furthermore, this drives service business unit is part of a larger service division, which also includes services for electric motors, among others. The SSU for drives in Finland does not interact directly with end customers. Instead, it operates through decentralized local sales units (LSUs), which serve as intermediaries between the back-end operations and the front-end customer interface.

The service portfolio consists of four service product families, which have varying production strategies. The oldest and still the largest product family is the spare parts business, which employs both Make-to-Stock (MTS) and Make-to-Order (MTO) production strategies. While traditional spare parts sales mainly follow MTS principles, occasional larger projects may have MTO characteristics. The other service product families, such as repair services, primarily adhere to MTO principles. Additionally, certain complex modernization project orders are executed using an Engineer-to-Order (ETO) approach. Advanced planning practices are becoming increasingly relevant for the SSU, as the share of service products with a planning element increases. Service products are presented in Table 2, and coded for further use within the empirical section.

Table 2: Introduction of the service products of the case organization within the scope of the empirical research

Service product code	Service product family	Description	Service category
SP1	Spare parts	Spare parts for corrective and preventive maintenance	Base services
SP2	Classic-phase	Extending the lifecycle of existing systems	Base services
SP3	Modernization	Extending the lifecycle of products and upgrading to newer technologies	Intermediate services
SP4	Repair	Maintenance, typically large projects	Intermediate services

Forecasting the demand of this highly diverse portfolio is a challenging task. Currently, the organization relies on simple forecasting techniques, maintaining relatively high stock levels, and responding reactively to fluctuations in demand. Collaboration and information sharing across different functions regarding future sales is limited, and there is no defined S&OP process in the organization. Among the various forecasting practices, spare parts forecasting is the most advanced one, supported by an automated external forecasting system. Forecasts for each service product family are primarily based on historical sales data, while future information is only occasionally considered.

As previously mentioned, LSUs are individual sales units with direct insight into the customer base. However, collaboration between the SSU and LSUs remains inadequate, and the back end does not receive sufficient information on the future sales pipeline. There have been some improvements, such as the occasional communication of confirmed large upcoming project orders to the SSU. However, the SSU still lacks visibility into future forecasts or sales strategies employed by LSUs. The SSU has previously analyzed this relationship and identified that significant improvements may require large-scale system integration projects between the SSU and LSUs.

To conclude, the case organization is transitioning from traditional spare parts sales to modern service solutions, such as subscription-based contracts. This shift requires a move from reactive operations to proactive planning, leveraging the growing capabilities of modern tools and solutions. Although significant progress has already been made within the organization, there are still opportunities for improvement in areas such as forecasting practices, the use of IBI, and cross-functional collaboration. To maintain its competitive advantages and market leadership, the organization must continue to adapt and evolve within the dynamic industrial service environment.

3.2 Research design

The purpose of the research design is to determine how the research questions are being answered (Saunders et al., 2019 p.173). Table 3 presents an overview of the research design adopted for this thesis. The main research question "*How can the digitalization of forecasting enhance demand forecasting practices in industrial services?"* has subjective and context-dependent characteristics, as do the related sub-questions. These questions are considered descriptive and can be answered with subjective theories. However, they also enable the exploration of the research problem from a practical perspective, facilitating a comprehensive understanding that integrates both theoretical and practical perspectives.

Table 3: Choices for research design

Research philosophy	Pragmatism
Approach to theory development	Abduction
Methodological choice	Multi-method qualitative
Research strategy	Interventionist research
Time horizon	Cross-sectional

Pragmatism highlights the importance of research problems and how to create practical solutions for the future (Saunders et al., 2019, p.151). Knowledge is intrinsically intertwined with human action, and the validity of theory is confirmed when that theory applies to the practical means of an organization (Kelemen & Rumens, 2008). The underlying problem of this research is the complexity of forecasting industrial service demand in a practical context. Furthermore, human action is closely related to forecasting practices. Thus, pragmatic philosophy properly addresses the questions of this research.

On the other hand, the research context has complex and unique characteristics, where theories and concepts may not be sufficient to create solutions. Interpretivism could support this kind of research, where interpretations of the researcher are at the core of the study and an empathetic stance, to understand the viewpoint of the people in the organization, is necessary (Saunders et al., 2019, p.149). Forecasting literature includes many practical solutions but still implies that every organization needs to find their own best practices suitable for their context. Furthermore, the forecasting process involves people on different levels of the organization who have varying views of the organization.

This research utilizes the abductive approach for generating theory. Abduction is an approach used to generate new theories based on existing knowledge and subsequently test these theories (Saunders et al., p.155). Prior studies in forecasting and S&OP have applied the abductive approach to proving the truth-value of findings by sharing results with case company experts at different stages of the research (Schlegel et al., 2021), to ensure efficient theory development of an under-studied area (Andersson & Jonsson, 2018), and to iteratively build a relevant coding structure for data analysis (Oliva & Watson, 2011). In this research, the novel model for forecasting practices is built based on current literature and expert interviews, which would indicate an inductive approach. However, this model is further tested and modified by the experts in the company, and thus the research moves back and forth between induction and deduction. Furthermore, pragmatism supports a well-defined abductive approach (Saunders et al., 2019, p.156).

The methodological choice for this research is a multi-method qualitative study, which includes more than one qualitative data collection technique (semi-structured interviews and focus groups in this thesis). There is varying knowledge and unclear meanings of the research phenomenon in the case organization, and a qualitative study supports research in this kind of context well (Saunders et al., 2019, p.179). Prior studies of forecasting and S&OP have similarly applied multi-method qualitative approaches combining primary and secondary data (Andersson & Jonsson, 2018; Oliva & Watson, 2011; Schlegel et al., 2021), which enables data triangulation to corroborate any weaknesses in the data (Andersson & Jonsson, 2018). Semi-structured interviews are used in this research to build an understanding of the current state of forecasting and S&OP practices within an industrial service context. Consequently, the novel model is conceptualized based on findings from interviews and literature review. To ensure the research makes a practical contribution, the novel model is developed according to the context of the organization, which requires qualitative data analysis techniques. The researcher actively participates in focus group sessions so that theory and other participants' practical knowledge can be efficiently combined.

Research strategy is the plan of actions to achieve the objectives of the research by answering research questions (Saunders et al., 2019, p.189). The selected research strategy for this thesis is interventionist research (IVR), which is a form of case study, and for which is typical to iteratively contribute theory and practice while closely collaborating with the case company (Suomala et al., 2014). Single case studies have been conducted earlier in this research field proving their applicability (Andersson & Jonsson, 2018; Oliva & Watson, 2011; Schlegel et al., 2021). Schlegel et al. (2021) highlight that the S&OP research context necessitates a thorough understanding of industry-specific business planning processes and behaviors, and a single case study supports this requirement.

An intervention of the researcher, referring to a new proposal for the case company, is at the core of the interventionist research, enabling access inside the company (Suomala et al., 2014). The novel forecasting model built for the case company is the intervention of this research providing access, particularly, through focus groups arranged to develop and refine the model. Interventionist research balances between theory and practice, and researchers must ensure that neither the practical nor scientific contributions are abandoned (Suomala et al., 2014). Regular meetings are held during this research project involving the researcher and the steering committee from the company to sustain the balance mentioned above.

The time horizon of a study can be cross-sectional, where the phenomenon is studied at a particular, short period of time, or longitudinal, referring to studying change and development over a long period of time (Saunders et al., 2019, p.212). This research is cross-sectional because it studies the current practices in the case organization and develops the novel model based on information at the current point of time. The empirical part of this research has two separate phases in chronological order, and therefore the research has longitudinal characteristics as well. However, the implementation of the novel model cannot be researched and evaluated in the time scope of this thesis, and thus the research is cross-sectional.

3.3 Data collection

This thesis mainly relies on primary data in both empirical parts, while secondary data are also collected in the first empirical part to support the findings from the primary data. The first empirical part, which consists of the current state analysis, gathers primary data through semi-structured interviews and analyzes text documents from previous internal studies in the company. The second empirical part is implemented through focus groups involving experts representing various functions within the organization.

Semi-structured interviews enable the collection of data on complex phenomena with causalities, as interviewees can flexibly answer questions in their own words (Saunders et al., 2019, p.444). According to Schlegel et al. (2021), semi-structured interviews offer a balance between adhering to a predetermined structure and allowing flexibility in the conversation. This approach ensures that the interviewer can guide the dialogue while also exploring unexpected topics that may arise. The highly contextual nature of the research phenomenon requires flexibility, and therefore semi-structured interviews serve these needs. Furthermore, even a heterogeneous sample from different backgrounds can be interviewed, because the order and logic of questioning can be modified when using the semi-structured approach (Saunders et al., 2019, p.445). The data for the current state research was collected through semi-structured interviews, and all the relevant stakeholders from the organization, who had hands-on experience in the forecasting process, were involved in the sample. Different service products are forecasted in their own way, and a semi-structured approach supports collecting varying terms and meanings. The selection of the interviewees is presented in Table 4.

Table 4: Introduction of interviewees

Interviewee	Role	Contribution	Duration
I1	Sales manager 1	Front-end information	32 min
I2	Sales manager 2	Responsible for forecasting in benchmark organization 2	29 min
I3	SP2&3 process owner	Responsible for forecasting	57 min
I4	SP4 process owner	Understanding of back-end operations	58 min
I5	Production planning lead	Responsible for planning production of service products	56 min
I6	Supply team lead	Responsible for forecasting	1h 7 min
I7	Inventory management specialist	Responsible for forecasting systems	1h 3 min
I8	S&OP specialist 1	Responsible for S&OP in benchmark organization 1	56 min

I9	S&OP specialist 2	Responsible for S&OP in benchmark organization 2	53 min
I10	Sales development lead & SP3 commercial manager	Understanding of installed base forecasting and LSU collaboration	33 min

The structure of the interviews was divided into two main sections: S&OP and demand forecasting. Although no defined S&OP process existed, interviewees were guided to answer what kind of collaboration already exists and how a systematically organized S&OP process could contribute to the organization's needs. Two S&OP experts from benchmark organizations were selected, representing different divisions within the same business line as the case organization. These interviews serve as benchmarks for the case organization, as they have had systematic forecasting processes for a long time. While the benchmark organizations are not industrial service units, examining their forecasting practices can help to identify and design best practices for the case organization. Demand forecasting questions gave a specific understanding of the current state of forecasting practices, and all the people responsible for forecasting were interviewed. Furthermore, a sales manager, albeit not directly related to forecasting practices, was also included to discuss access to front-end information.

For the current state research, secondary data were gathered from internal documents regarding forecasting practices and earlier studies conducted for different operational purposes. Altogether six documents were found relevant to include in the thesis context including documented process descriptions and study reports. The topics of the studies were, however, related to S&OP, such as material availability and inventory management. In addition to the interview data, the secondary document data helped to understand the current state and to build a practically relevant, novel model for the company based on the identified context (Saunders et al., 2019, p.352). These internal documents cannot be comprehensively presented in the thesis due to confidentiality, but their analysis is conducted generally to support the research.

