MASTER

Improving sell-in forecasting accuracy and internal alignment among stakeholders through alternative forecasting methods

A case study of the case company

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Management summary

Supply chain management (SCM) has been introduced to achieve lower logistical costs, optimal inventory levels, and better customer service. SCM manages businesses as closely connected chain links extending beyond the organisation's boundaries to include suppliers and customers. Demand volatility or fluctuations in customer demand due to various factors like advertising, weather, market trends, and seasons poses a significant challenge to inventory management and capacity planning. Demand forecasting, estimating future product sales, is the first step in dealing with uncertainty and volatility. Forecasting can lead to better service to the client and fewer inventory stocks and costs. However, it is a difficult task to perform at a high level of precision due to the many uncertainties involved.

The retail industry faces rapid developments in structure and growth in online business, and their future planning depends on demand forecasts. To forecast the demand for a retailer, data about sell-in, sell-out and stock of the distribution center is needed. The forecast is currently based on judgmental forecasting, but a better forecast of the supplier can be made by adding historical data to this process. This extra data should increase the forecasting accuracy in the highly volatile demand of the retailer. The main focus of this study is to determine if alternative forecasting techniques may more accurately predict sell-in than just judgmental forecasting at the case company and to what extent this can promote greater internal alignment among the stakeholders in the forecasting process.

The action research was conducted in two stages, the first of which aimed to quantitatively measure the performance of three established time series forecasting techniques based on historical sales data on 5 Stock Keeping Units (SKUs) from the case company. The second stage involved constructing and evaluating a forecasting dashboard designed to improve forecasting accuracy and promote internal alignment among stakeholders.

Stage 1 covers the quantitative technique to find the best-performing forecasting method. The forecasts are tested on data from 5 The case company SKUs sold in Watsons shops. The forecasting methods are tested on data from the last two years of those SKUs to find the best-performing method and are measured by the Root Mean Squared Error (RMSE) value. Based on empirical data and practical reasons, time series are preferred above causal models. Five factors are discussed to select the forecasting methods used in this study, and it concluded that Holt-Winters, Croston and SARIMA would be tested in this study. These quantitative methods can help the stakeholders to identify trends, seasonality and calendar events and may lead to better forecasts. Results showed that the SARIMA method outperformed Holt-Winters and Croston forecasting techniques in terms of accuracy for all five SKUs.

In stage 2, the goal was to get insight into the possible improvements in internal alignment by using SARIMA and integrate this in the dashboard to predict the retailer sell-in demand using historical data. To build the forecasting dashboard, exploratory interviews are held. These interviews mark the awareness of the problem and give suggestions for solving this problem in the organization. Evaluative interviews were used for the development of the dashboard. The stakeholders involved were interviewed using semi-structured interviews. The stakeholders mentioned the positive aspects of the dashboard, challenges and points of improvement. The feedback given is used to improve the dashboard. A final focus group is held to evaluate the final version of the dashboard. The forecasting process using this dashboard is evaluated, and the outcomes are discussed. The dashboard's layout allowed stakeholders to easily and quickly have a look at the historical data, leading to a more

frequent and better discussion about the forecasts. Evaluative interviews and the final focus group revealed that the dashboard had a positive impact on the internal alignment among stakeholders, led to increased accuracy in forecasting sales and will lead to lower costs (Peteraf & Reed, 2007)

Overall, the results of this study indicate that alternative forecasting techniques, in particular SARIMA, in combination with judgmental forecasting, can predict the sell-in more accurately. Using a forecasting dashboard can increase internal alignment among stakeholders highlighting the importance of utilizing quantitative forecasting techniques and technology-driven solutions to improve forecasting accuracy and internal alignment among stakeholders.

Preface

This graduation thesis is dedicated to the sales team within the case company. Forecasting is a big challenge within the sales team of the case company. With little use of technology or software, forecasts are made, which can significantly impact the coverage by the clients, the costs of stock, and the achievement of sales targets. This document contains the thesis for the graduation program of the master Innovation Management for the Managing Innovation Processes track at Eindhoven University of technology. This research was performed by Thieu Antonissen, a graduation student, and was guided by Arjan Markus (TUe), Néomie Raassens (TUe), and company supervisor (The case company).

