CHALMERS

Towards Better Demand Forecasting Using Artificial Intelligence

Bachelor's thesis in Industrial Economy

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Förbättrad efterfrågeprognostiering med hjälp av artificiell intelligens

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PREFACE

This bachelor's thesis was written at the Department of Technology Management and Economics at Chalmers University of Technology. The study is the result of a collaboration with Fortos Management Consulting AB and we want to thank them for their support throughout the whole process. We also want to express our gratitude to the companies that were willing to participate in the interviews, despite the outbreak of covid-19, without them the study would never have been possible. Lastly, we want to thank our supervisor Hafez Shurrab, doctoral candidate at the division of Supply and Operations Management, for his aid and guidance throughout the study.

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SUMMARY

Balancing customer demand and supply capacity is crucial for business survival, especially in competitive environments that are subject to short product life cycles and require minimal waste. Most high performing companies rely on demand forecasting to better balance demand and supply, but still embrace significant errors. In this respect, many emerging technologies are finally becoming mature, opening up a new world of potential improvements that forecasting can benefit from. One of these technologies is artificial intelligence (AI), whereby tasks that previously required human cognition now can be solved better and more efficiently. Therefore, the study aims to increase the understanding regarding the potential improvements AI can bring to supply chain performance in the context of demand forecasting in manufacturing companies.

Related literature was first reviewed to identify baseline knowledge and develop a theoretical framework. Afterwards, interviews with manufacturing companies in the region of Gothenburg were performed in order to gather qualitative data. The results from seven interviews show that AI within demand forecasting is not used to a wide extent in the region of Gothenburg. Businesses that have implemented AI have seen several improvements as a result, while companies still using traditional forecasting methods are facing challenges to realise potential improvements. Multiple prerequisites needed for implementing AI have been identified. Some prerequisites were identified in both literature and interviews, while others only appeared in one or the other.

The conclusion is that AI is expected to improve; *better downstream planning, quick adaptation to erratic demand, increased service levels, decreased working capital, and reduced manual work* by being implemented in demand forecasting. The general prerequisites are; *clean data, sufficient technological infrastructure, available resources, understanding of the improvements AI can bring,* and *sufficient competence of AI*.

Keywords: *Artificial Intelligence, Demand Forecasting, Improvements, Prerequisites, Machine Learning, Operations planning*

Note: The report is written in English.

SAMMANFATTNING

För företags överlevnad är det av stor vikt att balansera utbud och efterfrågan, framförallt på konkurrensutsatta marknader som karaktäriseras av korta produktlivscykler som samtidigt strävar efter minimalt svinn. Trots att de flesta högpresterande företag är beroende av efterfrågeprognostisering för att kunna anpassa utbudet efter efterfrågan, upplever många företag brister med nuvarande prognostiseringsmetoder. Detta i kombination med att nya teknologier nu är redo att användas kommersiellt öppnar upp för potentiella förbättringar som efterfrågeprognostisering kan dra nytta av. En av dessa nya teknologier är artificiell intelligens (AI) som möjliggör effektivare lösningar av uppgifter som tidigare krävt mänsklig kognition. Syftet med denna studie är att öka förståelsen för de potentiella förbättringar som AI kan åstadkomma i försörjningskedjor, inom området efterfrågeprognostisering i tillverkande företag.

Litteratur inom området sammanställdes och analyserades för att få en ökad förståelse för ämnet samt för att etablera ett teoretiskt ramverk. Intervjuer med tillverkande företag i Göteborgsregionen genomfördes för att samla in kvalitativa data. Resultaten från de sju genomförda intervjuerna visar att AI inte är vanligt förekommande inom efterfrågeprognostisering i Göteborgsregionen. Företag som har implementerat AI har upplevt ett flertal förbättringar till följd av implementeringen, medan företag som fortfarande använder traditionella prognostiseringsmetoder har svårare att se vilka förbättringar som kan erhållas. Flera förutsättningar för AI har identifierats, varav några fanns i antingen litteratur eller intervjuer, medan andra förekom i båda.

Slutsatsen är att de förväntade förbättringarna med AI inom efterfrågeprognostisering är; *bättre planering av leveranskedjan, snabbare anpassning till oregelbunden efterfrågan, ökade servicenivåer, lägre kapitalbindning* och *minskat manuellt arbete*. De generella förutsättningarna är; *högkvalitativa data, tillräcklig teknologisk infrastruktur, tillgängliga resurser, förståelse för förbättringar som AI kan åstadkomma* och *tillräcklig kompetens inom AI*.

Nyckelord: *Artificiell Intelligens, Efterfrågeprognostisering, Förbättringar, Förutsättningar, Maskininlärning, Verksamhetsplanering*

Notera: Rapporten är skriven på engelska.

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1. Introduction

Demand forecasting is an important activity for manufacturing companies when deciding on the requirements of production capacity as well as the quantities and timing of material requested from suppliers. For sales forecasts to be useful, it is important to achieve high accuracy. Martinsson and Sjöqvist (2019) state that the forecasting accuracy in the Swedish automotive industry is between 50-90%, which raises a question concerning potential improvements of such relatively low accuracy in the light of promising emerging technologies like artificial intelligence (AI). The potential of AI in demand forecasting is, therefore, a worthwhile area of research. The following sections provide a background on the topic and present the aim and problem formulation of the study.

1.1 Background

According to Chase (2013), forecasting in the last twenty years has become more complex due to the increased amount of entities that need to be forecasted in global, mass producing companies. Given the sheer numbers of products that are being produced, many of which have short life cycles, forecasting has become more expensive and time-consuming, calling for more efficient methods. Additionally, mass-producing manufacturers involve many stakeholders and have a lot of capital at stake (Bozarth, Warsing, Flynn, & Flynn, 2009). Therefore, ensuring low forecasting errors is of high importance. Not least, the globalisation of supply chains has led to increased lead times and more communication barriers between actors, resulting in forecasts of longer timeframes, which are always less accurate (Chase, 2013). In a more fast-paced world, product life cycles shrink, and to avoid having unsaleable inventory, forecasts need to be as accurate as possible.

Huff and Sultan (2014) state that poor forecasting accuracy results in unnecessary costs for companies, which in turn affects their performance. Uncertainty about the future requires a larger inventory in order to satisfy potential orders or needs. Larger inventory implies costs from storage workers, obsolete items, and increased working capital. On the other hand, insufficient safety stock could result in longer lead time and worse customer relations, which could, in turn, lead to loss of potential sales. Other problems that arise from poor sales forecasts are the so-called “Bullwhip effect” (Lee, Padmanabhan, & Whang, 1997) as well as deteriorated supplier relationships (Huff & Sultan, 2014). The bullwhip effect is a phenomenon resulting from information lag within the supply chain causing order and inventory fluctuation to grow larger upstream in the supply chain (Lee et al., 1997).

AI has been receiving high attention in supply chain management research. Problems that were previously assumed to require human cognition, e.g. recognising complex patterns, drawing conclusions, and forecasting, are now solvable with the help of AI-powered machines (Dash, McMurtrey, Rebman, & Kar, 2019). Furthermore, AI within the context of demand forecasting, as a part of supply chains, holds potentials for companies to improve their businesses by developing new strategies and becoming more resource efficient. AI-based forecast techniques can help either by automating forecasting completely or by efficiently processing big data sets, which leads to cheaper, faster, and more reliable forecasts. According to Dash et al. (2019), reaching almost 100% forecasting accuracy is now possible through new advanced forecasting models utilising AI.

Despite the increased attention of AI within supply chain management, extant literature provides limited insights into the potentials AI can bring to supply chains. Yet, there seem to be positive industrial expectations concerning such potentials. Accordingly, the study aims to increase the understanding regarding the potential improvements AI can bring to supply chain performance in the context of demand forecasting in manufacturing companies, in the light of previously mentioned challenges within this area.

1.2 Problem Formulation

According to Min (2010), information about future customer requirements is important to perform capacity planning, inventory control, workforce scheduling, new product development, and promotional campaigns. One way to align the company's strategy with customer requirements is through using the operational performance objectives; speed, quality, cost, flexibility, and dependability (Slack, Brandon-Jones, & Johnston, 2013). The translation of customer requirements into performance objectives could, thus, serve as guidance for the company's strategy towards market positioning and development of competitive advantages. Achieving such performance objectives through the support of proper resource and process deployment needs extensive demand forecasting (Chase, 2013). However, the role of AI in the improvements of these objectives remains understudied, which presents the foundation for the first research question:

1. What type of improvements, related to the performance objectives, are most expected to be achieved by applying AI in demand forecasting?

By answering this question, it is inevitable to touch upon how AI can affect companies, society, and sustainability from a broader perspective. The exploration and development of new technologies for demand forecasting could prove beneficial, but also be challenging (Murray, 2019). Four of the United Nations' global goals have been identified as the most influenceable within improvements of AI in demand forecasting. The identified goals are; Goal 8: Decent work and economic growth, Goal 10: Reduced inequalities, Goal 12: Responsible consumption and production, and Goal 13: Climate action (United Nations, 2020). Answering the first research question will make it possible to discuss how these goals are affected by implementing AI in demand forecasting.

According to Chui and Malhotra (2018), understanding the performance improvements associated with AI is still not enough for implementation. They further state that for companies to take advantage of AI's potentials, it is important to identify the prerequisites that allow for successful implementation of AI in this context. The scope of the study consists of identifying the requirements necessary for implementing AI in demand forecasting that are universal over industries. This leads to the second research question:

2. What are the general prerequisites for applying AI in demand forecasting operations?

By understanding the general prerequisites needed for applying AI, an additional sustainability goal is addressed. Increased understanding of what is needed to successfully implement AI will ease implementation and can thus contribute to achieving Goal 9: Industry, innovation, and infrastructure (United Nations, 2020).