Finally, focus groups were utilized to collect more detailed primary data by discussing topics around the intervention. The structure of focus group sessions was built around the implementation of S&OP with an emphasis on demand forecasting procedures. The participants were selected according to S&OP best practices so that every relevant function (sales, procurement, production, and finance) would be represented. Due to the large number of participants, the focus groups were organized into two groups, and both of them had two separate meetings together to ensure efficient discussion. Furthermore, organizing multiple focus groups contributes to recognizing trends and patterns among interviewees' opinions (Saunders et al., 2019, p.471). A semi-structured approach was

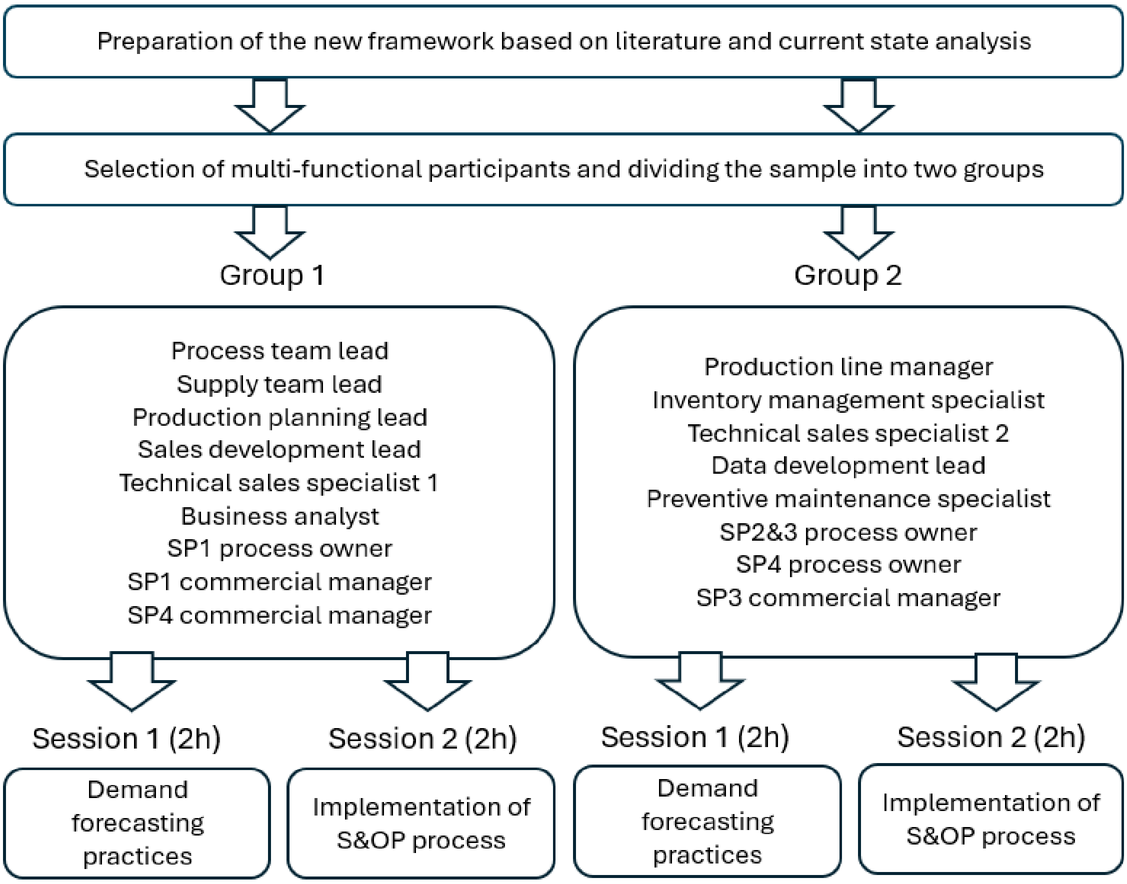

Figure 11: Implementation of the focus group sessions

used for these focus groups, and all the topics and questions were predetermined by the researcher. However, the chosen approach enabled a free flow of discussion, and the contributions of participants were occasionally used to steer the direction of the session. The implementation of focus groups including the introduction of participants is presented in Figure 11.

The focus groups were facilitated by two facilitators, the other one being the researcher. This enabled the researcher to focus on leading the conversation while the other facilitator was responsible for the tools and reporting of comments. The researcher did not emphasize their own opinions too much to ensure that the expertise of participants could be collected without bias. Comments and findings were gathered on a Mural board. In addition, focus group sessions were recorded with Microsoft Teams.

The structure of focus group sessions was built according to the backcasting method. First, the proposed future goal conducted by the researcher was commented on and agreed together. Consequently, the whole group discussed the necessary actions required to achieve the future goal, and the three most critical actions were determined. Furthermore, a roadmap was built on how to implement these actions step-by-step. At the end of the second session, the entity of two sessions was summarized to build a coherent understanding of forecasting practices and the S&OP process among all participants.

3.4 Data analysis

Data analysis in both empirical parts was carried out by using template analysis, which is a modified form of thematic analysis, where the purpose is to find recurring themes and patterns across the dataset (Saunders et al., 2019, p.660). Template analysis enables moving back and forth between inductive and deductive approaches to theory development (King & Brooks, 2017), which supports the abductive approach of this research. The analysis stage included four main actions relevant to the thematic analysis technique and it was modified with the characteristics of template analysis: 1) getting familiar with the data, 2) coding a sufficient amount of data and developing an initial coding template, 3) searching for themes and identifying relationships, 4) refining themes and testing propositions (King & Brooks, 2017; Saunders et al., 2019, p.652).

Before a comprehensive analysis, all data from different sources were prepared to a suitable form for the template analysis, and simultaneously the researcher got familiar with them. Interviews were done on Microsoft Teams and transcribed using their transcription tool Stream. Furthermore, all interviews were listened to afterward and transcription errors were fixed. Internal documents were prepared for data analysis by document summaries so that those findings could be added to the dataset of other collected data (Saunders et al., 2019, p.649). In practice, during the document summary, the key points of documents were listed, and further analyzed how they applied in the context of this research. Focus group findings were collected into a Mural board, providing a convenient way to summarize key points, and thus prepare the data for the template analysis. All focus group session recordings were listened to afterward to ensure that all relevant comments not included in the Mural board could be collected.

The initial template was produced based on ‘priori’ themes from literature and modified with a subset of data from the first interviews (King & Brooks, 2017). These themes were coded and consequently grouped hierarchically into clusters to produce a coherent diagram with different levels of themes. According to Oliva and Watson (2011), an iterative coding process contributes to minimizing researcher bias and ensuring that the categorization is comprehensive enough, particularly, when the phenomenon is under-studied or highly contextual. The top level in this research included forecasting and S&OP since collaboration between different functions was early on identified as a major contributor to forecasting practices. The subset of data from the first interviews helped to contextualize the template more specifically for the characteristics of demand forecasting in industrial service businesses. The final template was observed and discussed with the steering committee of the thesis to find comprehensive relationships between different themes. Thus, the analysis did not depend merely on the researcher's interpretations.

4. RESULTS

This chapter presents the results of the empirical research of the thesis consisting of semi-structured interviews, document analysis, and focus groups. Current state research includes semi-structured interviews and document analysis, and thus, the results of them are discussed first. After the results of the current state research, the results from the focus group sessions will be discussed. The structure follows the chronological order of the research process.

4.1 Current state analysis of demand forecasting practices

The current state analysis is divided into three sections, each addressing one of the sub-questions of the research. The objective of the current state analysis is to gain an understanding of the existing forecasting practices within the case organization. The main results from the current state analysis are summarized in tables within each section.

4.1.1 Current data management practices in forecasting

This section presents what kind of input data the case organization currently uses in forecasting and what are their capabilities for data management regarding forecasting. Thus, this section supports responding to SQ1: *"What kind of data management is needed to support demand forecasting in industrial services?"* Forecasting data sources of benchmark organizations are presented at the end of the section. Current data management practices related to forecasting are summarized in Table 6.

Historical sales data is currently a basis for all forecasting practices in the case organization. More precisely, the planners use historical material consumption to estimate future demand. SP2&3 process owner described the current usage of data in forecasting:

> *"These forecasts are based purely on history, what we have produced."*

Supply team lead notes similarly that spare parts forecasting is also based on history:

> *"The base forecast is based on the material consumption of past 12 months."*

According to interviews, other relevant internal or external sources of information are not utilized efficiently, which is mainly caused by the lack of collaboration with the front-end LSUs. The internal information that is rarely communicated to the back-end operations includes, for example, ramp-up service products, large project sales, and preventive maintenance orders. Furthermore, the visibility of quotations is limited and the data quality is low. SP2&3 process owner mentioned that no external market information or trends are included in forecasts either. Supply team lead stated that they have already identified development areas regarding the information flow between the LSUs and the back-end operations:

> *"There are certain elements (of information) that could be easily received from the front end through different collaboration platforms. For example, these preventive maintenances, which these sales unit countries operate, would be a low-hanging fruit just to ask from them."*

All interviewees identified the potential of IBI, although it has not yet been properly exploited in the case organization. The installed base of machines is not a new source of information in the case organization, and a suitable tool to collect and preserve IBI already exists. Although technical and sales information of all sold machines is collected to the IBI system, the supply team lead mentioned, that customers have not widely taken the provided system into use, and only about 30% of the new machines are registered:

> *"There has been some incentives and campaigns, such as extended warranties, for registering new machines to the installed base system, but they have not been successful."*

Without customer registration, further follow-up on these machines is not possible, which means that valuable information, such as maintenance logs, is not being updated. IBI could benefit from the whole partnership between the case company and its customers due to better predictable maintenance needs. SP2&3 process owner mentioned that there have already been initiatives by the R&D function to investigate what variables should be utilized in forecasting with IBI in modernization services. Supply team lead describes the benefits of IBI:

> *"From there (the IBI system) we could internally in sales forecasting take into account that how much do we have installed base of a certain age, and could there be for example a need for preventive maintenance, and should we communicate these upcoming events to back-end operations. In contrast, if there are no view of the installed base, it may cause bullwhip effect and sudden peaks in demand in certain materials."*

The IBI system includes various product- and customer-related information. The data can be categorized into two groups depending on whether the end customer registers the machine or not. The different types of IBI are presented in Table 5. All sold machines are documented into the system and certain sales and technical information exist for the entire installed base. The registration of machines by end customers would enable the collection of up-to-date data on failures and maintenance cases occurring along the product's lifecycle. Sales development lead pointed out that the registration impacts the usability of the IBI in forecasting:

> *"Basic information, such as the year of sale, can already be utilized in forecasting practices for some service products. However, accurate forecasting of, for example, repair services would require reliable information of historical maintenances."*

Table 5: Different types of IBI in the case organization

Type of IBI	Use case
Basic IBI	Long-term high-level forecasting to illustrate the direction of business
Date of sale	
Date of commissioning	
Technical specification	
Additional IBI after registration	Long-term high-level forecasting to illustrate the direction of business and accurate short-term forecasting based on historical maintenances
Maintenance policy	
Maintenance log	
Failure log	
Exact location	
Photo of the machine at customer	

According to the interviews, system architecture in the case organization enables maintaining forecasting data and transferring it across relevant tools. Historical material consumption for forecasting is maintained in the enterprise resource planning (ERP) system, and it has been integrated with forecasting tools, which will be presented in the next subchapter 4.1.2. Forecasts are shared with suppliers either via email or via a certain collaboration tool. This depends on the purchasing type of a given component.

Table 6: Data management practices in interview organizations

Theme	Topic	Case organization	Benchmark organization 1	Benchmark organization 2
Data management	Forecasting data	*All forecasts are based on historical sales data*	*Forecasts are based on future sales pipeline and quotation base data*	*Forecasts are based on future sales pipeline and quotation base data*
	External information	*Only occasional future projects are included when back-end teams are informed*	*All relevant external market information is included*	*Occasional external information is included*
	Sharing with stakeholders	*Forecasts are shared with suppliers via email or via collaboration system*	*Forecasts are shared with suppliers via collaboration system*	*Forecasts are shared with suppliers via collaboration system*
	Systems	*Systems for managing historical sales and installed base data*	*Forecasting systems integrated with ERP systems*	*Forecasting systems integrated with ERP systems*

A customer relationship management (CRM) system is utilized in both benchmark organizations as one of the main data sources for forecasting, providing a quotation list with probabilities as a view to future. This practice is based on probabilities of valid quotations, which front-end LSUs should update regularly. Data validity has been a challenge, however, since different LSUs report future sales to Salesforce quite differently.