This document provides the thesis for the graduation assignment at the case company

Terminology & abbreviations

AG:	Article Group
BG:	Business Group
BU:	Business Unit
CCM:	Customer Collaboration Manager
CDP:	Customer Demand Planner
Consumer:	The person who buys the products from the retailer
Customer:	The retailer buying from the case company
CY:	Current Year
DC:	Distribution Center
EU:	European Union
KAM:	Key Account Manager
LY:	Last Year
LLY:	Last Last Year
MAG:	Main Article Group
MCC:	Mother & Childcare
MG:	Male Grooming
NNN:	Triple net lease
OHC:	Oral HealthCare
RRP:	Recommended Retail Price
Sell-out:	The number of products sold from the retailer tot the end customer/consumer
Sell-in:	The number of products The case company sells to their retailers
SKU:	Stock Keeping Unit

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1. Introduction

1.1 Forecasting in the retail industry

To achieve lower logistics costs, optimal inventory levels, and better customer service, supply chain management (SCM) was introduced (Nakano, 2009). SCM consists of a company's demand, supply, and stock, whereby planning capacity and inventory can save costs and contribute to better SCM. SCM manages businesses as closely connected chain links, extending beyond the organisation's boundaries to include suppliers and customers (Helms, Ettkin & Chapman, 2000). Supply chain inventories are prone to fluctuations and uncertainties. These uncertainties can arise for many reasons, such as the activities of partners. When the partners cannot deliver a product to or from the warehouse, this can lead to uncertainties in the company's inventory management. Inventory management and capacity planning rely on future product sales estimates (Kourentzes, Trapero & Barrow, 2020). Small changes in the end products can cause fluctuations in inventory and orders, which become amplified as one moves up the supply chain. The phenomenon of amplification of oscillations through the supply chain is known as the bullwhip effect (Lee et al., 1997, Chen et al., 1998, Xu et al., 2011).

Steady customer demand for the products makes it easy to manage the stock. However, this constant demand is not likely. Constantly changing consumers' behaviour leads to fluctuations in demand, which is called 'demand volatility' (Walker & Weber, 1984). It exists due to many intrinsic and extrinsic factors. Various variables, such as advertising, weather, market trends, and seasons can influence consumer behaviour and affect demand fluctuations (Gilliland 2010). Product promotions, in particular, are a widespread practice in the retail industry and can lead to fluctuations in demand (Abolghasemi, Beh, Tarr & Gerlach, 2020). When there is a price promotion of a product, the demand is likely to rise. Demand volatility makes demand forecasting difficult and poses excess costs for out-of-stocks, inventory levels, and capacity utilization (Christopher and Holweg, 2011). Demand forecasting is estimating future product sales, which is, according to Merkuryeva, Valberga & Smirnov (2019), the basis of all managerial decisions in logistics and SCM.

Due to the underlying volatility and many uncertainties, demand forecasting is usually challenging to perform at a high level of precision. Still, it can provide critical information to support planning and decision-making (Syntetos et al., 2016). Demand volatility can be reduced and controlled, but it is inevitable (Abolghasemi et al., 2020). Techniques and approaches are proposed to deal with demand volatility, such as increasing inventory levels. While this will help to counter demand volatility, it comes at a high cost to the business (Meindl and Chopra, 2001). Another strategy could be to increase capacity (Meindl and Chopra, 2001). However, increasing capacity is not attractive to businesses as it may incur high costs for their business operations. These strategies help solve problems related to demand variability, but they may not be cost-effective. Demand forecasting is a prerequisite for strategies to manage demand fluctuations (Hope and Fraser, 2003). Demand forecasting is the first step in dealing with supply-chain uncertainty and volatility. Forecasting can lead to better service to the client and less inventory stock and costs. Therefore, demand forecasting is essential and challenging to execute well. Businesses that do well have a significant competitive advantage over those whose forecasts fail (Hyndman & Athanasopoulos, 2018). The retail industry is facing rapid developments in structure as well as the growth in online business and the competitive environment. Their future planning depends partly on the demand forecast (Fildes, Ma & Kolassa, 2019). At the organizational level, forecasts are essential to marketing, sales, production/purchasing and distribution. Data about sell-out and stock of the distribution centre (DC) is needed to forecast the demand for a retailer.

Sell-out refers to a product sold from a retailer to a consumer (exploratory interview Custom Collaboration Manager). These data, in combination with the stock centrally located in the DC, gives historical data of the retailer. Additional data is needed for a supplier to perform a forecast based on historical data. The additional data includes the sell-in data, which is the data about a product bought by the retailer from the supplier (exploratory interview Custom Collaboration Manager). As shown in Figure 1, the product is sold by the supplier (sell-in) and brought to the DC (stock), where it is distributed to the physical shops. Lastly, the consumer buys the product in the shops (sell-out). The forecast is based on judgemental forecasting, but combining these data allows a forecast of the supplier based on historical data. For future sales, the supplier should look at more than historical data (Arunraj, Ahrens & Fernandes, 2016). It is influenced by external factors such as new products entering the market, competition, product promotions and changing needs (Arunraj, Ahrens & Fernandes, 2016). These extra data can influence future demand and should be looked at in combination with historical data. The external factors can lead to a highly volatile demand for the retailer and supplier. Therefore, this thesis aims to study how to improve demand forecasting in the business context. The business context and case company will be discussed in the next sub-chapters.