1.3 Delimitations

The study focuses on demand forecasting in manufacturing companies in the region of Gothenburg. Demand forecasting is more critical in manufacturing environments, as opposed to environments that purely rely on purchasing from suppliers, since operations like production capacity and product development, not only inventory, need to be planned in line with demand requirements and variability. This allowed for eliciting insights from a reasonable number of companies where demand is crucial due to the proper complexity level of their operations. The size of the addressed geographical area is limited to the region of Gothenburg to control the results considering the allowed time and resources more practically. Above all, the region of Gothenburg is home for many large and high performing manufacturing companies operating in many industries such as the automotive, aerospace, hygiene and health, and pharmaceutical sectors (Business Region Goteborg, 2020), which increases the transferability of the sample of the study to other similar settings.

The subsequent chapters of the thesis are; literature review, methodology, analysis, discussion, and conclusion. The literature review provides a theoretical framework, identifying improvements achieved by, and prerequisites needed for, implementation of AI in demand forecasting. Further, the methodology describes how the study was conducted, which included a literature review, empirical data gathering through interviews, and data analysis. The results are presented in the analysis chapter, which are then evaluated in a following discussion. Based on the discussion, a conclusion is drawn that answers the research questions.

2. Literature Review

The first section reviews literature describing demand forecasting, its traditional methods, and how it contributes to operational performance objectives. Subsequently, a description of AI follows including two related technologies. The last section presents a theoretical framework based on extant literature concerning improvements and prerequisites when applying AI.

2.1 Demand Forecasting

Larson and Rogers (2015) explain that all industrial companies rely on a supply chain: the "chain" of suppliers, producers, and carriers, both internally and externally making production possible. According to Kilger and Wagner (2008), the goal of supply chain management is to fulfil customer demands. In order to achieve this, many decisions must be made before the customer demands the products, for example, the decision to refill inventory in a store before a customer enters. These types of decisions, where a choice must be made before the customer demand is known, rely on demand planning; the process of forecasting the demand for a product (Jonsson & Mattsson, 2009). According to Chase (2013), demand forecasting is a vital process in a large variety of industries since accurate demand forecasts help in reducing wasted resources in the supply chain. For example, purchasing material quantities and demand-driven production are often based on sales forecasts, and low forecast accuracy implies higher inventory levels and many periods of capacity over- or underutilisation (Jonsson & Mattsson, 2009). Thus, demand forecasting has an impact on many functions like capacity and material planning. Long-term strategic decisions are also based on forecasts, such as expanding to larger offices or constructing new plants (Chase, 2013).

2.1.1 Traditional Methods for Demand Forecasting

The underlying premise of any forecasting method is that the actual demand will follow some pattern, often associated with a trend, seasonality, or causal relationships (Chase, 1997). The pattern is then complemented with some random influences. According to Chase (2013), the forecasting methods can be divided into two main categories, qualitative and quantitative methods. Qualitative methods are defined as "*those that rely on the subjective assessments of a person or group of persons*" (p. 83), and quantitative methods are defined as "*those that rely on past sales history alone or are built on a relationship between past sales and some other variable(s)*" (p. 83). For him, all companies' forecasting methods often contain some subjective judgements. Managers often support judgmental forecasting over quantitative methods, and it is usual that the managers lack familiarity with quantitative methods (Sanders & Manrodt, 2003).

The most common qualitative forecasting methods are independent judgment, committee judgment, sales force estimates, juries of executive opinion (Chase, 2013), and the Delphi technique (Chatfield, 2000). These methods are judgements or estimates done by either individuals or committees in different parts of the organisation based on knowledge and gut feelings (Chase, 2013). Thus, the methods differ in terms of who is performing the forecasts and which operation that oversees it. For example, "sales force estimates" are done by the sales force, and "juries of executive opinion" are done by top management. The Delphi technique distinguishes itself slightly from the other methods since it is an iterative process where a group of experts give their opinion and share feedback with each other in order to reach consensus (Chatfield, 2000).

Qualitative forecasting has three main disadvantages: bias, limited processing capacity, and short-term validity. Forecasts based on qualitative methods tend to be biased towards the individuals that developed the forecasts (Chase, 2013; Caniato, Kalchschmidt & Ronchi, 2011; Sanders & Manrodt, 2003). Additionally, using qualitative methods relies on the limited human capability of considering and processing information since qualitative data is mostly know-how knowledge or textually descriptive (Sanders & Manrodt, 2003). Qualitative methods depend upon observations and understandings of the market trends and dynamics, and due to qualitative methods being subjective, they are not consistently accurate over time (Chase, 2013).

Quantitative methods are divided into the two categories time series and causal (Chase, 2013). Time series methods assume that future sales will follow the same pattern as past sales. Some classes of time series methods are naive or random walk, moving averaging, exponential smoothing, decomposition, and ARIMA. Causal methods rely on the assumption that future sales are closely related to changes in some other variables. The most common causal methods are simple regression, multiple regression, ARIMAX, and unobserved components models.

Quantitative forecasting has three disadvantages: dependency on input data quality and the relationship between the dependent and independent variables, large data set requirements, and low long-term accuracy. The dependency on data implies that quantitative methods are only as good as the data they use (Caniato et al., 2011). Time series methods require large amounts of historical data and adjust slowly to changes in sales, and time series-based forecasts tend to be inaccurate when the forecast horizon is long and if the current data contains large fluctuations. As for the causal models, forecasting accuracy is dependent on the relationship between independent and dependent variables (Chase, 2013). The independent variables need to be identified and estimated accurately and they require more time to develop, a strong understanding of statistics, and large data storage.

Qualitative and quantitative forecasting methods can be combined by first performing both methods independently and, then, combine them, either objectively or subjectively (Sanders & Ritzman, 2004). Objective combining can, for example, be calculating the average between the quantitative and qualitative forecast, while subjective combining takes contextual information into consideration. The combination can decrease the effects of bias, inaccurate assumptions, and model errors. In the best scenario, the combination of the methods will cancel each other's errors. However, according to Sanders and Ritzman (2004), the combination method can lead to a low sense of ownership due to the high objectivity, which is a disadvantage with the method.

To rely on forecasts for decision making, the accuracy needs to be ensured. Accuracy can be measured in several ways, usually by comparing how the forecast differs from previous reference sales data (Fiig, Härdling, Pölt, & Hopperstad, 2014). Common methods for this are; mean deviation, mean absolute deviation, and mean square error. Another common measurement is forecast error bias: an average deviation number indicating if the forecast is optimistic or pessimistic (Enns, 2002).

2.1.2 Performance Objectives

This section describes some performance objectives and relates them to demand forecasting. According to Slack et al. (2013), a business' operations goals can be summarised in five performance objectives: quality, speed, dependability, flexibility, and cost. The objectives serve as guidance for a business to differentiate itself from its competitors.

According to Slack et al. (2013), the performance objective "speed" is defined as the time between the customer order entry to order delivery. For them, fast decision-making and smooth flow of material are key aspects to secure quick response to customers. Aminov, De Smet, Jost, and Mendelsohn (2019) state that speed regarding a company's decision-making process is strongly associated with the company's overall performance. Their study further showed that the companies that made quick decisions were twice as likely to make high-quality decisions, which could hence generate higher returns. Since improved demand forecasting implies greater support to make quick decisions, it arguably leads to improved operational speed performance.

According to Slack et al. (2013), the performance objective "dependability" measures to what extent customers can rely on the supplier to deliver the products or services when needed or as previously agreed. This includes delivering orders, with the right quantities, to the right destinations, at the right time, and as specified by customers and promised by suppliers. Some studies refer to dependability as perfect order fulfilment (e.g. Hofman, 2004). Dependability is often realised through efficient use of resources, which eventually leads to time and money savings (Slack et al., 2013). In this respect, improved demand forecasting can lead to improved dependability provided that the improved forecast accuracy leads to better utilisation of resources.

Slack et al. (2013) describe flexibility as an indicator on how well the supplier can change the process in an operation. This includes the ability to realise time compression or increased production scales to deliver certain orders, the ability to rearrange the production processes to meet heterogeneous customer demand or high product variety, and the ability to show resilience against disturbances. According to Bursa (2013), many markets of today call for substantial flexibility as they are characterised by uncertain demand and fast changes, and to compete in such environments, companies must sense and foresee market changes, where forecasting is crucial, and quickly adapt to these changes.

Lowering costs provides benefits, both in terms of gaining greater profit margins and a competitive advantage, which makes companies less vulnerable to price fluctuations and other causes of instability (Slack et al., 2013). Improving the demand forecasting process along the supply chain can reduce supply chain costs by enabling lower inventory requirements (Jaipurira & Mahapatra, 2014).

Quality as a performance objective depends entirely on customers' expectations on the product or service (Slack et al., 2013). The perceived quality can, in other words, depend on the performance of other mentioned objectives and is thus not addressed as an independent performance objective in the study.

As discussed earlier, improved demand forecasting can lead to improved speed, dependability, flexibility, and cost. The coming sections describe AI and how it can enable improvements in these supply chain performance objectives by improving demand forecasting.