In addition, considerable human judgment is needed to recognize the current trend from opportunity data.

In conclusion, the case organization utilizes mainly historical sales data for forecasting, while only occasional future projects are incorporated into the forecasts. In contrast, benchmark organizations utilize future-oriented data from the CRM system. Forecasts are already shared with suppliers in every interview organization. The case organization has an installed base system, which could be used as a data source for IBI. However, the depth of the IBI depends on customer registration.

4.1.2 Current demand forecasting methods

This section presents the results of interview questions related to forecasting methods, and thus SQ2 "*What kind of characteristics of a demand forecasting model would match the requirements of industrial services?*" is also addressed. All interviewees recognized intermittent demand patterns leading to difficulties in forecasting industrial services. There was no consensus among interviewees about the capabilities of forecasting methods to generate accurate forecasts for highly variable demand. Furthermore, the results of interviews indicated that a service organization might need multiple forecasting methods to serve the characteristics of all their service products. Supply team lead pointed out that there are various demand profiles even within the same product family:

> *"There might be about 50 000 different components in our spare parts offering and the volume for single component is quite small and fluctuating. However, there are also kind of high-runner items which are consumed and sold regularly."*

Although accurate forecasting may require individual forecasting of each service product family, they all use materials from the same warehouses, and thus, it is necessary to investigate the entity. Supply team lead mentioned that rapid reactions to machine breakdowns at customer sites require maintaining safety stocks. Currently, the forecasting accuracy of service products is at a low level, and there is a risk that less critical orders use material resources from the most urgent ones. Interviewees agree that forecasting practices inside the organization should be more coherent. Currently, different functions build their own forecasts, because information is not properly shared, and there is not enough understanding of how different forecasts are related to each other.

Inventory management specialist introduced their FSS which is used mainly for spare parts, and which automatically calculates a baseline forecast based on historical material consumption and forecasting accuracy. The document analysis indicated that the system first classifies each component according to their demand characteristics, and consequently chooses a suitable forecasting model. The FSS included basic statistical models suitable for forecasting smooth, erratic, lumpy, and intermittent demand patterns. The models were simple moving average, exponential smoothing, and SBA. The system enables human interaction, as baseline forecasts it produces can be adjusted, as discussed by supply team lead:

> *"I could say the system forecast is a base forecast based on the consumption of past 12 months. If we know some campaigns or projects in advance, the planner can add them on top of the base forecast."*

Inventory management developer stated that forecasting models need to be adjustable by humans in case future information is not included in the baseline forecast. However, adjustments should be based only on reliable information to avoid overly high forecasts, as SP4 process owner said:

> *"Once was this case with many failures of the same component, and the back end decided to prepare for exchanging all these machines to ensure a great customer experience. Forecasts were adjusted according to it, but eventually the demand was way lower than expected without a clear information from customer level."*

The forecasting accuracy for spare parts is measured and evaluated by the FSS, while company experts are not tracking the performance of these metrics. Instead of forecasting accuracy, operational metrics, such as the availability of materials, are considered to be enough to follow.

The interviews revealed that forecasting practices for other service products are not as advanced as for spare parts. SP2&3 process owner described that their modernization and classic-phase products are forecasted based on historical material usage utilizing a simple trend line. The estimate is created by taking an average of the consumption in the past 12 months, and that average value is then placed for every month two years ahead. Thus, those forecasts are not capable of catching sudden demand peaks typical for these project-based product families, as described by SP2&3 process owner:

> *"Flat forecasts are currently created. It might not be high quality. It doesn't take into account potential growth of sales or demand or any kind of upcoming peaks."*

Although all process owners agree that forecasting practices should be improved, the current state is not seen as catastrophic, as operational metrics are still on an acceptable level. Furthermore, repair or reactive maintenance needs are inherently unexpected events and according to interviews, industrial service demand cannot be predicted with perfect accuracy. In these cases, the information flow of confirmed orders from the front end to the back-end operations should be straightforward to minimize the harmful effect of the sudden demand peak.

The lack of information from front-end LSUs is seen as a significant barrier to improving forecasting. According to SP4 process owner, the organization is capable of producing even unpredictable and complex orders with their competent production employees, which lowers the need for accurate forecasting. However, production planning lead implies that the operations could still be much better optimized if the view to the future was available. Furthermore, supply team lead mentioned that an increasing number of service sales is proactive, referring to services such as preventive maintenance and large modernization projects of old equipment, highlighting the need for more proactive planning.

Document analysis revealed that the organization faced significant availability challenges a few years ago, and internal studies were conducted to avoid this in the future. The main improvements were system developments to improve information validity and communication developments to streamline information-sharing channels. In addition, the project team identified the need for the S&OP process to further improve communication and forecasting accuracy.

Overall, all interviewees agreed that current forecasting practices in the case organization were looking backward too much, relying significantly on historical sales data. They proposed that the incorporation of future information into forecasts should be improved. Due to the lack of collaboration with the front-end LSUs, the responsibilities of forecasting are unclear and even piled up to the back-end operations, as supply team lead stated:

> *"It has gone upside down, that people ask our sourcing experts for those forecasts, that what do we (sourcing experts) estimate, that how much would we sell based on the last year consumption. So, it is also very retrospective method."*

Sales manager 1 presented how their team utilizes life-cycle models and maintenance intervals to forecast spare parts for repair business needs. He added that this practice closely resembles the use of IBI in forecasting. However, this information is not shared with other functions in the organization and is mainly for the sales team's planning purposes.

IBI is already being utilized for forecasting in the product development of newer modernization products, highlighting its potential value in other forecasting applications as well. Sales development lead and SP3 commercial manager defined how IBI is currently used for forecasting. The variables used in the model are the date of sale and the expected year for modernization after the sale. Thus, these forecasts can be generated without customer registrations utilizing only basic IBI in Table 5. The logic of the model is to estimate how many machines in the installed base would need modernization in a certain year based on the year of their sales. As all customers are not doing these modernizations when suggested, there is a determined percentage value that is considered. The installed base system provides a convenient way to export all machines and their technical specifications at once. Sales development lead concluded the use of the current installed base forecasting model, indicating that it is still not accurate for short-term forecasting needs:

> *"The model is currently used as a basis for all R&D projects and new launches in modernization business, and I think it is the most advanced application of installed base forecasting here. It is still quite high-level yearly forecasting, and we need quotation base probabilities for an accurate short-term view and resourcing."*

While the benchmark organizations have applied more systematic forecasting practices, neither one of them utilizes hardly any statistical methods. The main contributor to their forecasts is the collaboration between different functions. Benchmark organization 1, that is mostly a volume business, builds their forecasts by collecting area forecasts from different sales unit managers and then adds them together into one overall forecast. Their S&OP process owner 1 said that these baseline sales forecasts are mainly based on opportunities from their CRM system and on meetings between front-end sales units. Their forecasts are partly relying on human judgment since complete data are not always available. The entire process of collecting forecasts through collaboration is rigid and requires numerous meetings, as they currently aim to ensure that every product is forecasted accurately.

Benchmark organization 2 has both volume products and project-based products with larger order sizes and longer intervals. Their volume products are forecasted according to a future opportunity list in their CRM system, and salespeople use their experience and vision to build monthly monetary forecasts. This monetary value is allocated to three different product families according to historical sales data. Sales manager 2 argued that statistical models by themselves would not be accurate in forecasting the complex demand of machine manufacturer with highly customized products and expensive components. He continued by saying that artificial intelligence models, which could combine historical sales data and future quotations identifying trends, could replace the current practice which relies heavily on human judgment.

By looking at demand profiles, project-based products of benchmark organization 2 are somewhat similar to certain service products in the case organization except for spare parts. For forecasting project-based products, their salespeople choose the most probable projects from the quotations within the CRM system. In the case of months with zero demand they utilize budget forecasts to fill the gap, which means a certain monetary value is allocated according to future quotations.

The main findings regarding current forecasting methods in the case organization and benchmark organizations are summarized in Table 7. Additionally, Table 7 includes the main results of performance management-related questions, as discussed in this section. Due to the perspective of researching the service portfolio as an entity, not all details of individual service products are reflected in Table 7.

Table 7: Current forecasting methods in interview organizations

Theme	Topic	Case organization	Benchmark organization 1	Benchmark organization 2
Forecasting methods	Statistical models	*Statistical models are used for three service product families*	*Statistical model used only for comparison with expert forecasts*	*Not using statistical models*
	Other models	*Installed base forecasting model is used for certain modernization products*	*Expert forecasts from different sales areas, which are added to an overall forecast*	*Expert forecasts from different sales areas, which are added to an overall forecast*
	Human judgment	*Little human judgment is used to modify forecasts, and forecasting practices rely on expertise of few people*	*Requires expertise to create the forecast with limited information*	*Requires expertise to create the forecast with limited information*
	Systems	*Spare parts forecasts are automatically generated by the FSS*	*Salesforce opportunities mainly used, a centralized tool for collecting all area forecasts*	*Salesforce opportunities mainly used, Excel-SQL tool for generating forecasts*
Performance management	Metrics	*The FSS measures forecast accuracy itself; modernization and vintage forecasting accuracies are tracked in Excel*	*PowerBI reports track overall and area forecasts*	*PowerBI reports track overall and area forecasts*
	Improvements	*The FSS adjusts forecasts based on historical performance, without human evaluation*	*Forecasts are continuously refined based on historical performance*	*Forecasts are continuously refined based on historical performance*

To sum up, statistical models are used in the case organization for three service product families, whereas repair services are not statistically forecasted. Installed base forecasting is applied for certain modernization products. Human judgment is involved in modifying forecasts, but the process lacks consistency and relies heavily on individual expertise. Benchmark organizations prioritize collaborative forecasting processes, involving different functional areas, and use expert opinions for complex demand scenarios rather than relying on statistical models alone.

4.1.3 Current S&OP practices

Results of S&OP-related topics will be discussed in this sub-chapter seeking insights to SQ3: *"How can a systematic S&OP process support forecasting demand in industrial services?"*. Table 8 summarizes the main results of this section by comparing the case organization to benchmark organizations. The results from forecasting-related questions already indicate a need for improvements in communication and collaboration to improve planning practices in the case organization. The necessary internal data and external information for accurate forecasting may exist but the back end is unaware of them because preventive maintenance cases, for instance, are not communicated by the LSUs. There is no defined S&OP process in the case organization, but some E2E-processes already include characteristics close to S&OP practices, as supply team lead mentioned:

> *"Last year a global workshop manager started to ask forecasts from LSUs regarding repair projects and they have a light version of S&OP process there."*

Production planning lead added:

> *"What they do in workshop business is close to S&OP, at least the monthly meeting which they have."*

The practices among other service product families are less collaborative. SP2&3 process owner implied how both horizontal and vertical collaboration is limited, occurring mostly when problems arise:

> *"We have no collaboration with the sales. All forecasts are done by me. Some message channels exist between procurement and production if we notice that something is wrong."*

Both benchmark interviews emphasized that systematic collaboration is the core benefit of S&OP. Implementation of S&OP ensures that every function shares their own opinions and future knowledge that others would not have been aware of. Meetings provide an information-sharing platform that enables everyone to be more aware of what is happening across the organization, as described by S&OP process owner 1:

> *"S&OP meetings are the place where you can speak for your functions benefit, but ultimately for the benefit of the whole organization."*

Document analysis findings revealed that S&OP had previously been considered in the case organization but was ultimately abandoned due to insufficient information from LSUs. Sales manager 1 proposed that the operations of LSUs should be researched to integrate information sharing between front-end and back-end systems. S&OP process owner 2 said similarly, that forecasting practices and access to reliable front-end data have been identified as the most difficult tasks of implementing S&OP. However, S&OP process owner 1 pointed out that the S&OP process is likely beneficial even without perfect front-end information:

> *"I believe S&OP should be implemented even without perfect data just to open the communication channel. (…) We started to ask about large projects, and eventually the sales units understood the importance of informing us and they started to contact us themselves. Although the process was quite heavy, it was worth it,*

and now we can develop new tools and practices to automatize communication, since we have better contact with the front end."