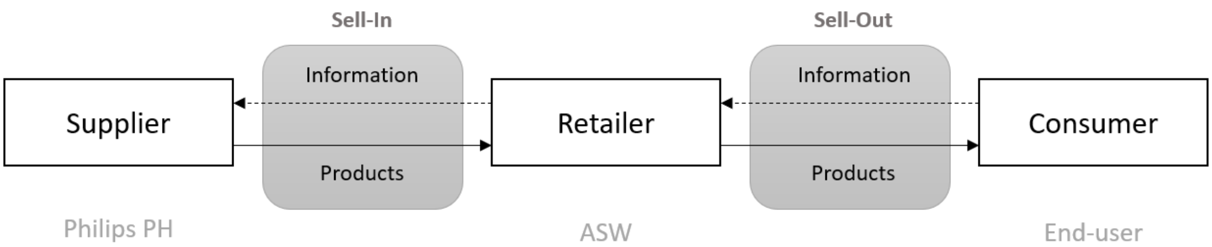

Figure 1: Sell-In Sell-Out visualization

1.2 Introduction to business context

1.2.1 Case company.

The case company has such a construction with sell-in and sell-out whereby the case company is the supplier, supplying its goods to its clients (the retailers), whereafter the retailer sells this item to its clients (the product's end-user). In this study, we will discuss the sell-in, sell-out and stock of the case company to its retailers and the end-users. The case company case is shown in Figure 1 below the boxes.

The flow of products is from the case company to the retailer and then to the consumer, shown in Figure 1 by the solid arrow pointing to the right. The flow of information is going the other way around, shown in Figure 1 by the dashed arrow pointing to the left. The retailer collects information about the number of products sold in its stores to the consumer. The case company receives information from the retailers about the number of items sold to the consumer and has information about the number of products sold to the retailer, respectively, the sell-out and sell-in of its products. Besides that, the case company knows the stock of its warehouse.

The case company is a multinational company that used to offer a broad product range, including consumer-oriented and healthcare products. At the base its products were classified into three businesses (the case company, 2013). Firstly, its Healthcare business, which includes all its Professional Healthcare products. Secondly, the Consumer Lifestyle business includes Personal Health and Domestic Appliances. Finally, there was the lighting business, which specializes in LED-based lighting solutions. Between 2001 and 2013, the company mainly focused on Domestic

Appliances, where the case company handled the traditional electronics market. However, over the past decade, the case company has grown into a medical technology company as it has undergone drastic internal changes.

In 2021, The case company generated 17.2 billion Euros with a net income of 3.3 billion. In the past, mainly from Domestic appliances, but this gradually moved to the Personal and Professional Healthcare sector. The company employs more than 78,000 employees from 120-plus countries and is a well-known worldwide company for health and tech. Its purpose is to improve people's health and well-being through meaningful innovation, supported by the investment of 1.8 billion in R&D in 2021 and the statement that they have improved the lives of 1.67 billion people since the start. Due to their vision, the case company divested three of its product portfolios. Firstly, a the case company Lifestyle entertainment Group divestiture consisting of audio and video. Secondly, it separated the case company Lightning and continued under the name Signify with its own stock listing. Moreover, recently, the case company sold Domestic appliances and Kitchen Appliances by selling the license to another company called Hillhouse Capital, which covers all household products (Zwirs & Guzel, 2021). The divestments of the case company in the past decade are shown in Figure 2.

What is left is the case company and the case company (The case company). The case company specializes in making hospital equipment and machinery and is divided into Diagnosis & Treatment and Connected Care, as shown in Figure 3 top-left. The case company (The case company) comprises the categories: Oral Healthcare, Mother & Child Care, Male Grooming and Beauty. The case company' ex CEO explained that the focus on Healthcare and Personal Heath aligns with its strategic fit for the company's future goal to become a health technology leader (The case company, 2022).