2.2 Artificial Intelligence

AI is a broad concept with a variety of application areas. According to Schuett (2019), the term was first used in 1955, and since then, various definitions have emerged. One of the most used definitions is; AI means *"the science and engineering of making intelligent machines"* (p. 3), where intelligence is defined as *"the computational part of the ability to achieve goals in the world"* (p. 3). Pan (2016) refers to an article where AI is defined as: *"the ability of machines to understand, think, and learn in a similar way to human beings, indicating the possibility of using computers to simulate human intelligence"* (p. 410).

AI has experienced continuous development since its advent and has expanded into several research fields, including machine translation, expert systems, pattern recognition, machine learning, and intelligent control (Pan, 2016). The exploratory research in these fields has led to the development of many technologies. According to Andersen et al. (2019), the development of faster, smarter, and more powerful computers enabled rapid development of AI: *"the technology is increasingly useful for 'cognitive' tasks previously considered restricted to humans"* (p. 8). In previous research, the focus of AI in demand forecasting has been mainly on machine learning and artificial neural networks (e.g. Amirkolaii, Baboli, Shahzad, & Tonadre, 2017; Carbonneau, Laframboise, & Vahidov, 2008; Dash et al., 2019), which is why these two topics are addressed in the study.

2.2.1 Machine Learning

Murphy (2012) defines machine learning as *"a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty"* (p. 1). That is, machine learning provides automated methods for analytics of big datasets. According to Mello and Ponti (2018), the area of machine learning can be divided into supervised learning and non-supervised learning. In supervised learning, the algorithm receives training sets consisting of input-output pairs and intends to converge to the best possible function. The aim is for the algorithm to be able to predict the outputs for previously unseen inputs with high accuracy. Non-supervised learning refers to the process of building up models after analysing the similarities and patterns in the input data.

2.2.2 Artificial Neural Networks

New forms of computing to perform pattern recognition tasks are influenced by the performance of biological neural networks (Yegnanarayana, 2006). An artificial neural network is a simplified model of the structure of the biological neural network and consists of interconnected processing units. A processing unit consists of two parts, a summing part, and an output part. The summing part receives several input values, weights them, and calculates a weighted sum. The output part produces a signal from the weighted sum. Since several processing units are interconnected within an artificial neural network, the inputs to a processing unit may come from the outputs of other processing units or external sources. The units are connected to each other by links which are associated with weight values, and the amount of output of one unit received by another depends on the strength of the link (Yegnanarayana, 2006).

2.3 Artificial Intelligence in Demand Forecasting

This section reviews potential improvements and prerequisites related to AI, which are then synthesised into a theoretical framework.

2.3.1 Improvements of Demand Forecasting using Artificial Intelligence

According to Dash et al. (2019), AI can contribute to accurate and reliable demand forecasts by processing, automatically analysing, and predicting great amounts of data. The authors also emphasise that the application of AI in demand forecasting does not only incorporate historical sales data but can also use near-real-time data to improve forecasting accuracy. Such data can be prices, advertising campaigns, local weather forecasts, or any data regarding variables connected to changes in demand. Furthermore, AI reduces manual work which facilitates companies' usage of data to make predictions, leading to reduced costs for making predictions (Duan, Edwards, & Dwivedi, 2019).

A more accurate and reliable forecast, achieved by using AI, allows businesses to optimise their sourcing, which helps reduce costs related to transportation, warehousing, and administration (Dash et al., 2019). A comparison of forecasting accuracy in demand, using traditional methods versus a method based on machine learning, made by Feizabadi and Shrivastava (2018), illustrates how accuracy in demand forecasting can increase by using machine learning. When applying machine learning, the accuracy of demand forecasts was improved by 6,4% on average, which led to a progress in working capital efficiency. The authors further state that the bullwhip effect can be mitigated to some degree when using machine learning in demand forecasting. When the bullwhip effect is mitigated, inventory fluctuation can be decreased (Yungao, Nengmin, Ada, Yufei, & Jinpeng, 2013), which can lead to reduced inventory costs.

According to McKinsey (2017), implementing AI in demand forecasting can decrease forecasting errors by 30-50%. AI enables access to real-time data, which can be used to adjust the forecasts automatically and continuously, leading to improved availability of products. Therefore, the stock-out situations are expected to decrease, reducing the costs of lost sales by up to 65%. In addition, AI handles unforeseen events efficiently by flexibly adapting to changes in the product mix or distribution network. Furthermore, transportation and administration costs can be decreased with more accurate forecasts.

AI can be useful when forecasting products or services with rapid changes in demand, since it enables quick responses to the changes (Calatayud, Mangan, & Christopher, 2019; Praveen, Farnaz, & Hatim, 2019). Hence, AI contributes to a self-thinking supply chain with great agility, adaptability, speed, and responsiveness. Efendigil, Kahraman, and Önüt (2009) also discuss the usefulness of AI in the form of artificial neural networks. The authors state that artificial neural networks, compared to quantitative forecasting methods, are more efficient for data affected by the special case, such as unforeseen events or promotion. This allows companies to be flexible and prepared for quick changes.

A more accurate forecast, accomplished by applying AI, can also lead to reduced inventory costs (Amirkolaii et al., 2017). Errors in demand forecasting means a difference between the forecasted demand and the actual demand, and according to Praveen et al. (2019), these errors can lead to high inventory costs, which could have been avoided with a more accurate forecast.

The article describes a model, utilising artificial neural networks, that was developed to increase the forecasting accuracy.

By using the model, minimising the mismatch between supply and demand, and hence the related costs, was possible, leading to an increase of the profit margins. Moreover, Ali, Sayin, Woensel, and Fransoo (2009) support this standpoint by concluding "*...it is clear that the accuracy of the forecast directly contributes to higher profits by reducing stock-out situations and lowering the level of safety inventory*" (p. 12 340). Below, Table 1 summarises the improvements that are achieved by implementing AI in demand forecasting and presents the first part of the theoretical framework. The improvements are linked to the corresponding performance objectives.

Table 1: Summary of the improvements that are achieved by implementing AI in demand forecasting. The improvements are linked to the corresponding performance objectives.

Performance objective	*Improvement*	*Description*	*References*
Speed	Quick response to demand changes.	With AI, the supply chain becomes more agile, and responds more quickly to market demand.	(Calatayud et al., 2019) (Praveen et al., 2019)
Dependability	Reduced understocking.	Applying AI in demand forecasting improves the availability of products.	(McKinsey, 2017)
Flexibility	Quick response to changes in product mix.	AI techniques are efficient for data with high variability. AI can handle data influenced by special cases which enables flexible adaptation to product mix in case of unexpected events.	(McKinsey, 2017) (Efendigil et al., 2009)
	Quick response to changes in distribution networks.	AI tools enables flexible adaptation to distribution networks in case of unexpected events.	(McKinsey, 2017)

Cost	Reduced inventory costs.	By using AI, forecasting accuracy is improved, and the bullwhip effect is mitigated. Higher accuracy will optimise the inventory level, leading to reduced inventory costs.	(Amirkolaii et al., 2017) (Feizabadi & Shrivastava 2018) (Praveen et al., 2019) (Ali et al., 2009)
	Reduced cost for demand planning work and administration.	AI technologies make organisations' demand forecasting work more efficient, which lead to reduced costs of making predictions.	(Dash et al., 2019) (Duan et al., 2019) (McKinsey, 2017)
	Reduced transportation costs.	A more accurate forecast, achieved by using AI, leads to optimised transportation planning, reducing the costs related to transportation.	(Dash et al., 2019) (McKinsey, 2017)

2.3.2 Prerequisites for Adopting Artificial Intelligence in Demand Forecasting

Extant literature shows that prerequisites needed for adoption of AI within a business can be classified into different categories. For example, Giada, Rossella, and Tommaso (2020) use the classes; *Technological*, *Economic*, *Organisational*, and *Cultural* when classifying barriers for implementing predictive maintenance. These classes were deemed suitable for mapping the prerequisites in the study. However, due to the complex nature of AI, the category *Knowledge* was added in order to appropriately classify the prerequisites related to adoption of AI.

Nilsson and Gerdtham (2018) argue that sufficient quantity and quality of data is the most vital constituent for problem solving using machine learning, and that incomplete data generates unreliable results from the AI algorithm. Chui, Manykia, and Miremadi (2018) add that the data must be labelled to be usable for machine learning. 24% of the respondents in their study claimed that "lack of available data" was a significant barrier in adopting AI, and 20% claimed that "limited usefulness of data" was another significant barrier. This further strengthens the argument that accessibility and quality of data is essential. Boone, Ganeshan, Jain, and Sanders (2019) state that sharing data between key suppliers can be an enabler in accessing valuable data in the supply chain. However, gathering or creating large amounts of data can be difficult for businesses since every new potential use case will need a new dataset, which challenges existing technological infrastructure for data storage (Chui & Malhotra, 2018).

To handle all the data, Nilsson and Gerdtham (2018) claim that the collected data need to be consolidated in data warehouses for the business to ease availability and get an overview of the data. This means that reliable infrastructure must be in place for the company to be able to store and quickly access the data. Furthermore, Makridakis, Spiliotis, and Assimakopoulos (2018) present that machine learning methods require significantly more computational capacity than traditional quantitative methods. Implementing machine learning methods effectively means increasing businesses' computational infrastructure for demand forecasting or finding ways to reduce the methods' complexity. This would require testing in order to decide on the trade-off between accuracy and lowered computational time. Chui and Malhotra (2018) found that 25% of respondents answer that "lack of supporting technological infrastructure to support AI" is one major barrier to adopting AI in their business.