All interviewees find S&OP as a success driver for more accurate forecasting, and the case organization would be capable of implementing it. Particularly the representatives from the supply and production side are looking forward to implementing a systematic S&OP process. Thus, there is already an interest in S&OP inside the organization and many employees were said to have experience of it in their earlier jobs. The interviewees did not identify any barriers that would stop the implementation of the S&OP process, and production planning lead concluded the feasibility of the implementation:

"I don't believe there would be any bigger challenges in implementing S&OP. We should just launch it define roles and what kind of data is shared across functions."

According to interviews, S&OP implementation would not need significantly different characteristics in an industrial service context in comparison to traditional production businesses. S&OP process owner 2 introduced that some of their products are similar to the service products of the case organization in terms of their project-based planning characteristics, and still, they implement S&OP in a rather traditional manner.

Executive participation is identified as one of the biggest success factors in implementing S&OP. S&OP process owner 1 pointed out that executives also receive valuable information, whether the business is going in strategically planned direction, and they can set short-term goals for the next S&OP intervals. Although they attend only the final S&OP meeting to confirm the plans prepared in previous meetings, their commitment to the process shows the others the importance of their efforts. S&OP process owner 1 stated:

"A few years ago, we had a very streamlined planning process, which was at some point noticed when we faced difficulties and functional plans were not aligned. We took executives along by adding pre-S&OP and executive meetings, and things started to improve step by step. Furthermore, the director of our unit shows great interest in our plans which motivates all planners."

The management of the case organization has not emphasized proactive planning activities previously, and thus, it is not included in the organizational culture either. According to supply team lead, changing characteristics of the service portfolio require changes in the planning activities:

"S&OP has not been in spotlight, as our business has been more reactive and smaller. We try to sell more services in advance but we should involve the proactive steering element also in our supply chain planning."

As mentioned at the beginning of this section, some improvements for communicating future sales have already been made. Different functions have improved their practices as much as possible with the current conditions, but a coherent process is missing, as inventory management specialist implied:

> *"There are small projects for improving planning practices but an overall vision is lacking, that how the whole portfolio should be handled."*

Supply team lead stated similarly emphasizing the role of management:

> *"We might need a cultural change in the management of the business and in the customer interface to define how forecasts would contribute to the whole business."*

Table 8: Forecasting organization and process in interview organizations

Theme	Topic	Case organization	Benchmark organization 1	Benchmark organization 2
Forecasting organization	Vertical collaboration	*Front-end LSUs are not involved in the forecasting process*	*Close collaboration with LSUs through frequent meetings*	*Regular meetings for collaboration with LSUs*
	Horizontal collaboration	*Collaboration between back-end functions is limited*	*Close collaboration through a monthly S&OP process between back-end functions*	*Close collaboration through a monthly S&OP process between back-end functions*
	Management support	*Management has not emphasized planning yet in the organization*	*Management attends monthly executive S&OP meetings and shares short-term goals*	*Management supports the S&OP process*
	Responsibilites	*Each function creates their own forecasts without clear responsibilities*	*Systematic forecasting process and clearly defined responsibilities*	*Systematic forecasting process and clearly defined responsibilities*

Currently, the case organization lacks vertical and horizontal collaboration, as the front-end LSUs are not involved in forecasting and communication between back-end functions is limited. There is no systematic S&OP process, and responsibilities for forecasting are unclear. Additionally, management has not emphasized planning activities, contributing to the current fragmented approach. In contrast, both benchmark organizations use S&OP to facilitate regular cross-functional meetings, supporting clear communication channels.

4.2 Developing a framework for digitalizing demand forecasting in industrial services

The results of the focus group discussions will be presented in this sub-chapter. The chapter follows the order of the proposed initial framework in Figure 10. First, findings related to data collection and data requirements for forecasting will be presented addressing SQ1. This is followed by results on forecasting methods and metrics, which respond to SQ2. The third sub-chapter includes the results related to the S&OP process, providing answers to SQ3.

4.2.1 Requirements for data collection

While the collection and management of historical sales data in the case organization is already at a sufficient level, the focus group discussions directed toward the need for more future-oriented data. This sub-chapter addresses SQ1: *"What kind of data management is needed to support demand forecasting in industrial services?",* focusing on findings on what kind of data already exists in the organization and what kind of new data types could be collected for forecasting purposes. The main findings of this section are presented in Table 9.

Both focus groups agreed that accurate future sales information would be the most beneficial data source for the back-end operations. However, the majority of service products fall under the category of corrective maintenance, where demand typically arises unexpectedly. Nonetheless, an increasing share of sales is coming from preventive maintenance and larger modernization projects, both of which have the potential to be forecasted and communicated more effectively to operations. Ongoing global sales development projects aim to enhance the collaboration and system integration with LSUs and focus group participants identified these improvements as a key objective for the future. Process team lead emphasized the importance of information from sales units:

> *"I think even a raw estimate coming from the sales would be better than nothing. If those can't be utilized, then it has to be done based on statistical information or on installed base data"*

Results from both focus groups suggest that the CRM system could be more effectively utilized in forecasting and operations planning. As mentioned in the current state analysis, benchmark organizations had the quotations data at the core of their forecasting process. While the existing CRM system has the capability of collecting probabilities for projects within quotations, LSUs are not consistently updating this information, and thus, the data is unreliable. Sales development lead remarked that:

> *"It would be really important to get the information of actual potential sales of projects, instead of seeing the whole quotation base of projects. With reliable probability information, possible future sales could be categorized according to their potential."*

The focus groups reached a consensus that the reliability of data within the CRM system needs improvement. According to the sales development lead, only about 10% of quotations from the LSUs are processed through the CRM system. As a result, the transparency of quotations is considerably weak, as pointed out by both technical sales specialists. It appeared during the focus groups that the low reporting rate may stem from the historical collaboration patterns between the back-end operations and the LSUs. In the past, the spare parts business was even more dominant and they were ordered through a different system. Thus, this has led to resistance in adopting the new system more comprehensively, despite its growing importance for back-end operations. SP3 commercial manager described the current situation as follows:

> *"The LSUs are only interested in increasing sales as easily as possibly. They don't see enough benefits to start reporting about future sales more in-depth. The counter argument usually is that do you want us to waste time filling in some information rows or actually making more money for the company searching for sales opportunities."*

The case organization cannot currently rely on receiving accurate sales information from LSUs through existing systems, although ongoing global projects may improve the situation over time. Both focus groups found that gaining visibility even into the sales strategies or sales budgets of LSUs would help forecasting future sales. Improved collaboration with the front-end teams and the establishment of clear communication channels could facilitate the sharing of sales strategies or budgets. Sales development lead suggested creating a standardized model to define how and in what form sales information should be requested from LSUs, and the whole first focus group supported the idea. This model should be designed to be easily adopted by LSUs while remaining comprehensive enough to provide relevant information for the back end.

The utilization of IBI for forecasting was identified as one of the top priorities for the organization's future strategy. While the current IBI system offers the potential for such use, both focus groups found that further in-house research is necessary to fully understand the use case in the context of the organization's complex service offering.

As was stated in the current state analysis, the percentage of machine registration by end customers is low, which hinders the organization from utilizing IBI more widely. Despite efforts to incentivize customers to register more machines in the system, not much has changed in their behavior. Sales development lead pointed out a key reason for that:

> *"One of the biggest reasons of why end customers do not register their machines to the system is that they do not want to do it strategically so that they can more freely tender out various local service providers. By registering their machines to our system, they feel like they are sticked to our services in the future."*

The percentage of registrations has improved over the years, but tracking the oldest machines in the installed base remains particularly challenging. A key finding from the focus groups was that the use of IBI is extremely difficult in cases where the past data is unreliable. Therefore, installed base forecasting is best to start simultaneously with the collection of up-to-date IBI. However, focus group participants mentioned that some newer service products have high-quality IBI. It was not clear how the older, low-quality data could be integrated with the newer, high-quality data, or if such integration is even possible. The focus groups suggested that these newer service products could serve as pilot projects for implementing installed base forecasting practices.

Achieving full registration of machines and regular updates of IBI by all end customers may be a long-term goal, but it is not immediately relevant in the short term. Both focus groups believed that encouraging end customers to register their machines should not be a great barrier, and an in-depth investigation and a development project could enhance the registration percentage. Furthermore, discussions in both focus groups implied that the current IBI available for the organization could be explored further to find causalities beneficial for forecasting practices.

Table 9: Main findings from focus group sessions for developing forecasting data management

Theme	Topic	Findings
Data management	Forecasting data	*The case organization should continue utilizing and maintaining historical sales data, as it enables statistical base forecasts in case future sales information is not available or as additional forecast*
	Forecasting data	*Installed base data management and utilization should be emphasized* *Explore the use case of installed base data:* *Initiate pilot projects for newer installed base machines with high quality data, as it is difficult to utilize for old machines due to low quality data* *Give effort to improve the registration rate of machines by end customers*
	External information	*Accurate information of future sales and quotation probabilities is necessary for short-term forecasting, and the collaboration with LSUs should be enhanced and the quotation base data quality improved* *Even a rough estimate from sales would be beneficial for the forecasting process* *Ways of developing the collaboration with LSUs:* *Consistent way of asking information* *Sharing of sales strategies and budgets*

To summarize, the findings on data management from the focus groups highlight that while historical sales data is utilized in the case organization, the focus should shift toward acquiring and managing future-oriented data. Improved collaboration with the LSUs is essential for accessing reliable sales probability information, which currently lacks quality. IBI has the potential for forecasting new machines, but poor registration rates by customers hinder its use for older machines. Piloting IBI-based forecasting with high-quality datasets from newer machines is recommended.

4.2.2 Requirements for forecasting methods and metrics

This sub-chapter focuses on the selection and evaluation of forecasting methods. Following the scope of the thesis, forecasting methods will not be analyzed on a mathematical level, but rather in a describing manner, addressing SQ2: *"What kind of characteristics of a demand forecasting model would match the requirements of industrial services?"* The suitability of the forecasting methods presented in Figure 8 will be evaluated. Although these methods are not being empirically tested in practice in this thesis, the expertise of focus groups participants is used to assess whether proposed methods could have a use case in industrial services. Tables 10 and 11 summarize the main findings of this section.

Both focus groups found similarly that all service product families of the case organization can be forecasted statistically to some extent, although some exceptions exist within product families. Furthermore, using multiple forecasting methods is necessary, as no single method serves the diverse demand profiles of all service products. According to the focus groups, the demand profile of a given service product has to be first identified before determining whether the service product can even be forecasted. The demand profile is influenced not only by the demand pattern, which can be smooth or intermittent but also by volume and product mix. As a result of focus group discussions, forecastable demand profiles can be roughly categorized. SP3 commercial manager roughly divided the service offering into two categories:

> *"Our services can be roughly divided into project sales and reactive sales, and forecasting is different in both of them. Information regarding upcoming projects can be better utilized in project sales, whereas statistical methods might be more useful in reactive sales, such as corrective maintenances."*

Sales development lead added that it is challenging to create an accurate statistical estimate in project business, particularly for short-term demand. On the other hand, SP2&3 process owner stated that statistical methods can be utilized for those project-based service products as well, to create a baseline forecast. However, in that case, it is necessary to determine a reasonable level of forecasting accuracy since it is obvious that sudden peaks in the short term cannot be accurately forecasted with statistical methods. According to business analyst, investigation of the historical sales data and usage of statistical methods could help to discover patterns and fluctuations in demand. SP4 process owner argued, that larger corrective maintenance projects would be particularly challenging to forecast with statistical methods, due to the unpredictable nature of the demand. Installed base forecasting was identified as a potential solution for improving the forecasting of corrective maintenance projects.