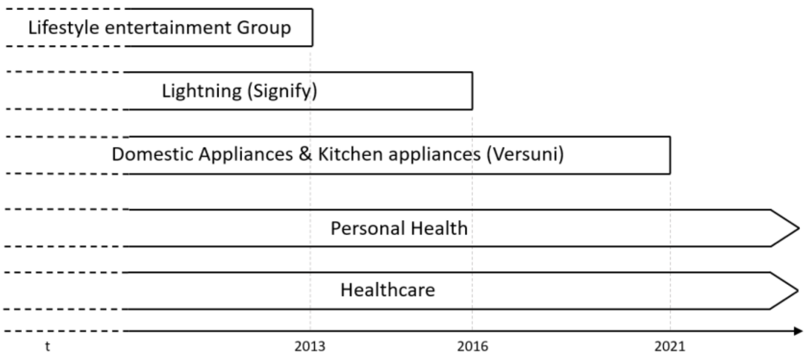

Figure 2: The case company divestments over time

1.2.2 The structure of the case company

The simplified structure of the case company s shown in Figure 3 top-left. The patients, customers and consumers are central to the case company' operations. The patient, customer and consumer are the primary divisions within the case company' portfolio. Each division can be split into regions/zones and/or countries. The case company is one of the case companies' divisions, mainly named ...

As stated above, the case company is divided into multiple pillars, and this division is one of them. Global is overarching across several zones. One of the zones is Western Europe (WE). WE are split up into 7 'countries', including, which is the environment this research is executed. A visualisation of the structure is given in Figure 3**,** top-right.

The structure of the case company is depicted in Figure 3 down-right. Every Key Account Manager (KAM) is responsible for their specific customers within the sales team. They negotiate and sell products to clients. These Key account managers, who can be seen as the company's sellers, are grouped into three groups. Every group of KAMs have their own segment and is divided into three channels. The channel is highlighted in blue in Figure 3 and consists of a channel manager, Trade Support Marketeer, Customer Demand Planner, and four KAMs. The three channels within the case company Benelux team are (1) the Online channel with customers like Bol.com and Coolblue, (2) the Chains channel with retailers like Mediamarkt and Krefel, and (3) the …. channel with retailers like Bomedys and the retailer.

The KAMs work closely with a Customer Demand Planner (CDP) and a Trade Shopper Marketeer (TSM). TSM is responsible for the transformation and innovation in the business. The CDP plans the demand for the retailers of the KAMs every month. However, he must ensure the case company warehouse has enough stocks to deliver to the retailers. Therefore, the CDP roughly plans a quarter in advance to ensure enough products are in its warehouse.

The planning of the CDP is very closely related to the KAMs negotiations, promotions, and sales. Therefore, the KAMs make their own weekly forecast based on upcoming promotions. The KAMs know their retailers and their customers the best so they can make a better prediction for their own clients on the number of products that will be sold to the retailer. The CDP plans the case company stock to be available for The case company Benelux from the case company EU distribution centre (DC) and the factory. This Benelux stock is thus not for one retailer but for a group of retailers. Every CDP plans the case company stock for all KAMs in one channel and thus for multiple retailers. The KAMs look more closely at how to divide the stock for their customers and if there is extra stock in the warehouse, which is called unhealthy stock (consisting of excess stock & ageing stock). The KAM can promote these items to their customers and may sell this extra stock. This way, there is a lot of interaction between the CDP and the KAM about managing the stock in the case company DC most efficiently.

The stakeholders involved in the demand forecasting process are the responsible KAM, the CDP, and the TSM or Channel Manager when needed. Sometimes the Channel manager is involved in the demand forecast process. The involvement of the Channel Manager is typically the case when there is much unhealthy stock at the end of the quarter or when the forecasted demand has a financial value far above the expected value.