Ali et al. (2009) found that performing demand forecasting with machine learning techniques can increase accuracy during periods with promotions, but it also brings additional costs. Data preparation, maintenance, and setup costs prevent adoption of new demand forecasting methods. Data preparation costs are significant and dependent on the model's complexity and the amount of data needed. Makridakis et al. (2018) found similar results showing that machine learning forecasts require extensive data pre-processing for optimal results.

One technical obstacle of new advanced forecasting techniques using machine learning is the lack of traceability. Makridakis et al. (2018) explain that further work is needed to assist forecasting practitioners in understanding how machine learning methods are generated: *"Obtaining numbers from a black box is not acceptable to practitioners who need to know how forecasts arise and how they can be influenced or adjusted to arrive at workable predictions"* (p. 20). Chui et al. (2018) refer to this issue as "the explainability problem", which arises from that deep learning and large or complex AI models have become opaquer. Because of this, explaining how, why, and when a decision was reached is difficult. In order to overcome this obstacle, one prerequisite for implementing machine learning in forecasting is sufficient technological competence within the company.

Andersen et al. (2019) argue that knowledge regarding the benefits of integration of AI in businesses is one of the necessary building blocks for the adoption of AI. Furthermore, the authors claim that top management needs a coherent strategy and a long-term vision to benefit from adopting AI at a large scale, which is only attainable if the top management has a holistic understanding of the technology and its benefits. AI capabilities must hence be integrated into the core of the organisation to realise the technologies' full value potential. Lorica and Nathan (2019) confirm that the most prominent bottleneck that prevents the adoption of AI is that the company culture does not recognise the potential of AI technologies.

Chui and Malhotra (2018) point out that one of the most significant prerequisites for successful adoption of AI within a company is the technical competence required for AI technologies. The authors state that 42% of the respondents experience a need for this competence. The lack of skilled employees is one of the key factors slowing down the adoption of AI within organisations (Lorica and Nathan, 2019). Further, the employees' willingness to change is of high importance to achieve a successful adoption of AI (Duan et al., 2019). Human decision makers are more likely to accept AI if it is viewed as an assisting tool for decision making, rather than as an automated decision-making process. A summary of the overall prerequisites for implementing AI is presented in Table 2, which constitutes the second part of the theoretical framework.

Table 2: Summary of the prerequisites for adopting AI in demand forecasting.

Class of prerequisite	*Prerequisite*	*Description*	*References*
Technological	Data availability and quality of data.	The data needs to be accessible, clean and of high quality.	(Chui et al., 2018) (Nilsson & Gerdtham, 2018)
	Sufficient technological infrastructure.	The technology needs to be able to store, access and process available data.	(Chui & Malhotra, 2018) (Makridakis et al., 2018) (Nilsson & Gerdtham, 2018)
Economic	Available economic resources to adopt AI.	Cost due to data preparation, system maintenance and setup of complex models.	(Ali et al., 2009) (Makridakis et al., 2018)
Knowledge	Awareness of the benefits of AI.	Top management needs to have a holistic understanding of the benefits with AI.	(Andersen et al., 2019) (Lorica & Nathan, 2019)

	Technical competences required for AI.	For successful adoption of AI, there is a need for appropriate competencies about AI technologies within the company.	(Andersen et al., 2019) (appliedAI, 2018) (Chui & Malhotra, 2018) (Chui et al., 2018) (Duan et al., 2019) (Lorica & Nathan, 2019) (Makridakis et al., 2018)
Organisational	Top management's ambition to change.	The organisation must recognise the need for AI and have a leadership with high commitment to AI.	(Andersen et al., 2019) (Chui & Malhotra, 2018) (Lorica & Nathan, 2019)
	Overarching AI strategy.	There is a need to understand how and where AI can be applied within the organisational structure.	(Andersen et al., 2019) (appliedAI, 2018) (Chui & Malhotra, 2018)
	Integration of AI into the core of the organisation.	AI capabilities should be integrated into the core to promote the value potential and buy-ins that the organisation does.	(Andersen et al., 2019)
	Sharing of data between stakeholders in the supply chain.	Sharing of data between trading partners and stakeholders can improve visibility since more data is available.	(Boone et al., 2019)
Cultural	Employees willingness to change.	It is important for employees to accept the different roles AI can play in the decision-making process.	(Duan et al., 2019)

3. Methodology

The methodology of the study consists of four major sections; research design, literature review, empirical data gathering, and data analysis. Research design describes the selected method and provides an outline for the following sections. The literature review presents the state of the art concerning the usage of AI in demand forecasting and resulted in a synthesised framework that was used as an instrument to guide the empirical data gathering and the data analysis.

3.1 Research Design

In order to answer the research questions, it is necessary to identify what improvements are expected and what prerequisites are general. According to Paré, Trudel, Jaana, and Kitsiou (2015), a literature review can be used for evaluating tendencies appearing within a research field. The literature review covers the topics; demand forecasting, artificial intelligence, and artificial intelligence in demand forecasting. The identified tendencies were used to synthesise a theoretical framework, which in turn was used as a guidance to collect and analyse the empirical data and to answer the research questions.

Answering the research questions requires an in-depth analysis of companies' perceptions of, and opinions about, improvements and prerequisites. According to Kothari (2004), a subjective assessment of attitudes and opinions can be achieved by conducting qualitative research. Based on this, a qualitative approach seemed appropriate and was selected for the study. To collect the necessary primary qualitative data of opinions, attitudes, experiences, processes, behaviours, or predictions, interviews are suitable (Rowley, 2012). Hence, interviews with industry representatives were conducted. The methodology of the study is summarised in figure 1.

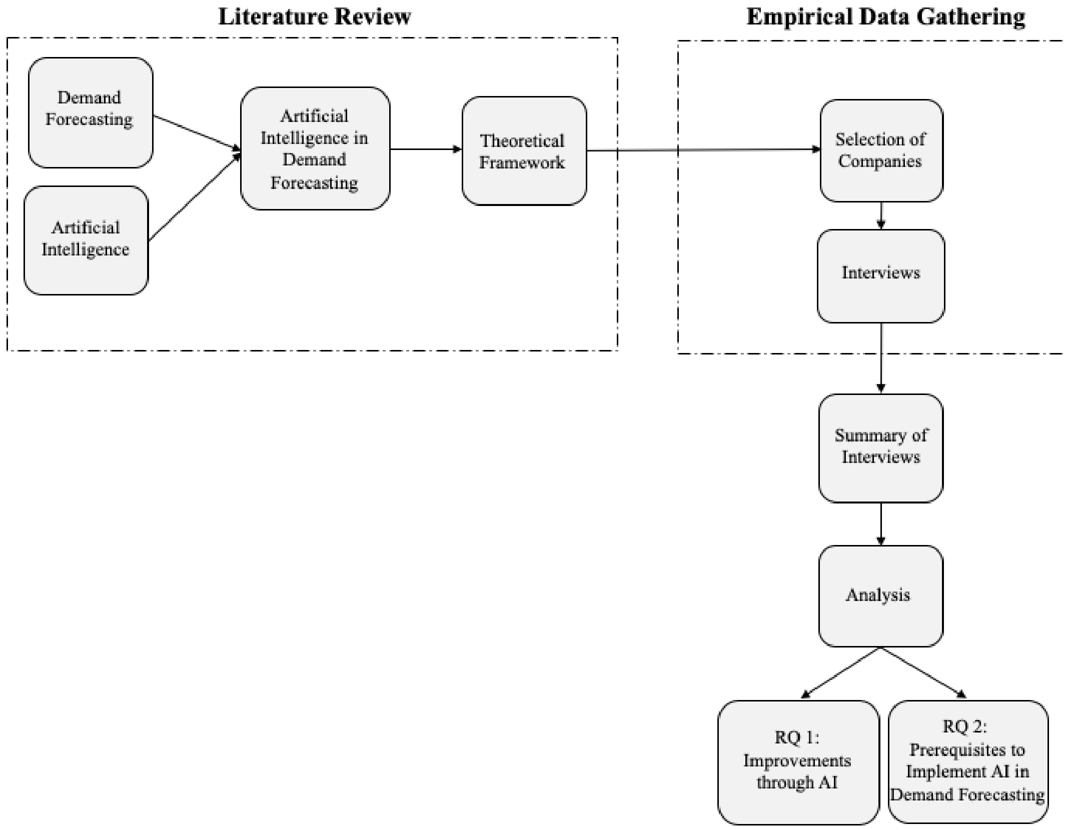

Figure 1: Summary of the methodology of the study.

3.2 Literature Review

The literature review mainly addressed academic articles about the usage of AI within demand forecasting, collected from databases such as Google Scholar, ProQuest platform, Scopus, and Dawsonera. Some examples of keywords that were used are "Improvements of Demand Forecasting using AI", "Artificial Intelligence", "Implementing AI in Demand Forecasting", and "Prerequisites for Implementing AI". In addition, reports and independent publications were also used. The result of the review is a synthesised theoretical framework that classifies the potential improvements and prerequisites of AI implementation in demand forecasting. The identified potential improvements were classified in terms of the contribution to the performance objectives (i.e. speed, dependability, flexibility, and cost), while the identified prerequisites were classified in terms of their types as; "Technological", "Economic", "Knowledge", "Organisational", and "Cultural". The framework served as a baseline for the interview guide.

Several methods can be used to improve the validity and reliability of a literature study. According to Glesne (2011), one approach is triangulation, using multiple sources to assure that the information is supported by several publications. Another one is using peer-reviewed literature, which will be prioritised since the information has been approved by other researchers and thus can be considered credible. These methods were applied in the literature review.