Both focus groups expressed interest in exploring installed base forecasting methods, although it was identified that implementing advanced installed base forecasting methods is not currently feasible. The participants explained this partly due to the small number of machine registrations by end customers and partly due to the lack of knowledge within the organization. Ideas for installed base forecasting were suggested, including forecasting methods themselves or using IBI as a supplement data source for adjusting baseline forecasts.

The proposed new methods for installed base forecasting included identifying causal relationships between actual sales and IBI values. These relationships could be explored by analyzing different variables within the IBI system. For instance, different sales patterns could be categorized according to specific sales areas. SP3 commercial manager provided an example related to preventive maintenance:

> *"It could be investigated if there is some correlation between the preventive maintenance schedule and actual sales of preventive maintenance kits. That information could then be generalized to a forecasting model, which indicates when certain services could be offered after the registration of the machine."*

Although it is recognized that a perfect registration rate of machines and up-to-date IBI may not be easily achievable, focus groups pointed out that higher-level forecasting could be done already. The basic IBI is already managed properly, and according to sales development lead it provides the opportunity for getting an overview of the installed base. This overview can help to determine which types of services might face the highest demand in the coming years. By evaluating the overview of the installed base, higher-level monetary forecasts could be created, illustrating the sales potential in various segments.

When used as a supplementary data source, IBI could enhance the baseline forecasts generated by other methods. Specifically, high-level monetary forecasts derived from IBI could serve as a valuable tool for refining and adjusting these baseline forecasts. The focus groups agreed that incorporating this kind of additional information would improve both the communication and evaluation processes around baseline forecasts. SP3 commercial manager demonstrated this:

> *"For example, forecasts for repair orders could be adjusted upwards if a large number of installed base machines are reaching an age where they typically begin to experience failures."*

The utilization of ML in forecasting was brought up during the second workshop. The participants identified the potential of ML models for processing large datasets and finding demand patterns from various data sources, such as from the installed base system pointed out by SP3 commercial manager. The workshops did not focus on ML models in-depth, as the organization needs to build solid forecasting processes first before employing more advanced tools. However, ML models would be beneficial to help manage the diverse service portfolio and complex system architecture around forecasting. Data development lead described actions around utilizing ML:

> *"We should also investigate the potential of using machine learning in supporting forecasting practices. However, it should be done so that we don't take it to use without a clear reason, otherwise it just makes things more complicated."*

Table 10: Main findings of focus group sessions regarding forecasting methods

Theme	Topic	Findings
Forecasting methods	General	*Combining multiple forecasting methods probably contributes to achieving accurate estimates*
	Statistical models	*All service product families of the case organization can be forecasted statistically to some extent, although some exceptions exist within product families. Large corrective maintenance and modernization projects are particularly challenging to forecast with statistical methods* *The use of different forecasting methods for different service products is necessary* *Overall, statistical models can be used as baseline references and to identify patterns and fluctuations*
	Other models	*Installed base forecasting methods should be emphasized, although their advanced applications are not currently feasible* *Higher level monetary forecasts can already be created illustrating the sales potential in various segments* *New ideas of utilizing installed base data in forecasting:* *Causal relationships between actual sales and IBD values* *A supplementary data source to support baseline forecasts*
	Other models	*Potential of ML models should be investigated, as they could help identifying demand patterns, utilizing large and various data sources that already exist*

The consensus of both focus groups was that utilizing multiple forecasting methods probably contributes to achieving accurate estimates of the future. According to sales development lead, current forecasting practices rely heavily on the expertise and experience of individual planners. By utilizing multiple forecasting methods as input for communication, more insights can be included in the forecasting process and the expertise spreads across the organization. The importance of using multiple methods is emphasized in situations where no single method has proven accurate enough, and where the quality of input data varies. This approach not only enhances the robustness of the forecasts but also fosters a more collaborative and informed forecasting process.

According to focus groups, the different characteristics of demand profiles of service products result in a need to forecast these products on different levels. Various planning levels were proposed in the workshops, including profit center, product family, service category, and product line level. SP3 commercial manager noticed that clear determination of different hierarchies is necessary, as product lines are not organized according to service products. Business analyst commented on the need for determining reasonable planning levels:

> *"If we started to receive better monetary estimates from the salespeople, it doesn't matter if we can't break it down for a quantitative material forecast. A same planning level for every service product would be optimal but that might not be possible. The most important thing is to make this so that the forecasts are comparable to each other."*

Supply team lead highlighted that low-volume, high-mix service products are difficult to plan on a high level. For example, forecasting these kinds of components at a service product family level can easily lead to excessive inventories of incorrectly forecasted, unnecessary components. Furthermore, highly customizable, project-based products are not reasonable to forecast on a high level in operations planning, as procurement must be sure of future needs when purchasing expensive components. However, production planning lead mentioned that components used by different service products often overlap, which could accidentally help balance inventories that were incorrectly forecasted. The first focus group agreed that understanding the interrelationship between material flows across various service products is important for successful forecasting and operations planning practices.

On the other hand, large modernization or repair projects are thoroughly planned at customer sites in advance, allowing their material needs to be exactly determined at a component level. Thus, reliable quotation information with probabilities of different orders would significantly contribute to the forecasting accuracy of large project orders. This level of detailed planning ensures that procurement and inventory decisions are aligned with actual project requirements, minimizing the risk of overstocking or shortages.

The classic-phase service product family is already forecasted at a frame level, as there is limited variation between orders. Planning Bill-of-Materials (BOMs) are used to decompose the frame-level monetary forecasts into component-level details. The focus groups implied that similar planning BOMs have occasionally been used successfully for other service products, particularly when certain future information is available. While planning BOMs do not directly contribute to forecasting accuracy, as they are used to allocate higher-level forecasts to more granular levels, the focus groups recognized that they are valuable tools. They suggested that broader utilization of planning BOMs could be beneficial, improving the alignment between high-level forecasts and specific operational needs.

According to the focus groups, the time horizon for forecasting varies between different service products and depends on the selected planning hierarchy level. SP3 commercial manager stated that while high-level, long-term forecasts can be useful for estimating the overall direction of the business, they offer limited value in planning for the short-term or even mid-term time horizons. Business analyst concluded how the view of the future changes as the time horizon extends in the context of the case organization:

> *"The further away we to the future we go from present, the flatter the forecast will be. The next month is somehow manageable, the second months starts to be shady and the third month is already very hard to estimate."*

Two of the four service products have delivery times of approximately four weeks, with some exceptions, which means that the production schedule is mostly fixed for that period. SP2&3 process owner pointed out that the future view for them is not clear either, and monthly inspections are necessary to update those forecasts for the nearest upcoming months. Spare parts forecasts are refined monthly by the FSS, which generates forecasts for the next 18 months. According to the production line manager, for repair services, where the delivery time is two weeks and the capacity to execute them is limited, all future sales information would be beneficial to enhance preparation and resource allocation. Given the unpredictable nature of repair services, it is challenging to set a precise forecasting horizon. However, a flexible approach that allows for adjustments based on immediate needs is crucial.

If the CRM system could be comprehensively utilized for forecasting, the focus groups found that it could determine a time horizon based on the validity period of quotations. The quotations are typically valid for three months, and their continuous monitoring would serve the needs of short-term forecasting, as confirmed orders are also executed in the near future.

Table 11: Main findings from focus group sessions regarding planning level and horizon, and performance management

Theme	Topic	Findings
Forecasting methods	Planning level	*Different service product families may require forecasting on different levels. For example, low-volume high-mix spare parts are difficult to plan accurately on a high level* *On the other hand, large modernization or repair projects are thoroughly planned in advance at customer sites, allowing their material needs to be exactly determined at a component-level* *The classic-phase service product family can be forecasted at a frame level, as there is limited variation between orders*
	Planning horizon	*Time horizon for forecasting service products should include short-term estimates starting from one month. While long-term forecasts can provide strategic value, the fluctuating nature of demand means that forecasts are reliable only about two months ahead.* *Continuous reviewing and refining of forecasts is needed to include the latest changes and developments to the forecast.*
Performance management	Metrics	*Forecasting metrics are an enabling tool for the continuous improvement of forecasting processes and operational efficiency* *Simple Excel-models are suitable for first analysis, while starting the journey towards a holistic PowerBI-report* *Forecasting accuracy, reliability of the forecasting process, and supplier performance should be tracked*
	Improvements	*Measures provided by the FSS should also be regularly inspected so that the organization does not blindly rely on system-generated forecasts without critical evaluation*

In conclusion, the time horizon for forecasting service products should include short-term estimates starting from one month. While long-term forecasts can provide strategic value, the fluctuating nature of demand means that forecasts are reliable only about two months ahead. Production line manager pointed out, that the actual product mix varies from month to month so much, that forecasts beyond two months are not optimally usable in production planning. Thus, continuous reviewing and refining of forecasts is needed to include the latest changes and developments in the forecast.

The focus group found forecasting metrics as an enabling tool for the continuous development of forecasting processes and operational efficiency. Process team lead argued that it would be important to implement them first in a simple way, ensuring that all relevant stakeholders have access to them. This approach was supported by both focus groups. Data development lead added that simple spreadsheet models are suitable for the first analysis while starting the journey toward holistic business intelligence reports. The second focus group also addressed the importance of understanding material flows and the interrelationships between different forecasts as part of the implementation process. Ultimately, this holistic approach would enable the organization to develop a comprehensive understanding of the forecasting process and the accuracy of various metrics.

The most proposed metric was a simple comparison between actual sales and forecasted sales. Data development lead additionally proposed metrics for assessing the reliability of the forecasting process by calculating forecasting error and bias. Inventory management specialist suggested that supplier performance could also be better evaluated by comparing the quantities delivered by suppliers to the forecasted quantities, which reflect the organization's requests from suppliers. As mentioned in the current state analysis, the accuracy metrics within the FSS are not monitored by experts. The consensus from the focus groups was that these metrics should also be regularly inspected so that the organization does not blindly rely on system-generated forecasts without critical evaluation.

4.2.3 Requirements for the S&OP process

This sub-chapter presents the results of the focus groups related to SQ3: *"How can a systematic S&OP process support forecasting demand in industrial services?"* A new S&OP process was proposed as input for the focus groups, where the participants critically evaluated its practicality and feasibility for later implementation within the organization. This section explores the suitability of the proposed S&OP process and discusses its implementation in the context of industrial services. The main results of this section are presented in Table 12.

The consensus from both focus groups was that the operations of the case organization could be planned through a systematic S&OP process, particularly when the business is focused on proactive services. All service product families of the case organization were identified to be suitable for inclusion in the S&OP process, although the benefit for corrective services was considered less significant. Supply team lead noted, that planning single spare parts through S&OP might not be practical due to the low predictability of demand, which makes statistical methods necessary in generating estimates. However, the focus groups agreed that involving all service products would be important to understand the overview and to ensure that the core spare parts business is not negatively impacted by the component consumption of other service products. SP2&3 process owner described the implementation of the potential S&OP process:

> *"Basically, all our service products can be planned with S&OP. The level of implementation should be chosen so that it is aligned with the benefits of planning through S&OP for certain products. I mean, if the benefit is little, the planning process should not be too heavy and time-consuming to implement."*

Both focus groups agreed that the proposed five-step S&OP process, developed based on the literature review and benchmark interviews, would be suitable for the case organization. The key role of the front-end LSUs was emphasized, and their commitment to the process was identified as one of the key priorities for the near future. SP3 commercial manager suggested that the commitment of LSUs could be started in key countries where collaboration and sales volume are highest. Sales development lead pointed out that the forecasting responsibility should be as close to the customer interface as possible:

> *"The pressure for sales forecasts should go to LSUs, cause they have the best information. The S&OP process should not go in the direction where forecasts are required from the back-end sales support units. They don't have any better information and are already employed enough in their tasks."*

According to the focus groups, the organization would not require significant organizational changes to begin implementing the S&OP process. Different functions are currently employing S&OP-related practices, such as demand forecasting and capacity planning, on their own. These practices should be integrated to support collaborative planning. No major barriers were identified during the focus groups and the discussion was directed toward initial steps for implementation. Process team lead suggested the next steps which others agreed to:

> *"The most important thing would be to get a mandate from the management and start the process. Once the process is started it can be continuously developed to our needs. Also, in case of better sales information we would be ready to utilize it."*

Commitment and acceptance from management were emphasized as key contributors to initiating the process, as its implementation impacts the planning activities of the entire organization and involves multiple employees. Moreover, the focus groups found that a designated person should take charge of the S&OP process. If S&OP were to be implemented as an additional responsibility on top of existing tasks, it would not receive the necessary attention and effort required for its effective development. It was also suggested that relevant stakeholders should be identified to participate in the initial pilot process, although the ultimate list of participants could be refined later in the meetings.