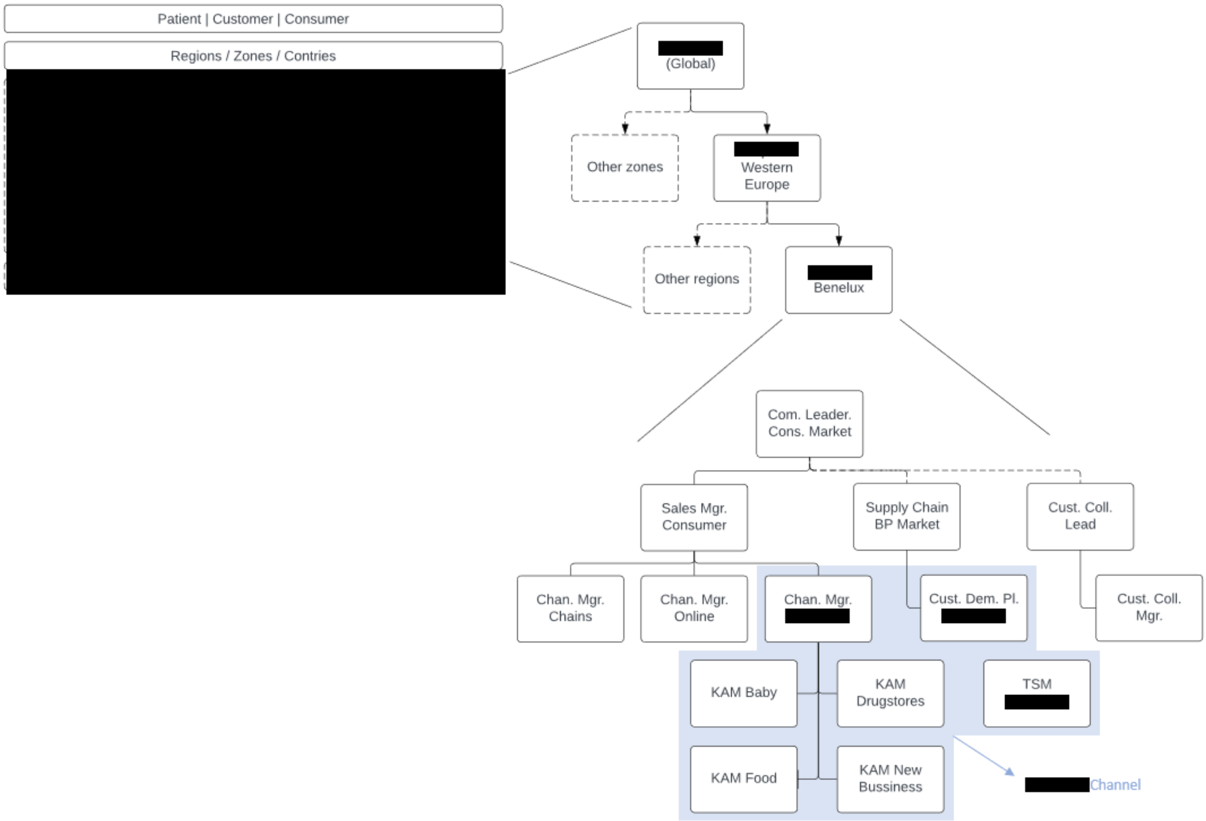

Figure 3: The structure and organogram of the case company

1.2.3 The products of the case company

As stated above, the case company comprises four product categories: (1) Male grooming, which is the shaving department for men with SKUs like a Bodygroomer, Trimmer, and Multigroom. Since 2017, Oneblade has been within this category as well. Oneblade, however, covers internally for some analysis its own category next to Male Grooming due to the success of this product. This split is done to divide the logistics and financial statistics from the Male Grooming category to track the financial performance of Oneblade in more detail. (2) Beauty is the female category within the case company. This category consists of skin care, hair removal, and hair care. A product like IPL, part of hair removal, can be seen as a seasonal product. When the weather outside gets better, the sell-in and sell-out of IPLs will rise, thus generating more sales during spring and summer than in autumn and winter. (3) Oral Healthcare is a category with a big competitor. Oral-B is the absolute market leader in this segment, making it a challenging category for the case company. The case company have their Sonicare electric toothbrushes and brush heads. Electric toothbrush SKUs have a price range between 25 and 200 Euros, making it a wide price range. Lastly, (4) Avent comprises baby and toddler products such as bottles, teats, and breast pumps. This category aims for a specific target audience. Therefore, some events where the target groups come to are essential for the case company. The Nine-Month Fair (Negenmaandenbeurs) is one of those events every year in The Netherlands.

1.3 Improving demand forecasting at the case company.

1.3.1 Quantitative and qualitative approaches to demand forecasting in the case company Sales environment

The scientific literature on demand forecasting classified the forecasting tools and methods into two families: quantitative (i.e., statistical) and qualitative (i.e., judgmental) approaches (Caniato, Kalchschmidt & Ronchi, 2011). Quantitative forecasting methods perform better when there is a proper amount of historical data available, and the phenomena are more or less stable. The qualitative approach, however, is more accurate when there is no or little historical data or circumstances are rapidly changing, making the past unable to explain the future (Makridakis et al., 1998; Filders et al., 2009). This can be the case for new products. The new product has no historical data, so the judgmental approach should perform better than the statistical tool. Extraordinary events or promotions are the weakness of the quantitative demand forecasting method. In the case company sales environment, these events or promotions often occur, making the quantitative model a less accurate model. However, the quantitative model can support the KAMs' decision-making by showing the quantitative data and analysis, for example, in a forecasting dashboard. The case company barely uses the quantitative approach. The KAMs use their judgmental forecast with their experience to ensure enough stock for their clients' orders (sell-in). The availability of data and the quantitative methods might help the KAMs to forecast the sell-in.