To ensure the reliability of the academic sources, the publications were evaluated based on the corresponding number of citations, and the respective academic journals were evaluated based on the corresponding impact factor. The reliability of the reports and independent publications, on the other hand, were not assessed based on the number of citations since recent publications would be disadvantaged. Instead, they were considered trustworthy since they were recommended by the supporting consulting firm.

3.3 Empirical Data Gathering

Empirical data was gathered by conducting interviews with companies, which were selected based on the three criteria; nature of operations, size, and geographical location. The selected companies needed to be large manufacturing businesses located in the Gothenburg area. It was of importance that the companies were of considerable size since that implies a higher complexity of their supply chains. These selection criteria provide a foundation for mapping the usage of AI in demand forecasting in the designated region. Lewis (2009) argue that usage of multiple sources, such as several interviews, improve the external validity, which refers to how well the results can be generalised across social settings. To achieve external validity, an interview-based study with seven companies from different industries were conducted. Below, Table 3 summarises the companies interviewed, where the company names are exchanged for generic names.

The interviews were conducted as semi-structured interviews since this, according to Rowley (2012), gives room for a comparison between interviews and the possibility for the interviewee to elaborate on certain topics, in order to gain further insights. A semi-structured interview is described as a combination of a few well-formulated open/closed-ended questions. Furthermore, the approach allows for some flexibility during the interview, including spontaneous follow-up questions, and changing the order or the questions asked. Seven interviews were conducted, with an average duration of 40 minutes, where the interviewees all worked within decision making in demand forecasting. Supplemental information regarding the companies, such as; market areas, customer base, and product portfolio, was collected from their respective websites. This contributed to a greater understanding of the companies and made it possible to triangulate certain findings from the interviews.

Table 3: Summary of the interviewed companies.

Company	*Title of interviewee*	*No. of employees world-wide*	*Description of product portfolio*
Gauging Solutions AB	Head of the order and production planning department	8 500	Products for level measurement in the three business areas; marine, tank, and process.
Core Drill Motors AB	Central demand planner	2 300	Manufacturer of machines and tools for the construction industry.
Hygiene Goods AB	Global demand planning excellence director	47 000	Personal care, consumer tissue, and professional hygiene.
Radar Solutions AB	Project engineer responsible for forecasting and data management	16 000	Radar solutions.
Welding Tools AB	Supply chain development manager	8 700	Welding and cutting tools.
Supply Chain Solutions AB	Environmental and quality manager	7 000	Printing and supply chain solutions.
Medical Products AB	Global supply chain planning director	8 000	Disposable healthcare products, surgery products, washing fluids, and operating room solutions.

Internal reliability refers to how well interpretations of the data match (Bryman, 2012). To ensure internal reliability, three group members were present in each interview, and in addition, the interviews were recorded in case of missing details. The interviewees were also given the opportunity to confirm the interpretation in order to further improve the internal reliability of the empirical data gathering and data analysis. The three group members that were present discussed and summarised the results in direct connection to the interviews to avoid variation of interpretations. This enhanced internal validity regarding both the empirical data gathering and data analysis, which refers to the reliability of the conclusions drawn from the study (Slack & Draugalis, 2001).

According to Bryman (2012), external reliability means to what degree the study can be repeated. Since the common knowledge about AI implementation in demand forecasting may differ in the future, the external reliability of the data cannot be guaranteed. Regarding the interviews, some ethical challenges need to be taken into consideration. To prevent breaches of personal privacy and leakage of sensitive information, the companies and employees interviewed are kept anonymous.

3.4 Data Analysis

The empirical data analysis was conducted using a content analysis, where the first step was to compile the interview responses into texts, and the recordings were used to complement any missing information. Flick, von Kardorff, and Steinke (2005) state that content analysis is useful for structuring communicative material. Further, a content analysis aims to sort out various parts of the material, which can then be compared with each other and analysed based on predefined criteria, i.e. the theoretical framework in this study.

In the second step, the interview notes were used to summarise the primary narrative of the detailed interview, while the reflections and perceptions of the other interviewing participants were used to corroborate this narrative. When discrepancies were found, the interviewees were referred to. Moreover, the detailed interview description was reviewed by the interviewees to obtain higher accuracy. As for researcher biases, one student analysed the data of the interviews using the theoretical framework, and the students jointly assessed and refined the elicited improvements and prerequisites of AI implementation in demand forecasting. Accordingly, the final interview-based answers to the research questions were introduced after iterations of inductive coding as recommended by Glaser and Strauss (2017). For instance, to identify the potential improvements of AI implementation in demand forecasting, the relevant text was coded and, if applicable, related to the theoretical framework categories. To ensure the relevance of the improvements, they needed to have an impact on the performance. Evidences from the data of the interviews needed to motivate how AI led or may lead to increased or reduced performance.

Apart from the answers elicited from each interview, the reasoning for the difference between the perceived answers across that interviews was done. Primarily, aspects representing the planning environment and demand forecasting process at each company served as dimensions. For instance, when an interviewee, unlike interviewees from other companies, downplays the improvement role of AI implementation in demand forecasting at his or her company, aspects like demand variability, and market conditions may explain such opinions. That is, comparable aspects across interviewees were also considered to provide a further contextual understanding of the interview-based answers to the research questions.

4. Analysis

The following sections include a summary of the interviews and an analysis of improvements and prerequisites. In the summaries the company names are disguised, due to confidentiality reasons, representing their area of operations. The interview answers are compared with each other in the analysis of improvements and prerequisites.

4.1 Summary of Interviews

This section presents the results from the interviews, where each company is represented below their respective subheading.

4.1.1 Gauging Solutions AB

At Gauging Solutions AB, the demand is generally even, with small increases at closures. The demand is also affected by the size of ongoing projects. The company sells its products through hubs around the world and does not communicate directly with the end customers. Their forecasts are, therefore, based on forecasts received from the hubs but can be manually modified based on subjective judgment. According to the interviewee, there is potential to improve the demand forecasting method, especially through better communication between the hubs and Gauging Solutions AB. Today, the hubs and the company use different ERP systems, leading to inefficient communication, and a highly prioritised improvement is, therefore, to establish a more coordinated business environment.

AI is not used in demand forecasting or any other area today. However, the company is currently working on a project to implement AI within the shipping department. AI implementation is also a part of Gauging Solutions AB's long-term strategic plan. The interviewee does not perceive Gauging Solutions AB to be an industry-leading company in the area of AI, but since they act within a technologically intensive field, it is of importance to stay updated.

The interviewee believes that the most important possible improvements enabled by AI relate to cost savings derived from reduced manual work and more accurate forecasts. When discussing prerequisites needed for implementation of AI, the interviewee mentioned two major factors; overcoming technical difficulties and allocation of resources to AI-based methods. The technical difficulties are due to the company's small IT department, and in order to implement AI, there is a need for external assistance. Moreover, Gauging Solutions AB needs to prioritise and allocate internal resources to make an implementation of AI possible.

4.1.2 Core Drill Motors AB

The demand for Core Drill Motors AB is seasonally even but with slightly higher demand in the summer since the company's customers often work outdoors. This is, however, not considered when forecasting demand. Core Drill Motors AB is currently moving away from qualitative forecasts to quantitative statistical models. An ERP system is used to aggregate the forecasts for every regional warehouse. They use several different key performance indicators to decide forecasting accuracy, and today they have 70-80% forecast accuracy. They tend to generally overestimate the demand and the interviewee believes this is because the regional sales offices want to be sure that they can deliver what the customer demands. The statistical method is used when the sales office generally has low accuracy, and, then, the demand is estimated using, for example, moving average or exponential smoothing. Core Drill Motors AB has seen an improvement in forecasting accuracy after the implementation of statistical models. However, improvements related to the increased forecast accuracy are not yet apparent due to the current implementation.

The company does not use AI in their forecasting and the interviewee believes that the competence and knowledge about AI within the organisation is almost non-existent and very low compared to competitors. Furthermore, management attention regarding the potential of improving supply chain performance is necessary, which the interviewee believes is an issue that has been addressed lately. Also, financial capital is required, and the team needs to be keen and competent for the implementation to be successful. The interviewee cannot estimate the impact of AI in demand forecasting but believes it has potentials. The potential from improved forecasting accuracy lies mainly in decreased inventory levels which ties a lot of capital and freeing the workforce from certain tasks that AI can perform.

4.1.3 Hygiene Goods AB

Hygiene Goods AB has a broad product portfolio and therefore their demand is varied and depends on the specific product. The demand of consumer goods is erratic and highly affected by promotions, for example in the case of toilet paper, while the demand for the remaining products is more stable. In the past, Hygiene Goods AB performed demand forecasting based on manual input. Recently the company implemented a statistical forecasting method, which is based on around 40 algorithms using several variables as input. The statistical method improved the company's forecasting accuracy by 2-3% yearly, measured in mean percentage error, in most of the business areas.

Last year, the company implemented a solution based on machine learning as a forecasting method, in the business area of consumer goods. As previously mentioned, the demand of consumer goods is highly erratic, leading to complex forecasting. By implementing machine learning it was possible to add the parameter of price point in promotion, resulting in more accurate forecasts. Since the implementation last year, the company has experienced an 8-9% improvement of the accuracy. The interviewee explains the company's positive experience of using AI in the challenging times due to covid-19: "*... using AI, we can naturally predict much better because things are changing daily*" (19th of March 2020).

Hygiene Goods AB has a global manufacturing process with shared resources among the plants. With higher forecasting accuracy the company can allocate the shared resources more efficiently and to the right places, leading to better downstream planning and increased service levels. The resources are allocated to the products with the most accurate forecasts, since these products are most likely sold. Furthermore, the improved accuracy enables decreased working capital in terms of lower safety stocks.