Table 12: Main findings from focus group sessions regarding S&OP-related topics

Theme	Topic	Findings
Forecasting organization	S&OP suitability	*All service product families of the case organization were identified to be suitable for inclusion in the S&OP process, although the benefit for corrective services was considered less significant* *Involving all service products would be important to understand the overview and to ensure that the core spare parts business is not negatively impacted by the component consumption of other service product families* *The proposed five-step S&OP process would be suitable for the case organization*
	Vertical collaboration	*The central role of the LSUs was emphasized, and their commitment to the process was identified as a key priority. The commitment of LSUs could be started in key countries where collaboration is closest and sales volumes are highest*
	Horizontal collaboration	*Different functions are currently employing S&OP-related practices, such as demand forecasting and capacity planning, on their own. These practices should simply be integrated to support collaborative planning*
	Management support	*Commitment and acceptance from management were emphasized as key contributors to initiate the process*
	Responsibilities	*A designated person should take charge of the S&OP process*
	S&OP pilot	*Simplicity and similarity to benchmarks would be the most important factors in selecting the pilot product family* *The S&OP process should initially be implemented using simple systems. The specific tool is less important than its ability to transfer the forecast data into other necessary planning systems*

The focus groups found that S&OP should be implemented through a pilot project focused on a specific product family. Various service product families were suggested for the pilot, each with different supporting arguments. SP2&3 process owner suggested selecting a pilot product that is relatively easy to forecast and does not require advanced tools, allowing the process itself to be tested and evaluated. On the other hand, product line manager proposed choosing a product family similar to that of the benchmark organization, which would enable the case organization to learn from their experiences and adopt best practices. SP3 commercial manager suggested that a service product with the longest delivery times would be an ideal candidate for the pilot so that the planning element of the process would be emphasized and developed. Overall, the focus groups thought that simplicity and similarity to benchmarks would be the most important factors in selecting the pilot product family. Inventory management specialist described that pilot systems should also be easy to utilize:

> *"It (the S&OP process) would be reasonable to start with simple systems, such as Excels, where the collaboratively collected sales data could be maintained. First, we should put effort in the process before taking a rigid system into use."*

Focus groups agreed that the S&OP process should initially be implemented using simple systems supported by the finding that benchmark organization 2 is still employing simple spreadsheet files at the core of their process. The first focus group continued that the specific tool is less important than its ability to transfer the forecast data into other necessary planning systems.

In summary, the findings indicate that all service product families in the case organization are suitable for the proposed five-step S&OP process, although its benefits for corrective services are limited. Vertical and horizontal collaboration are key areas of focus, with an emphasis on engaging the LSUs in high-collaboration countries. Existing S&OP-related practices, such as demand forecasting and capacity planning, need integration for coherent planning. Management support and a designated leader are critical for successful S&OP implementation. A pilot S&OP project using simple systems should be initiated to refine the process before adopting more complex tools and a wider scope.

5. DISCUSSION

This chapter aims to link the empirical results presented in Chapter 4 to the theoretical background presented in the literature review in Chapter 2. This transition back to the etic level after empirical research is emphasized in the context of interventionist research, as the focus tends to be deeply on the practical development of a given case company (Suomala et al., 2014). Finally, a refined version of the initial framework will be presented, summarizing the digitalization of demand forecasting practices in industrial services.

5.1 Data management for forecasting industrial services

This sub-chapter discusses data management-related findings and answers SQ1: *“What kind of data management is needed to support demand forecasting in industrial services?”* The literature review identified four data types for forecasting demand of industrial services and presented them in Figure 10: historical sales data, knowledge of future events, big data from supply chain, and IBI. Although use cases in demand forecasting were identified for all of them during the empirical section, the practical applicability of big data and IBI was currently low.

Historical sales data is used as a main data source for forecasting in the case organization, as pointed out in interviews by supply team lead and SP2&3 process owner. However, the consensus from interviews and focus groups was that current forecasting practices rely too much on historical data, and more effort should be given to collect future insights. This aligns with existing research emphasizing the limitations of historical data in demand forecasting for intermittent demand patterns (Dekker et al., 2013). Knowledge of future events can be used as input for qualitative expert forecasts or to adjust baseline forecasts.

The focus groups found that accurate information on future sales and probabilities of quotations are necessary for short-term forecasting in the case organization. The collaboration with front-end LSUs was weak, and a limited amount of data was received from the sales for forecasting. Accurate quotation data in CRM was a core asset for the forecasting processes of the benchmark organizations. As sales manager 2 from benchmark organization 2 argued, historical sales data and patterns are not feasible for forecasting complex industrial project orders, as the variation appears to be large. The interviews in the case organization as well as the focus groups implied that the improvement of the quotation data quality is a key priority.

Due to the challenges of collecting accurate IBI, causal methods, typically linked to installed base forecasting in the literature (Van Der Auweraer et al., 2019) cannot be utilized in practice. Applicable methods will be discussed in the next sub-chapter 5.2. While up-to-date information is a requirement for using IBI in forecasting, particularly collecting information on where and how end customers are using their products is challenging (Stormi et al., 2018; Van Der Auweraer et al., 2019). This is in line with the findings of this research where data collection challenges were caused by customers' low registration rate of new machines to the installed base system. Even for registered machines, services such as maintenance may not be documented in the maintenance log, thereby weakening the quality of IBI. The focus groups believed that there should be a way to improve the quality of IBI by collaborating with the end customers.

Supply chains offer a wide variety of data throughout the value creation process, which could be utilized for forecasting purposes (Hazen et al., 2014), as typical challenges, such as data availability and quality could be overcome by applying big data analytics (Hofmann & Rutschmann, 2018). Due to the characteristics of big data (Seyedan & Mafakheri, 2020), advanced techniques involving ML are often necessary for processing and utilizing it (Hofmann & Rutschmann, 2018; Petropoulos et al., 2022; Seyedan & Mafakheri, 2020). Using big data and ML models in forecasting was identified as a promising avenue in the case organization while requiring technological investments.

To conclude the answer to SQ1, the limitations of historical sales data in forecasting industrial services highlight the need for integrating future-oriented data such as quotation probabilities into forecasts. IBI holds the potential for accurate forecasting of industrial services, but current challenges in data quality limit its applicability. Although existing data management tools can support various data types, consistent data quality relies on customer and sales engagement practices. Addressing these challenges requires emphasizing reliable and collaborative data-sharing mechanisms across functions to fully leverage IBI and future-oriented data in forecasting industrial services. While big data also provides promising avenues by capturing extensive information across the supply chain, its effective use relies on advanced techniques beyond data management, which will be discussed next in the context of forecasting methods.

5.2 Demand forecasting methods for industrial services

Four categories of forecasting methods were identified in the literature review to be suitable for the context of industrial services, as presented in Figure 5: statistical methods, judgmental forecasting, ML techniques, and installed base forecasting. This section discusses their feasibility for industrial services, seeking to answer SQ2: *"What kind of characteristics of a demand forecasting model would match the requirements of industrial services?"* While the literature review provided insights into general applicability, the empirical section explored these methods' practical feasibility in a specific contextual environment.

In the case organization, spare parts are currently forecasted through the FSS, which has various statistical models that are chosen based on the classification of the demand pattern. While research on installed base forecasting argues that smooth and intermittent demand forecasting methods overlook the fundamental factors driving spare part demand (Petropoulos et al., 2022; Van Der Auweraer et al., 2019), forecasts generated by the FSS are considered accurate enough. Particularly, since the IBI quality is low, the FSS with statistical models based on historical sales data is necessary. Furthermore, the focus groups found that statistical models could be used to generate baseline forecasts for other service product families as well, although they should not be the basis for forecasting.

Judgmental adjustments were identified as necessary when statistical forecasts are being used as baseline forecasts, as is the case with spare parts forecasting in the case organization. It appeared that occasional adjustments were already made through the FSS, although the lack of communication with the LSUs has kept the flow of additional information limited. To avoid bias, small and overly large adjustments should be avoided (Baecke et al., 2017), as upward adjustments, for example, often stem from the forecaster's over-optimism or wishful thinking (Fildes et al., 2009). SP4 process owner described a similar experience from the case organization, where forecasts were adjusted heavily upward due to a speculative peak in future sales, but the expected peak in sales never occurred.

Both benchmark organizations relied on judgmental forecasts based on quotation data, front-end information gained from LSU meetings, and final evaluation by experts. The consensus within the case organization was to start the transition from using historical sales data to using up-to-date, front-end data through expert forecasts. Previous research has identified volatile market conditions causing challenges for statistical models, as there are no signs of exceptional events in the dataset (Baecke et al., 2017; Goodwin

& Fildes, 1999). The findings of this research would recommend prioritizing judgmental forecasting as the baseline forecast for the process instead of statistical methods.

The focus groups suggested exploring ML models due to their potential to identify demand patterns by utilizing large and various data sources that the organization already has. For example, ML-based models that merge historical sales and quotation data could replace or assist current practices of judgmental identification of trends. Data development lead called for patience so that ML models are not implemented without understanding the reason and benefits. The promising findings of applying big data and ML models in improving forecasting accuracy identified in the literature (Aamer et al., 2020; Carbonneau et al., 2008; Hofmann & Rutschmann, 2018; Seyedan & Mafakheri, 2020) are in line with the empirical results of this research, as its potential for the case organization was identified being worth of further research. However, Makridakis et al. (2020) highlighted the results of time-series studies, where ML models have been less accurate than statistical models, particularly when time-series have been heterogeneous. Utilizing big data through ML models also requires data-related capabilities from the organization, such as data expertise, technological infrastructure, and potential technological investments (Hofmann & Rutschmann, 2018).

In the literature, forecasting methods using IBI are primarily causal models (Figure 5), typically relying on data that is only available after customer registration (Table 5), limiting their current feasibility in the case organization. While empirical findings suggest that IBI could complement baseline forecasts as an additional data source or be a data source for high-level monetary forecasts, using IBI for detailed causal forecasting appears impractical at this time. As the challenges of IBI collection are a commonly identified phenomenon, causal installed base forecasting methods in the literature seem to currently have limited applicability in general.

The focus groups found forecasting metrics enabling continuous development of forecasting processes as well as operational efficiency. Evaluation of forecasting methods was highlighted as a key step in the forecasting process (Armstrong, 2001; Petropoulos et al., 2022). The general forecasting process in Figure 1 had an iterative element going back from the evaluation of methods to the selection of methods. Currently, there is no process for evaluation in the case organization. However, methods such as FVA analysis, mentioned in the literature review, could be useful in the future to assess how single activities, such as judgmental adjustments, contribute to forecasting accuracy.