'*More insight into the data we have about the past can give us a better understanding of the sell-in for the next period. The visibility for the KAMs is an important aspect of this.'* (Particpant 1)

1.3.2 Implementing a suitable forecasting method for the case company.

In this study, we present an action research case developed for the case company in the Benelux to implement the best appropriate forecasting method so that it can contribute to internal alignment between the involved stakeholders concerning the ordering from the Europe DC and minimizing stock in the warehouse.

'The case company is one of the main players in the Personal Health market, and stock is currently one of their main points of improvement.' (Participant 1)

An accurate forecast to predict the demand of their customers is fundamental to having healthy stock in their DC. The need for the case company products is partly seasonal and is strongly dependent on product promotions. Due to these characteristics, this case is quite interesting. The availability of long series of historical data and a certain demand stability are typical conditions for adopting a quantitative method (Caniato, Kalchschmidt & Ronchi, 2011). However, changes in the market, the product promotional sensitive products, and the seasonality create a need to include information that is not structured in the forecasting process and, therefore, cannot easily be managed by a statistical method, thereby necessitating a judgmental approach (Caniato, Kalchschmidt & Ronchi, 2011). The case company currently uses a simple form of judgmental forecasting primarily. The KAM and CDP know the baseline of a product. When there is a promo in the upcoming period, they will discuss it and add a particular percentage to the baseline sales, which will be their forecast for that product. This process, however, could be extended by using a quantitative approach, which can also consider the trend, seasonality, or other factors influencing product sales.

Some approaches take into account the growth of the sell-in over the years (Moving average), whereby the more recent data points are given more weight (Exponential smoothing), or where economic, competitive, or internal variables are taken into account (Regression model) and even considering the Seasonal aspect (SARIMA) (Brown, 1959; Holt, 1957; Hyndeman & Athanasopoulos, 2018; Winters, 1960). These quantitative methods can be used to support judgmental forecasting to better predict their retailers' upcoming demand. The quantitative data can be visualized in a dashboard. This dashboard provides a user-friendly tool to identify and analyse historical data for feature forecasting purposes.

At this moment, the stock is not managed that well. The European inventory is too high, according to the European Sales Leader, which causes too many costs. Within the Benelux team, the importance was raised to match sell-in and sell-out better. The case company supplies most of its online retailers daily, thus closely matching the sell-in and sell-out. However, this is not the case for all of the case company' retailers. They do not have the capacity to forecast collaboratively with the case company but order every week and in large chunks. The KAMs, with retailers as their clients, can use and visualize old data from sell-in, sell-out, and stock to predict chunks in sell-in to help reduce EU inventory, and in turn, reduce costs.

1.4 Problem definition

This paper will focus on the retailer's demand for the supplier, which will be caused by the consumers' demand for the retailer's products. As stated earlier, there are three channels, and every channel has three KAMs with their account(s). For this case, we are looking in more detail into just one KAM (participant 1) within the channel. The sales retail department of the case company acts in a two-stage supply chain with a single supplier, selling its products to consumers through a single retailer. More specifically: the sales retail department of the case company sells and forecasts the demand of its retailer and, indirectly, the demand of the customers of the case company products. The case company industry relies primarily on product promotions. The reason for this is the products The case company sells. These are products with high margins and fierce competition from other companies selling similar products. Besides that, the case company has some products whereby the product itself does not have such a high margin and is thus cheaply sold. Still, the attributes of the product which must be bought frequently to use the product are relatively expensive with high margins. More specifically, the handles within the case company Oral Health Care (OHC) are relatively cheap, but the brush heads have a high margin. Because of the product promotions, competition and margin, the demand of the retailer, one of the case company biggest retailers, is highly volatile, which makes forecasting more difficult.