The interviewee pointed out two major prerequisites needed when implementing machine learning in demand forecasting; clean data, i.e. correct and relevant, and overcoming the problem of people not trusting the outcome. To overcome the leap of faith in people not trusting the outcome from the forecasts generated by machine learning, the company focused on showing the improvements. By comparing the results from the manual approach with the machine learning approach, the company could prove to the employees that manual intelligence did not add any value to the forecasts. In relation to the overall industry and based on Hygiene Goods AB's size as a global actor, the interviewee perceives their maturity in AI as very low. Compared to their competitors, the interviewee believes that the company is not in the leading position, but that they are two thirds on the way to catch up.

4.1.4 Radar Solutions AB

The process of obtaining an order within this industry is long and the demand fluctuates. A single deal can take several years from starting a discussion to placing an actual order. Due to this, forecasting occurs on a six-month basis through a “business case review”, which the interviewee believes is too seldom. The forecasts are based on the possibility of a deal going through and the different deals are categorised as “safe” or “less-safe”. These deals are then analysed by the company’s ERP system and a basis for production and purchasing is made. Although the interviewee believes that significant improvements can be made due to flaws in the current forecasting methods, the accuracy is not measured today since it is not prioritised by the management.

As for today, AI is not used for any activity within the company related to the supply chain. The interviewee believes that the use of AI within demand forecasting could provide benefits to the company by enabling the handling of big data sets. This could then be used to optimise order quantity and shorten the project lead time. However, he adds that AI would most likely require large investments, but he is certain that the lowering of costs will make up for it significantly. The use of AI within demand forecasting could also provide real-time forecasts which should be more accurate than six-months since a lot can change within such a long period. Radar Solutions AB is somewhere in the forefront regarding the knowledge of AI, since their radars are using it tremendously. However, AI is mainly used on a product-specific level and not on a company level.

Although the company is at the forefront of AI knowledge, the interviewee still points out that the major barriers are knowledge and top management’s incentives to make use of it. To overcome these barriers, the interviewee suggests that the technology should be visualised to create awareness of the technology, especially among the top managers. By doing so, the managers may see greater incentives to invest in such technology. The biggest difficulty with an eventual implementation of AI-technologies should be, according to the interviewee, to modify or replace the current ERP system in order to customise it to these new AI solutions, hence it puts high demands on the company providing the system.

4.1.5 Welding Tools AB

According to the interviewee, the yearly demand at Welding Tools AB is smooth for most products and mainly correlated with the economic cycle. At present, Welding Tools AB does not use AI in demand forecasting. Instead, they use computerised statistical forecasting methods that predict future demand based on historical sales data, along with other parameters. The forecasts can then be adjusted manually by planners if anomalies are spotted. Forecasts are made for both individual stock keeping units and on aggregated levels over product families. The company performs long-term planning on a timeframe of 12-24 months, while they also perform short-term planning to support operational decisions by using forecasts.

The company perceives that they have a satisfactory forecast accuracy and do not fully understand the possible improvements AI could bring. The forecasting error lies within a few percent and the company has chosen to keep a larger safety stock instead of trying to improve the accuracy. Having that said, Welding Tools AB has not yet investigated the possibility of AI-assisted forecasts and does not see the potential benefits from it.

The interviewee believes that several prerequisites inhibit adopting AI-based forecasting. Foremost, Welding Tools AB does not prioritise improving forecasting accuracy over utilising their limited resources in other areas that can be more critical from a competition perspective. Besides, Welding Tools AB has a concern regarding the perceived lack of traceability using AI, arguing that there must be a clear explanation and motivation behind all decisions in their demand planning. The company is not yet focusing on evaluating new forecasting methods, nor aiming for utilising AI in other parts of the company. However, they consider themselves open for using AI in the future, if resources are available and the benefits outweigh the investments.

4.1.6 Supply Chain Solutions AB

Supply Chain Solutions AB uses an ERP system to first compile the customers' forecasts and then perform a subsequent requirement planning. The ERP system can provide demand forecasts for time periods of six months, for example, and it can be great variation in this demand. The interviewee claims that the forecasts' accuracy is insufficient, and that the forecasts often need to be adjusted manually based on experts' judgements. The poor accuracy also contributes to high inventory levels and therefore the company experiences a need for improving their forecasting process.

AI is not used in the company's demand forecasting today, but there is an interest in the technology and how it may improve the process. One potential improvement the company sees is reduced inventory levels. However, according to the interviewee, the company does not have sufficient knowledge about AI to implement it. The company would either need a supplier that could help with the implementation or an information system with integrated AI services, and hence mentions availability of competent and mature AI suppliers, that can help with implementation for a reasonable price, as a prerequisite. To implement AI technologies, decision makers for supply chain improvements at the company would need more information about the different systems available to assess related benefits and ensure return on investment.

4.1.7 Medical Products AB

Medical Products AB's customers work with professional healthcare and the sales are not as sensitive to economic fluctuations as other sectors due to the non-cyclical nature of the industry. Hence, the demand is relatively even, with some increases at procurements and some seasonal variations. The company performs statistical calculations based on historical data to forecast the demand. To measure the accuracy of the forecasts, the company uses the key figure mean average percentage error. The company has a 28% forecast error with a three-month horizon, which is seen as a median in the industry. The interviewee explains that the company does not have a need to reduce their inventory costs due to the high profit margins in the industry. The company prioritises high inventories to be able to deliver to customers if they can maintain their profitability.

Currently, AI is not used in demand forecasting or in other areas of the organisation, but the interviewee sees potential in implementing AI techniques and believes that AI can lead to improved forecast accuracy. According to the interviewee, due to the company's high profitability, there is no incentive to improve internal processes, which is a prerequisite to implement AI. The company's focus is to sell as much as possible, and, therefore, the internal priorities are, instead, focused on sales and product development. Furthermore, the interviewee does not see the lack of technical competences required for AI as a barrier. There is no competence in the company today, but thanks to their high profitability, the company can hire consultants and bring in expertise if needed.

4.2 Analysis of Improvements and Prerequisites

Out of the seven interviewed companies, only Hygiene Goods AB has implemented AI in their demand forecasting. Therefore, the improvements and prerequisites of Hygiene Goods AB are based on experiences, while for the other companies, the improvements and prerequisites are based on perceptions. All the companies are in consensus that AI can improve the forecasting accuracy, and five companies relate the increased accuracy to further performance improvements. These findings are summarised in Table 4 below. Since two of the seven companies, Medical Products AB and Welding Tools AB, could not identify any performance improvements, they are not included in the table.

Table 4: Summary of the mentioned improvements achieved by implementing AI in demand forecasting. The improvements are linked to the corresponding performance objectives and companies.

Performance objective	*Improvement*	*Description*	*Companies*
Speed	Quick adaptation to erratic demand.	AI can utilise more parameters in the forecasts, resulting in quicker adaptation to erratic demand and unforeseen circumstances.	Hygiene Goods AB
	Shortened project lead time.	AI handles big data sets efficiently and is thus contributing to a shorter project lead time.	Radar Solutions AB
Dependability	Increased service levels.	AI enables more efficient allocation of shared resources, leading to increased service levels.	Hygiene Goods AB
Flexibility	Better downstream planning.	AI enables more efficient allocation of shared resources, leading to better downstream planning.	Hygiene Goods AB
Cost	Decreased working capital.	Decreased working capital due to smaller safety stock requirements.	Hygiene Goods AB Supply Chain Solutions AB Core Drill Motors AB Radar Solutions AB

	Reduced manual work.	AI automates the forecasting process, leading to reduced costs for manual work.	Gauging Solutions AB Core Drill Motors AB

Hygiene Goods AB mentioned that since the implementation of AI, they have obtained four major improvements; *quick adaptation to erratic demand*, *increased service levels*, *better downstream planning*, and *decreased working capital*. On the other hand, the remaining companies only believe they will gain one or two improvements from the implementation of AI. The most frequently mentioned improvement is *decreased working capital*, which was brought up by four of the companies. According to all these four companies, the decreased working capital stems from reduced inventory levels. Furthermore, *reduced manual work* was mentioned in two of the interviews, making this the second most common improvement. Both companies attribute this to AI automating the forecasting processes.

Several of the identified improvements were only mentioned by one company, most of these by Hygiene Goods AB. Many of the companies acknowledged a low competence and maturity within AI because it has not been prioritised. The reasoning behind the low priority differs between the companies, where lack of resources, low incentives due to high profitability, and limited understanding of potential improvements from AI were some of the issues brought up.

To be able to implement AI and realise the potential improvements previously mentioned, the interviewed companies identified several prerequisites. These prerequisites are summarised in Table 5. All the companies identified at least one prerequisite, and all of them, therefore, appear in Table 5.

Table 5: Summary of the mentioned prerequisites for adopting AI in demand forecasting.