According to Petropoulos et al. (2022), forecasting methods and their accuracies can be evaluated by benchmarking other methods, using error metrics, or testing statistically.

The focus groups suggested that forecasting the same product family with multiple methods probably leads to more accurate forecasting, supporting the evaluation by benchmarking other methods. Interviewees from the benchmark organizations mentioned that they are tracking forecasting accuracy and errors, but even for forecasting accuracy, the acceptable limit is large. Thus, using error metrics or statistical testing for evaluating forecasting methods in industrial services may not provide significant value to the process.

The FSS in the case organization measures forecasting accuracy and errors and modifies forecasts based on past performance. However, company experts do not actively verify the system's accuracy. While the calculation logic of the FSS is reportedly well understood, the organization's lack of oversight makes the system at least partly a "black box" (Moll & Yigitbasioglu, 2019; Tiitola et al., 2024), as forecasts are accepted without regular evaluation. Previous research has already identified that a forecasting system will be acceptable as long as judgmental adjustments are easily enabled and it is perceived beneficial for all human actors (Fildes & Goodwin, 2021). The focus groups proposed that the measures provided by the FSS should also be regularly inspected in the future so that the organization does not blindly rely on system-generated forecasts without critical evaluation.

To conclude the answer to SQ2, judgmental forecasting based on future-oriented data should be prioritized in industrial services, particularly for short-term forecasting where statistical methods alone often fall short. For longer-term forecasting, statistical methods and installed base forecasting can be valuable, especially for identifying trends in time-series data. While installed base forecasting methods identified in the literature are not currently applicable, IBI retains potential if data quality improves or methods evolve to leverage existing IBI effectively.

Traditional statistical forecasting methods based on historical sales data and supported by FSSs remain relevant, as data-related issues limit other methods. Consistent evaluation of forecasting metrics is important to maintain forecast accuracy and enable continuous development. Additionally, the potential of ML techniques to process large, variable datasets highlights a broader theoretical shift toward AI-driven forecasting models that could combine historical data with real-time insights.

5.3 The S&OP process supporting forecasting in industrial services

The generic S&OP process (Chapter 2.2) is mainly researched from the perspective of traditional manufacturing companies, and this research examined its applicability to industrial services. This section links the S&OP-related empirical findings to the previous research, and seeks to answer SQ3: "*How can a systematic S&OP process support forecasting demand in industrial services?*" Maintaining the scope of the research, the discussion is primarily focused on the overall S&OP process implementation and its role in demand planning.

Focus groups results indicated that while the demand and operations for all service product families could be planned through an S&OP process, the benefits vary by service type, with less impact expected for corrective services. A core finding was that the organization's shift from reactive services toward an increasing share of proactive services, such as preventive maintenance and modernization projects, requires a more systematic planning approach. As companies are in general transitioning from remote monitoring services to optimization, control, and ultimately, autonomous systems, incorporating advanced functionalities (Kohtamäki et al., 2019), S&OP becomes even more valuable for industrial services. Forecasting the entire service portfolio requires separate forecasts for each product family and various forecasting methods. As suggested by Kristensen and Jonsson (2018), dividing S&OP into multiple individual processes could help address the detail complexity inherent in this service-oriented context. While corrective services managed through the FSS may benefit less from S&OP, all service products in a single planning process remains important due to shared warehouse resources, allowing for better coordination of material consumption across product families.

Implementing the generic five-step S&OP process was identified as suitable for the case organization, and the empirical findings provide practical details for the implementation aligned with previous research. While functions already employ S&OP-related practices, these should be integrated to support collaborative planning. Lack of collaboration with front-end LSUs remains a critical barrier, as high-quality front-end data is crucial for accurate forecasting. The planning horizon for S&OP typically spans 3-18 months (Tavares Thomé et al., 2012), though focus groups recommend a horizon starting at one month for short-term needs. The value of planning up to 18 months was identified, although the visibility significantly decreases after two months. Continuous reviews and adjustments are necessary to reflect rapid shifts in service product demand.

Research highlights that constructive engagement can commit all functions to the planning process, even in a case with conflicting objectives, and motivates them to contribute to a unified forecast (Danese & Kalchschmidt, 2011; Oliva & Watson, 2011). This finding may apply to the case organization, as its forecasting process matures in the future. However, focus groups noted that the interest of LSUs in collaboration is low, suggesting that decentralized sales units likely require additional incentives or higher-level pressure to actively participate in S&OP.

To conclude the answer to SQ3, effective short-term forecasting in industrial services requires strong vertical and horizontal alignment, which can be facilitated by a systematic S&OP process. The benefits of implementing S&OP appear to increase as the organization shifts from reactive to more proactive service types. In an organization with a diverse portfolio, separate forecasts and forecasting methods are necessary for different product families, while shared planning helps to coordinate resources.

Regular execution of the S&OP process, with frequent adjustments to forecasts and plans, is necessary to reflect rapid changes in demand. While constructive engagement may encourage all functions to align with the S&OP process, organizations with decentralized sales units may need additional incentives or top-down support to ensure full commitment from the entire sales function.

5.4 Framework for digitalizing demand forecasting in industrial services

The purpose of this chapter is to gather findings from each section of the thesis to create a final framework for digitalizing demand forecasting practices in industrial services, answering the main research question "*How can the digitalization of forecasting enhance demand forecasting practices in industrial services?*" Although the current state analysis revealed that forecasting practices within the case organization were not systematically applied, different functions already utilized various digital tools to support different stages in the forecasting process. Figure 12 presents how digital tools support forecasting in industrial services based on findings from the literature review and the empirical section.

Separate systems for obtaining information highlight the specific needs of industrial services to utilize multiple data sources, tailored for various service products. ML applications can enhance data collection and cleaning in the obtain information -phase, whereas they can be utilized for forecasting models in the next phase to process the large amount of input data. In the final phase, forecasts are transferred to procurement and production plans in the ERP system. In addition, forecasts can be shared with suppliers and other relevant stakeholders through collaboration systems.

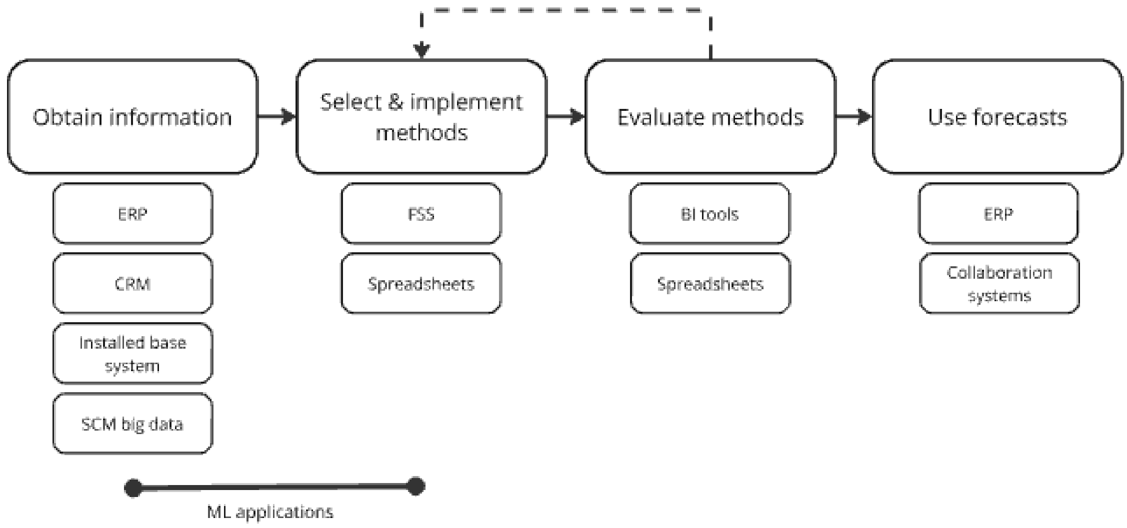

Figure 12: Digital tools along the forecasting process

The illustration of the digital tools along the modified forecasting process in Figure 12 helps industrial service organizations understand how the conversational (Hall, 2010) or the maieutic (Busco & Quattrone, 2018) roles of MA can be sustained. Here, digital tools serve as supporting elements for forecasting practices and communication, not as replacements for human insight. While the case organization currently emphasizes the computation discourse (Tiitola et al., 2024) in the use of the FSS, the need to increase the role of the judgment discourse (Tiitola et al., 2024) was identified, particularly by tracking the performance of the FSS and achieving a balanced approach to MA digitalization. Overall, digital tools were shown to enhance forecasting the large and complex service portfolio of the case organization, thus contributing to the ongoing debate about the potential of digitalization to improve MA practices.

Focus group findings further suggested that the case organization should establish a systematic process for forecasting, enabling continuous development and facilitating the digitalization of forecasting practices. Supply expert proposed that achieving this requires a cultural change toward guided planning practices initiated by the management, ultimately fostering deeper collaboration with LSUs. Korhonen et al. (2021) support this approach by emphasizing the need to comprehensively understand and identify processes before applying advanced digital tools.

Figure 13 presents the final framework for digitalizing forecasting practices in industrial services. The final framework draws on the initial framework by gathering findings from the literature review and empirical section. The S&OP process is proposed to facilitate the systematic monthly planning task. The scope of the S&OP process should be determined according to the specific needs of each organization. Contextual details indicate to practical findings presented in the results chapter.

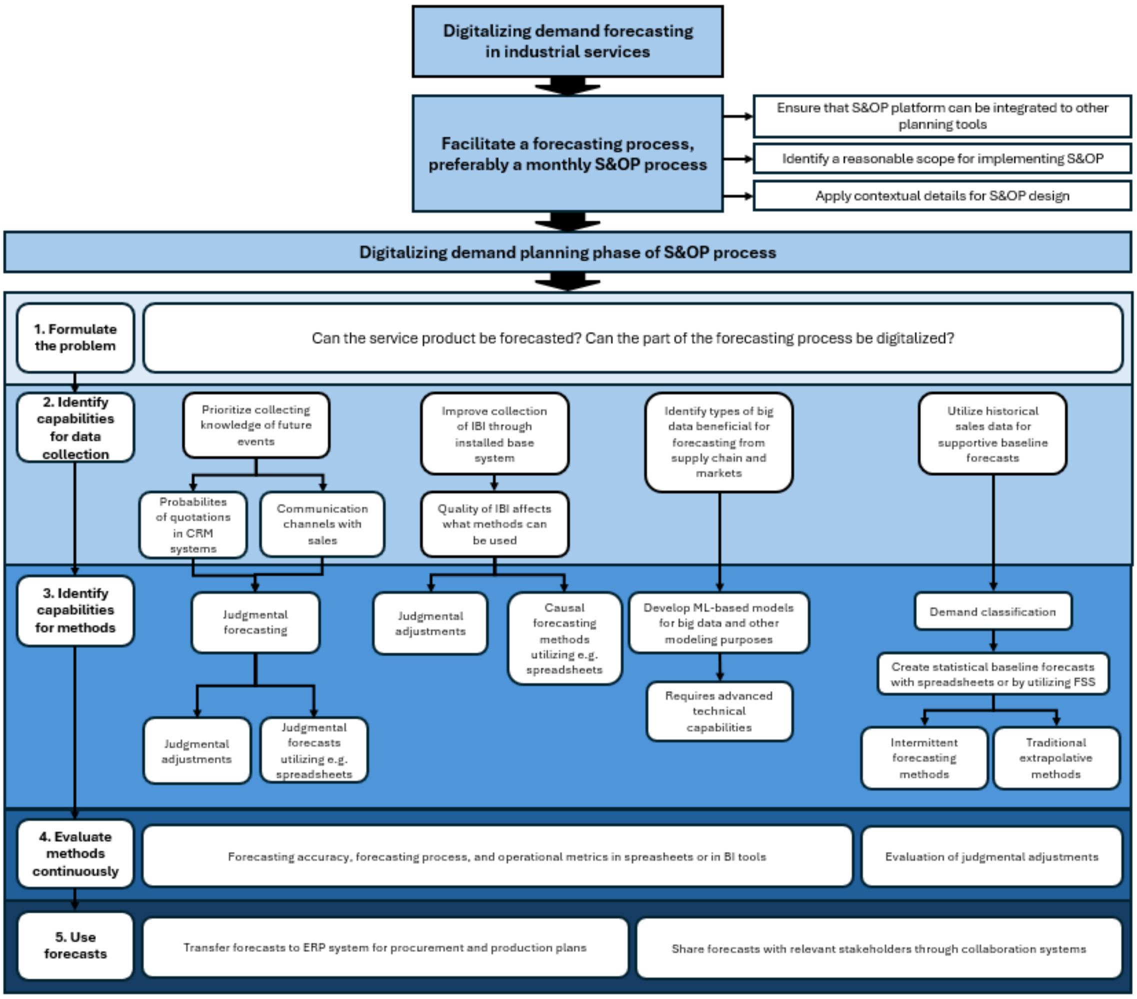

Figure 13: Final framework for digitalizing demand forecasting in industrial services

To conclude the answer to the main research question, this study reveals that digitalization can improve demand forecasting in industrial services by enabling a more structured, data-driven approach across each phase of the forecasting process. By integrating digital tools, industrial service organizations can enhance data collection, refine forecasting methods, and facilitate effective communication, ultimately leading to more accurate and adaptable demand forecasts.