Predicting the next period more accurately due to a quantitative forecasting technique combined with their intuition and expertise (judgmental forecasting) can help the KAM and CDP better predict the future sell-in. The forecasting technique uses quantitative historical data to make a prediction which can be used as the basis whereafter the KAM and CDP discuss their forecasts for the upcoming period(s). Both use their own ‘forecast’ and plan on different time frames. These two employees do collaborate a lot. The CDPs will schedule the next period (a month) to ensure the case company has enough stock in its warehouse to deliver its clients' orders. The KAMs, however, know their clients the best. They negotiate with them, know the competition, and offer discounts. Factors such as discounts and competition can influence the retailer's sell-in. Applying the best-performing forecasting technique and visualizing this in a forecasting dashboard can help predict the next period more accurately and lead to more internal alignment between the KAM (with their forecast) and the CDP (with their forecast)

Therefore, this study will focus on evaluating forecasting methods for The case company to forecast better the intermittent demand of a particular retailer in the retail industry, which may lead to more internal alignment among the stakeholders in the forecasting process. This study is designed around the following research question:

'How can alternative forecasting methods outperform the use of solely judgmental forecasting within The case company regarding the prediction of sell-in for various future time periods, and to what extent can this lead to more internal alignment among the stakeholders involved in the forecasting process?'

This research consists of a two-stage approach. The first stage will be measuring the performance of the quantitative methods in the context of demand forecasting. The outcome of this stage will enable the identification of the best-performing quantitative method, which will subsequently be incorporated into a forecasting dashboard. The second stage will have a qualitative approach. Here, interviews will be held to evaluate the dashboard and explore whether the quantitative approach combined with the judgmental forecasting method will lead to more internal alignment between the stakeholders involved in the forecasting process. Quantitative techniques will be used as the artefact. This will include demand forecasting methods, which will test the performance. Within the retail industry, traditional statistical methods such as the Bayesian approach, auto-regression, exponential smoothing, Holt-Winters model, and ARIMA and SARIMA based on the Box and Jenkins methods are usually used to forecast sales (Ren, Chan & Sigin, 2020). Traditional methods are used in the retail industry due to three major reasons: (1) they are easy to use and implement, (2) they predict and calculate prediction results very quickly, and (3) finally, they have closed-form expressions that make them easy to combine with other business decisions such as inventory management (Ren, Chan & Sigin, 2020). Machine learning (ML) techniques are not addressed in this study. These techniques can accurately predict sales but will not be applied due to 4 reasons. (1) interpretability: ML models can be very complex and challenging to interpret, (2) data requirements: ML often requires large amounts of data to train effectively, (3) they can be prone to overfitting; and (4) they can be sensitive to changes in data.

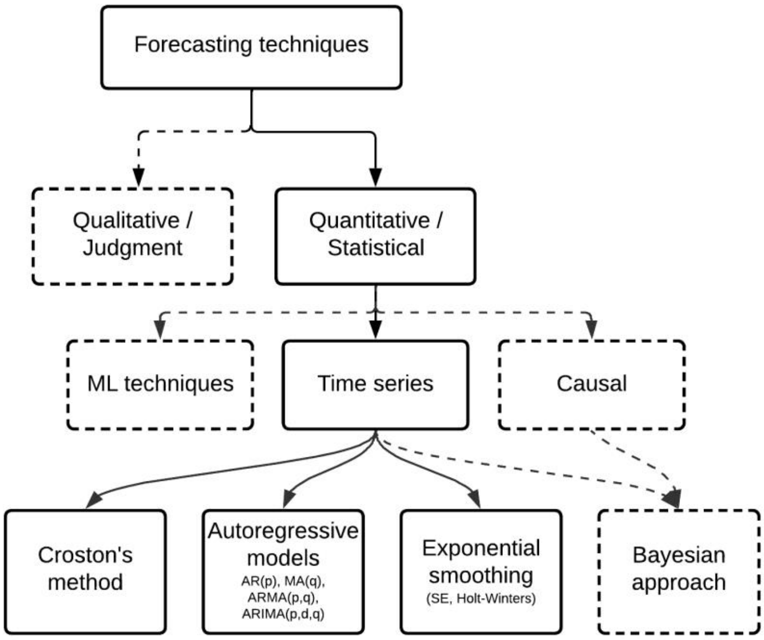

Figure 4: Simplified forecasting tree of selected forecasting methods

This research will include the Holt-Winters forecasting technique, the SeasonalARIMA method and the more advanced Croston's method, which is the most widely used forecasting method for intermittent demand time series (Kourentzes & Petropoulos, 2016). These three forecasting methods are visualised above in Figure 4 and are chosen based on five factors (Chambers, Mullick & Smith, 1971) developed to select forecasting methods. This will be discussed in more detail in chapter 3.4.1. The chosen three methods will be compared using sell-in, stock, and sell-out data for 2021 and 2020 to predict 2022 sales for the case company. Whereafter, interviews will be held to test the internal effect and more unanimity of the forecasting method and dashboard to predict the retailers' demand among the stakeholders in the forecasting process.