Class of prerequisite	*Prerequisite*	*Description*	*Companies*
Technological	Clean data.	To be able to generate forecasts with AI, correct and relevant data needs to be available.	Hygiene Goods AB
	Sufficient technological infrastructure.	In order to overcome technical difficulties, companies must obtain the technology needed to implement AI.	Gauging Solutions AB Supply Chain Solutions AB Radar Solutions AB
Economic	Available resources.	For investments in AI to be realised, available resources in terms of capital is required.	Welding Tools AB Core Drill Motors AB
Knowledge	Understanding of the improvements AI can bring.	Since AI requires investments, knowledge about the improvements AI can bring is important, in order to ensure return on investment.	Welding Tools AB Supply Chain Solutions AB
	Sufficient competence of AI.	To enable efficient use and tracing of solutions, AI implementation demands competence of AI among the employees.	Welding Tools AB Core Drill Motors AB Radar Solutions AB
Organisational	Prioritising resources to AI.	Companies need to prioritise and allocate resources to make an implementation of AI possible.	Welding Tools AB Gauging Solutions AB
	Top management's attention to improving supply chain performance.	Since demand forecasting is a part of the supply chain, management needs to acknowledge improvement measures for the supply chain, for investments in AI to make sense.	Core Drill Motors AB Medical Products AB Radar Solutions AB
Cultural	Acceptance of the AI-based forecasts.	When manually produced forecasts are replaced with AI technologies the employees must trust the outcome.	Hygiene Goods AB

	Employees must be motivated to adopt AI.	Moving towards AI-based forecasts changes the employees' way of working and they need to be motivated and receptive to these changes.	Core Drill Motors AB

As presented in Table 5, three of the prerequisites were each brought up by three companies and can, therefore, be classified as the most common. These are; *sufficient technological infrastructure*, *sufficient competence of AI*, and *top management's attention to improving supply chain performance*. On the other hand, Medical Products AB did not recognise *sufficient competence of AI* as a prerequisite since they can easily purchase expertise if needed. Furthermore, the two prerequisites experienced by Hygiene Goods AB, the only company which has implemented AI, are not mentioned by any other company.

5. Discussion

This chapter covers a discussion of the results related to the research questions, followed by an evaluation through the perspective of sustainability and ethics. Finally, limitations regarding the methodology of the study are discussed.

5.1 Answer to Research Question One

The first research question is: “What type of improvements, related to the performance objectives, are most expected to be achieved by applying AI in demand forecasting operations?”. To answer this question, the theoretical framework is compared with the analysis, where the improvements found in both are evaluated as expected. The improvements mentioned by Hygiene Goods AB are also considered as expected, since these have been experienced by an implementation of AI in demand forecasting.

Several trends and patterns were observed in the analysis. One observation is that Medical Products AB and Welding Tools AB did not have the perception that performance improvements were achievable. These companies’ inability to visualise potential improvements could be explained by a lack of competence of AI. Both companies are satisfied with their current forecasting processes, and hence they have low incentives for implementing AI. Low incentives can thereby be a reason to why these companies are lacking competence of AI, and thus not being able to bring up any potential performance improvements. In addition, both companies prioritise customer satisfaction through high safety stocks over improved forecast accuracy. Since they perceive that their forecasting processes are adequate, they have not evaluated the potentials of AI.

The majority of companies interviewed have smooth demand patterns, namely Welding Tools AB, Medical Products AB, Core Drill Motors AB, and Gauging Solutions AB. Smooth demand is generally easier to forecast, and, therefore, the benefits of forecasts with AI could diminish, which may lead to lower incentives for implementing AI. This can explain why these companies mentioned fewer potential improvements than companies with erratic demand, i.e. Hygiene Goods AB and Radar Solutions AB. Amirkolaii et al. (2017) support this, by stating that companies with erratic or lumpy demand have a high interest in implementing AI within supply chains. Accordingly, the following proposition is set forth:

P1: Companies with erratic or lumpy demand have more incentives to implement AI in demand forecasting than companies with smooth demand.

Another finding is that Hygiene Goods AB, the only company using AI, mentioned more improvements than any other company in the study. The mentioned improvements by the remaining companies are fewer, which implies that improvements can be difficult to predict beforehand, and that AI can have more significant potential than expected. Furthermore, Hygiene Goods has an erratic demand pattern in consumer goods, which is the area where AI has been implemented. As previously mentioned, the characteristic of this demand holds potential for more and larger improvements than companies with a smooth demand pattern. This could be the reason why Hygiene Goods AB has experienced a higher number of improvements than was mentioned by the other companies.

In addition, another discovery is that Hygiene Goods AB has achieved both increased service levels and decreased working capital by implementing AI in the forecasting process. This can be contradictory since reduced inventory often results in decreased service levels (Jonsson & Mattsson, 2009). However, this case demonstrates that more accurate forecasts can lead to an improvement in both areas. An explanation to this unusual combination of improvements could be that AI generates more accurate forecasts and better information, resulting in improved safety stock planning, reducing both over- and understocking.

A comparison between the theoretical framework and the analysis findings makes it possible to conclude the most expected types of improvements to be achieved by applying AI. One improvement not discussed in the literature, mentioned by Radar Solutions AB, is *shortened project lead time*. Since the improvement is not found in the literature nor mentioned by any other company, it does not have sufficient evidence to be seen as an expected improvement of implementing AI. The shortened project lead time, as an improvement, may be specific for the industry or the company, which can explain the lack of support. Another improvement that is not discussed in the literature is *better downstream planning*, which was experienced by Hygiene Goods AB. This could be due to a lack of published research regarding the improvements of AI on downstream planning, or this improvement is specific for the company or industry. Since Hygiene Goods AB can prove that this is an actual improvement from implementing AI, it is considered as an expected improvement.

There were some improvements identified in the literature that were not put forward by any of the companies in the study including *quick response to change in product mix*, *quick response to changes in distribution networks,* and *reduced transportation costs*. The interviewees have responsibility areas related to demand forecasting, and, therefore, it can be difficult to imagine improvements outside this area, and there can, thus, be potential improvements not mentioned in the interviews. Improvements only found in the literature cannot be considered as expected in the study, since no companies have achieved or mentioned them.

Several improvements were mentioned by the companies that are discussed in the literature. Hygiene Goods AB experienced *quick adaptation to erratic demand* and *increased service levels* by implementing AI. Both improvements can be found in the literature, referred to as *quick response to demand changes* and *reduced understocking* by e.g. Calatayud et al. (2019) and McKinsey (2017). This implies that these improvements are expected to be achieved for companies implementing AI in demand forecasting.

The most frequently mentioned improvement in the interviews was *decreased working capital*, driven by reduced inventory. This is in line with the theoretical framework, referred to as *reduced inventory costs* by e.g. Amirkolaii et al. (2017). Decreased working capital, therefore, seems easier to visualise beforehand, compared to other improvements. An explanation for this could be that this improvement is closely related to increased forecasting accuracy. The improvement of *reduced manual work*, mentioned by Gauging Solutions AB and Core Drill Motors AB, was also found in the literature (e.g. Dash et al., 2019), referred to as *reduced cost for demand planning work and administration*. The companies mentioning this improvement have not implemented AI, but since the improvement is discussed in the literature, it can be deemed more reliable than improvements not receiving attention in the literature. To conclude, *decreased working capital*, and *reduced manual work* are mentioned by several companies and supported in the literature and can, thus, be seen as expected improvements.

5.2 Answer to Research Question Two

The second research question is: "What are the general prerequisites for applying AI in demand forecasting operations?". In this section, the theoretical framework is compared with the analysis, where the prerequisites found in both are evaluated as general, which also provides the answers for research question two.

Hygiene Goods AB mentioned the two prerequisites *clean data* and *acceptance of the AI-based forecasts*, which no other company recognises as prerequisites. This could imply that companies which have implemented AI in demand forecasting may experience different specific prerequisites. To familiarise with the prerequisite of *clean data*, a significant degree of expertise within the subject of AI is required. Clean and high-quality data are also frequently needed in order to use AI and allow it to improve accuracy over time, and, therefore, this topic is more relevant to corporations that have already implemented the technology. In the relevant literature, the requirement of clean data is referred to as *data availability and quality of data* (e.g. Chui et al., 2018), which validates that *clean data* is a general prerequisite. On this topic, the discrepancy between the literature and the interview results could be explained by the common low competence within AI, which was discussed in multiple interviews, e.g. Core Drill Motors AB.

The prerequisite of *acceptance of the AI-based forecasts* is disclosed after implementation and it can, therefore, be difficult to visualise beforehand, which can be the reason why it was not frequently mentioned in the interviews. Additionally, this prerequisite can be related to the explainability problem, discussed by Chui et al. (2018), and the prerequisite of *technical competences required for AI,* identified by e.g. Makridakis et al. (2018), since a higher level of competence can increase the understanding and acceptance of the forecasts generated by AI. However, the prerequisite of *acceptance of the AI-based forecasts* was not explicitly addressed in the literature and is, therefore, not considered a general prerequisite on its own.

Several prerequisites can be deemed fundamental but were still only mentioned in two or three interviews. This could be explained by the fact that companies only raised the limitations they face today. For example, only companies that today notice an issue with top management's focus on AI and supply chain improvement would mention this as a prerequisite. Medical Products AB do not prioritise improving their supply chain performance, since their profit margins are high, and they instead consider it more valuable to focus on R&D and increasing sales. Therefore, they perceive *top management's attention to improving supply chain performance* as a prerequisite because they experience this issue. This prerequisite was not explicitly identified in the literature concerned with AI in demand forecasting, probably because this is a more overarching supply chain prerequisite.

The literature has an over-representation of the prerequisites for technical competence compared to the interview results where only Welding Tools AB, Core Drill Motors AB, and Radar Solutions AB brought this up. As previously mentioned, the competence within AI is generally low among the interviewees, which could serve as an explanation to this gap. Without proper knowledge of what competences are needed for AI, it is difficult to realise what the company is lacking. Medical Products AB do not see expertise as a limitation, because the company have financial means to acquire competences from external sources if needed. In contrast, Andersen et al. (2019) emphasises the importance of *integration of AI into the core of the organisation* and having an *overarching AI strategy*, which could be challenging if competence is brought in from outside of the organisation for a short period of time. Since *sufficient competence of AI* was discussed in several interviews, and in the literature as *technical competences required for AI*, it is deemed to be a general prerequisite for implementing AI in demand forecasting.