While digitalization enhances long-term forecasting by identifying broader historical trends and leveraging probabilistic data, short-term forecasting may benefit less directly from digitalization alone. Short-term demand often requires immediate, context-specific adjustments based on real-time information, which relies on cross-functional collaboration and engagement. Therefore, a hybrid approach combining digital tools with human judgment is necessary to address the volatility in short-term needs. However, digitalization can improve data collection, which supports short-term forecasting as well by enhancing communication and data-sharing with the front end. By unifying multiple data sources, digital tools enrich data foundation that incorporates historical and future-oriented information. In summary, the proposed final framework highlights that digitalization can support a wide range of activities in demand forecasting.

6. CONCLUSION

This chapter concludes the thesis by presenting its contribution to the research field of servitization, limitations of the study, and suggestions for further research. The objective of the thesis was to examine how digitalization could enhance forecasting practices in industrial services. The thesis approached this objective through a comprehensive literature review and empirical research in a case organization.

The objective of the thesis was achieved by answering research questions in the previous chapter. Particularly, the main research question was addressed in the framework for digitalizing demand forecasting in industrial service in Figure 13.

6.1 Theoretical and managerial implications

This thesis contributes to the ongoing debate on profitable servitization in the industrial sector (Baines & Lightfoot, 2013; Kamal et al., 2020; Brax et al., 2021). Practical difficulties with implementing the servitization strategy lead to challenges in maintaining the profitability and flexibility of the organization (Brax et al., 2021). Addressing these challenges, this study approached the servitization debate from an MA perspective by examining the digitalization of demand forecasting. In doing so, the study contributes to the limited body of literature on forecasting in industrial services (Dekker et al., 2013; Stormi et al., 2018), specifically by focusing on the forecasting needs of base and intermediate services.

This study directly engages with the recent forecasting literature, addressing the gap where advancements in forecasting methods and digital tools have not been realized in practice (Armstrong et al., 2015; Fildes & Goodwin, 2021). By exploring this gap empirically, this study reveals that advanced forecasting methods may not always add value within industrial services due to operational and contextual complexities. Instead, short-term forecasting in such volatile environments requires integrating up-to-date, future-oriented data to provide timely and accurate responses to shifting demand. By drawing on Oliva and Watson's (2011) finding of organizational alignment being at the core of successful forecasting, this study suggests collaborative activities to be particularly important for short-term forecasting. These findings suggest that practical application, particularly in rapidly changing environments, benefits more from collaborative approach and judgmental forecasting rather than from purely sophisticated, complex forecasting models. These findings could be relevant for other industries with similar dynamic and complex characteristics.

In contrast to the challenges of short-term forecasting, advanced methods and digitalization demonstrate advantages for long-term demand forecasting. By leveraging extensive historical data, big data, and IBI, digital tools can identify and track broader trends over time. These long-term forecasts benefit from digitalization's ability to integrate diverse data sources, such as CRM insights and IBI, which provide a more comprehensive view of demand patterns and lifecycle trends.

Furthermore, there appeared to be a lack of understanding of demand planning processes within supply chain companies, and particularly organizational factors had been neglected (Vereecke et al., 2018). By researching various dimensions related to the forecasting process, this study created a framework (Figure 13), which serves as a realistic roadmap for digitalizing forecasting practices. The framework is built for complex characteristics of forecasting industrial services, and the roadmap to digitalization might be more straightforward in different circumstances.

Installed base forecasting has recently received the most attention in the literature regarding forecasting methods for industrial services (Pinçe et al., 2021), and this study contributed to that field, as part of the wider framework. The practicability of installed base forecasting methods provided in the literature is limited, partly due to challenges regarding data management (Stormi et al., 2018; Van Der Auweraer et al., 2019). This study draws on previous research by identifying current data management capabilities in the case organization and providing a more comprehensive overview of the gap between theoretical potential and practical constraints of installed base forecasting.

The field of S&OP has a limited number of studies in different contexts (Kreuter et al., 2022; Kristensen & Jonsson, 2018), and this research may be the first effort to examine the design of S&OP in the context of industrial services. In a wider context, the research contributes to the evolving understanding of S&OP by demonstrating its applicability beyond traditional manufacturing. The results highlight that S&OP can serve as a unifying framework for planning in environments characterized by high service variability and complex demand patterns. The study found the general S&OP process (Wallace & Stahl, 2008) suitable for industrial service organizations and identified key factors for effective implementation. Findings show that the benefits of S&OP increase with a shift from reactive to proactive service types.

The research was conducted in close collaboration with the case organization, ensuring the development of several managerial implications. The final framework helps managers identify possibilities for digital applications and assess their current organizational capabilities for adopting advanced forecasting practices. Many digital solutions are associated with significant technological investments and system integrations, and the framework supports the debate about these kinds of strategic decisions. The framework addresses each phase of the forecasting process, enabling practitioners to set individual objectives for the development of each phase.

The S&OP-related findings of the thesis can help and encourage managers to initiate S&OP processes within industrial service organizations or other similar contexts. The empirical results present practical details for efficiently implementing S&OP. A systematic forecasting process was considered necessary for any developments and the S&OP process would serve this need by facilitating continuous monthly inspection and cross-functional communication. Simultaneously, demand plans can be shared with back-end operations to ensure vertical and horizontal alignment.

In summary, this study contributes to theory and practice by developing a structured approach to digitalizing demand forecasting in industrial services. The study responds to theoretical debates on MA's evolving role in the era of digitalization and addresses specific challenges in applying theoretical forecasting methods in a real-world setting. It highlights how digital tools, when combined with critical human oversight and collaborative processes, can support MA's evolving role in decision-making without compromising its fundamental functions of questioning and facilitating communication (Busco & Quattrone, 2018; Hall, 2010). The framework emphasizes a balanced approach that integrates digital tools at each phase of the forecasting process while retaining human judgment, providing a roadmap for organizations to achieve more accurate forecasting practices.

6.2 Evaluation of the research

In this sub-chapter, the study will be evaluated by the four criteria for defining a trustworthy qualitative study: credibility, transferability, dependability, and confirmability (Shenton, 2004).

Credibility ensures the research findings accurately represent the studied phenomenon (Shenton, 2004). In this study, credibility was enhanced by using well-established methods, such as semi-structured interviews and focus groups, which are widely recognized in qualitative studies. The researcher created credibility through a deep understanding of the case organization and triangulation of data by combining primary and secondary sources. Frequent debriefing with the steering committee prevented researcher bias and enabled a more comprehensive analysis of the findings.

Transferability refers to how well the research findings can be applied to other contexts (Shenton, 2004). The detailed description of the case organization and the forecasting environment contribute to transferability. In addition, the generalizable nature of the proposed framework for digitalizing forecasting in industrial services supports the potential for transferability. While the research was focused on a specific case, the organization was dealing with issues typical for industrial services.

Dependability concerns the stability of the research process over time, allowing future researchers to replicate the study (Shenton, 2004). The methodological choices of the study are presented in detail in Chapter 3, ensuring that the research process is transparent and well-documented. The interventionist research strategy allows iterative adjustments to both the research process and the forecasting practices being developed. Thus, dependability in other organizational contexts is improved, while maintaining a structured approach.

Confirmability addresses the objectivity of the study so that the findings would reflect the experiences of participants instead of researcher bias (Shenton, 2004). The thesis uses triangulation of qualitative methods and data sources to minimize researcher bias. A diverse set of participants from various organizational roles was selected for interviews and focus groups to support the confirmability of the findings. Furthermore, the use of an abductive approach, moving between theory generation and testing, verifies that the findings stem from the research data rather than from the researcher's opinions.

6.3 Limitations and suggestions for future research

While the research was demonstrated to be trustworthy with four criteria regarding qualitative research, the research methodology in this thesis has its limitations. The findings were derived through empirical research in a case organization, representing a certain industry with specific organizational characteristics. While the final framework was constructed to be adaptable and the characteristics of the case organization typical for industrial services, different factors might need to be emphasized in other organizations.

Additionally, the final framework was not evaluated in a real-world setting, which would require performing it as a monthly process enabling continuous development. However, the new framework has been discussed and refined with experts of the case organization in focus group sessions and steering committee meetings, and they recognize a significant potential in it. In fact, a pilot phase has already been initiated within the case organization.

The proposed framework should be longitudinally tested in future research to confirm its actual suitability for industrial services. This could involve studying the performance of S&OP in the context of industrial services, meaning the effect on operational and financial metrics. As this thesis provided a roadmap for digitalizing industrial services, future research could examine forecasting methods more comprehensively within the provided, realistic context. Thus, this is in line with the suggestion by Van der Auweraer et al. (2019), proposing more installed base forecasting studies with real data. ML models should also be studied within a real-life context to further analyze their potential, as they were initially seen as the largest future contributor to forecasting practices.

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APPENDIX A: THE INTERVIEW STRUCTURE

Personal section:

1. Name
2. Title / Current role
3. What are your responsibilities?
4. How many years of experience do you have in this role's field?

S&OP section:

1. What is sales and operations planning (S&OP) in your opinion?
2. How is S&OP implemented in your business unit?
3. How could a more advanced S&OP process improve the operations in your business unit?

Demand forecasting section:

- Data management:
  1. What data sources are used for demand forecasting?
  2. How is the data complemented by internal marketing information, such as upcoming promotions or pricing strategy?
  3. How is the data complemented by external market information, such as market trends and competitive activities?
  4. Are data shared or exchanged with suppliers and customers?
  5. How is installed base information collected and managed?

- Forecasting methods:
  6. What kind of forecasting systems are used?
  7. What kind of statistical methods and models are applied in forecasting?
  8. How could installed base information be utilized in forecasting?
  9. How is human judgement taken into account?

- Management of systems:
  10. How are forecasting systems linked with other systems?
  11. How accessible and user-friendly are these systems for employees?

- Performance management:
  12. How is forecasting accuracy measured?
  13. How do you use forecasting performance metrics to improve the process?

- The forecasting organization:
  14. How deep is functional integration between different business areas?
  15. How committed are different departments (e.g., sales, planning, production) to the forecasting process?
  16. How does management support the forecasting process?
  17. Who is responsible for the forecasting process, and is there a dedicated team?

- People management:
  18. Do forecasters have access to relevant training resources?
  19. How experienced are the forecasters in this area?