All seven companies declare that they have low maturity regarding AI in demand forecasting. However, Gauging Solutions AB has on-going projects with AI in other business areas, and Radar Solutions AB uses AI in their products. This implies that although companies have the relevant technical competence for AI, it may not be applicable within other business areas, since this might require specific competences across domains. It is, therefore, important to have AI integrated into the core of the organisation, as stated by Andersen et al. (2019). Accordingly, the following proposition is suggested:

P2: Technical competence for AI in one business area is not sufficient to be able to implement AI in demand forecasting.

Four different organisational prerequisites were identified in the literature, while the interviews only found two, with no overlaps. The prerequisite of *sharing of data between stakeholders in the supply chain* suggested by Boone et al. (2019) was not identified in the interviews, which might be due to the companies not relating this specifically to the adoption of AI. In contrast, the prerequisite of *prioritising resources to AI* was not found in the literature but mentioned in two interviews. Researchers may underestimate how important prioritising is within a company, since they are more theoretically orientated and may not be familiar with all the trade-offs a company can face. This insight comes with organisational experience, and the interviewees that mentioned this factor emphasised that this issue is a major limitation.

There are also similarities between interviews and literature regarding the prerequisites found in the classes; economic, technological, and knowledge. All the prerequisites underlying these classes were identified in both interviews and literature and can, therefore, be presumed to be general prerequisites. Among these prerequisites, there are some that stand out as more mentioned in both the related literature and interviews. The technological prerequisite of *sufficient technological infrastructure* is found in three different literature sources (e.g. Nilsson & Gerdtham, 2018) as well as in three interviews. Two interviews mentioned the need for *understanding the improvements AI can bring*, which is supported by Lorica and Nathan (2019), who referred to it as *awareness of the benefits of AI*. Lastly, *available economic resources to adopt AI* is addressed by e.g. Ali et al. (2009) and in two interviews as *available resources*. The comparison of interviews with literature shows that despite the identified differences concerning the prerequisites required for implementing AI in demand forecasting, there is still agreement in certain areas.

5.3 Discussion of Sustainable Development and Ethics

Five of the United Nations' global goals were identified as the most appropriate within the context of AI in demand forecasting, where the first one was Goal 8: Decent work and economic growth. One of the expected improvements is *better downstream planning*, which contributes to improved efficiency and productivity. Further, this could lead to economic growth without increased utilisation of the company's resources. The identified expected improvements; *quick adaptation to erratic demand*, *decreased working capital*, and *better downstream planning* can support Goal 12: Responsible consumption and production. Optimised decision making through AI can help establish a more sustainable management and use of natural resources. In addition, these improvements have potential in reducing waste along the supply chain and thereby reducing overconsumption and -production.

Demand forecasting has a large impact on the climate, and by *better downstream planning* and *decreased working capital*, the environmental impact can be reduced, as an effect of optimised transport planning and reduced risk of obsolescence. This contributes to the achievement of Goal 13: Climate action. However, challenges may also occur such as an increased consumption and resource depletion due to improved efficiency and the lowering of supply chain costs. Another challenge could be increased transportation as a consequence of reduced safety stocks, which may require more frequent deliveries of material.

The identified general prerequisites can help in achieving a successful implementation of AI, and AI as an innovation enables upgrading of technologies used in industries. An implementation of AI supports Goal 9: Industry, innovation and infrastructure, since one of the targets implies to an enhancement of the technological capabilities in industries.

AI's potential to *reduce manual work* within demand forecasting can have ethical consequences, which further can be connected to Goal 10: Reduced inequalities. This goal may pose a challenge since a consequence that might arise due to greater reliance on AI is increased social and economic inequalities. Greater reliance on AI can affect the labour market when human efforts are replaced by computers and robots. Yet, only two companies discussed the topic of reduced manual work and neither of them saw this as a problem but rather an improvement. Furthermore, they argued that this could lead to new or other tasks for the employees to perform. However, the companies' representatives may be reluctant to consider this aspect since the interviewees often worked within demand forecasting and would, thus, be directly affected by a change if AI is implemented.

5.4 Limitations

The study was initiated with a literature review where literary sources were subjectively chosen based on their relevance to the research questions. The selection of the literature could have been performed more objectively through conducting a literature study. A literature study with a more structured approach regarding the selection of sources using databases and keywords would have resulted in an in-depth analysis of the literature available on the topic. Since the purpose of the literature review was to increase the understanding of the subject and provide a foundation for the interviews, conducting a literature review seemed more appropriate. In retrospect, the literature review provided an applicable theoretical framework from which the results of the interviews could be analysed, and it can, therefore, be deemed as suitable for the study.

All the interviews were held with only one representative from each company. Interviewing more representatives from each company could have enriched the answers and contributed to more reliable results. The interviewees worked within demand forecasting operations and due to the general low maturity of AI among the companies, the competence could have been insufficient to fully answer the questions. Because of the time limit and the outbreak of covid-19, it was difficult to contact more than one representative from each company. Although all the representatives worked within demand forecasting, the area of responsibility differed, which might have an impact on the results, since the respondents had varied insights into their respective organisation. Moreover, interviewing only one representative from each company may imply a risk to bias towards their area of responsibility. For example, the interviewee from Hygiene Goods AB was responsible for the implementation of AI and might overestimate the improvements achieved by the implementation.

The intention was to conduct the interviews face to face with the representatives to facilitate communication and avoid misinterpretations. However, covid-19 affected the form of the interviews, resulting in that most interviews were performed over the phone. Furthermore, the pandemic caused two scheduled interviews to be cancelled, one of them being with the largest company in the region. The absence of these interviews has probably affected the result.

The literature presents several improvements and prerequisites that were not identified in any of the interviews. One reason for this discrepancy might be that only seven companies were interviewed. If more interviews would have been performed, the additional companies might have mentioned these improvements and prerequisites as well. Another possible way of reaching more respondents would have been to conduct a survey, which would have resulted in a broader set of data, possibly by including more companies that apply AI in demand forecasting. A survey would, however, provide less detailed answers and because of this, interviews were considered the most appropriate method for the empirical data gathering.

6. Conclusion

The study aimed at providing an overall picture for the potential improvements of, and prerequisites needed for, implementation of AI within demand forecasting in the region of Gothenburg. Findings show that the type of improvements that can be expected to be achieved by applying AI in demand forecasting include *better downstream planning*, *quick adaptation to erratic demand*, *increased service levels*, *decreased working capital*, and *reduced manual work*. The improvements are mentioned by the companies and found in the literature except for *better downstream planning,* which was only brought up by one company. However, this is still considered as an expected improvement, since it is experienced by a company that has implemented AI.

Findings suggest five general prerequisites needed for applying AI in demand forecasting including *clean data, sufficient technological infrastructure, available resources, understanding of the improvements AI can bring,* and *sufficient competence of AI.* All the general prerequisites were present in both the literature and in multiple interviews. The prevalence of the five prerequisites in different industries also supports the claim that they are general.

The identification of expected improvements and general prerequisites illustrate the attitude of manufacturing companies in the region of Gothenburg, towards an eventual future implementation of AI in demand forecasting. Through the study, companies providing AI solutions, such as consulting firms, can achieve a greater understanding of the maturity of AI among these manufacturing companies.

Due to the limitations of the study, the results can be considered general and in order to provide a broader or deeper perspective, further research is needed within this area. A broader study could be achieved by interviewing more companies, while interviewing more representatives of each company would contribute to the depth. Further research is also needed to investigate the improvements only identified in the literature, and not in the interviews, to increase the understanding and confirm if they are expected improvements. Evidence for both organisational and cultural prerequisites was found, although the results were inconclusive and could not be stated as general prerequisites, and this could also be a topic for further research.

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Appendix

Attachment 1: Interview guide used for the interviews translated to English

Background

- What is your role in the company?
- How long have you worked within this industry?
- Tell us about your background.
- How many employees does your company have?
- What areas are you responsible for?
- How large share of the company does your business unit represent?

Awareness & Interest

- How would you classify your company's demand?
- How does your company's demand forecasting work today?
- How does your company evaluate its forecasts?
- What information is used in forecasting?
- How would you appraise your company's current forecasting? how accurate is it?
- How much knowledge does your company have about AI?
- Is AI used today?

Current applications within demand forecasting

- If AI is used within demand forecasting, which AI-technologies are used?
- What are the technologies used for?
- Which data is being used?
- What improvements have you seen from AI?

Potential within demand forecasting

- Which advantages do you believe AI can bring to demand forecasting?
- Why do you recognize potential from AI within this area?
- How great potential lies within this area?
- Do you recognize any further areas of demand forecasting where AI could be applied?

Limitations & Challenges

- If AI is not used within demand forecasting, why?
- What prerequisites do you think are necessary in order to apply AI?
- What difficulties do you perceive with implementing AI in demand forecasting?

Current applications and potential within supply chain

- In what areas / operations do you use AI today?
- How mature do you perceive your company is with AI?
- How does your company compare to your competitors with AI in SC?
- Where do you believe the greatest potential o AI lies within your company and/or industry?
- Do you personally come in contact with AI in your daily work?

- How would you appraise your own knowledge about AI?

Wrap-up

- Is there anything that you would like to bring up that we have not addressed during the interview?

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