This research cannot only be used for managerial purposes within the case company but can prescribe a design in which a relatively simple forecasting technique can be used to support the judgmental forecasting techniques most KAMs use in large established companies. This way, this study applies not only to the case company but to every company where judgmental forecasts are used nowadays but have the data for forecasting techniques supporting them. This methodology with a two-stage approach whereby a quantitative forecasting model is used as an artefact is tested in a real-life environment using qualitative techniques, which contributes to the current literature. The two-stage approach with an estimating or predicting component is rarely used. Kisi, Mani & Rojas (2014) did, however, evaluate the efficiency of labour-intensive construction operations by using a two-pronged approach. They first estimated the optimal productivity by using system inefficiencies in the productivity frontier (top-down and qualitative). After that, they determined optimal labour productivity by removing non-contributory work in a simulation (bottom-up and quantitative). Alvi, Nabi & Greaves (2011) used a two-pronged approach to separate the domain knowledge from the operational knowledge. The study conducted in this paper distinguishes that it uses a quantitative approach by testing forecasting techniques, whereafter, this is evaluated using a qualitative approach. The main aim is refining the final tool to be used in The case company.

1.5 Reading guide

This study has been structured as follows. First, a deeper look into the literature is conducted to review the most promising forecasting methods in the retail industry and forecasting with a highly volatile demand leading to intermittent demand. Chapter 3 will cover forecasting within The case company and the components that influence their sell-in and sell-out. The data collection will be discussed, and three forecasting methods will be applied to the case company case to predict future demand. Lastly, the implementation and evaluation of the dashboard will be conducted. Chapter 4 covers the results where the analysis and testing will be presented. Three forecasting techniques will be tested on a selection of SKUs and compared to each other. Finally, the results will be concluded and discussed, managerial implications will be provided, and suggestions for further research in the field of intermittent forecasting will be given.

2. Theoretical background

2.1 Forecasting

Forecasting is a task that is central to many activities within an organization to use for capacity planning, the efficient allocation of scarce resources, and goal setting for measuring performance (Taylor & Letham, 2018). More generally, we can say that forecasting can predict 'events'. According to Hyndeman & Athanasopoulos (2018), the predictability of an event or a quantity depends on several factors, as shown in Figure 5, including (1) How well we understand the factors that contribute to it. Several factors influence the predictability of an event. When there is a good understanding of these factors, the predictability will be higher. (2) How much data are available? The more data available, the better an event can be predicted. When more data is available, components such as trends and seasonality can be seen better and more accurately. The availability of more data leads to better predictability. (3) Whether the forecasts can affect what we are trying to forecast. If a forecast affects the thing we are trying to forecast, it will be more challenging to have good predictability. An extra factor leads to the forecast, which is within the forecasting itself, making it more unpredictable. (4) How similar the future is to the past. If the future is similar to the past, the forecast can produce high predictability. The future is then close to replicating the past, making it easier to predict future events.

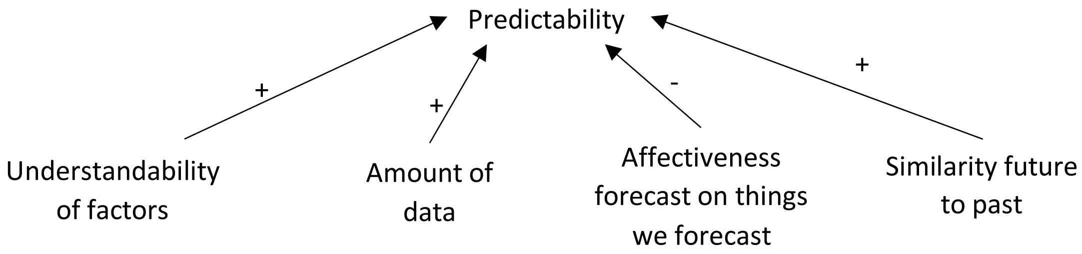

Figure 5: Factors influencing the predictability of the demand.

Hyndman & Athanasopoulos (2018) state that forecasting should be an integral part of the decision-making activities of management and divide forecasts into three terms of forecasting: short-term, medium-term, and long-term. The three forecasts are used for predicting different aspects of the business. Short-term forecasts can be used for scheduling personnel, production, and transportation. In contrast, the medium term is needed to determine future resource requirements and long-term for strategic planning, market opportunities, and internal resources (Hyndman & Athanasopoulos, 2018). According to Bowersox et al. (2002), forecasts consist of five components: base, seasonality, trend, promotions, and irregular demand. This visualisation can be seen in Figure 6. The next sub-chapters will discuss these five components.

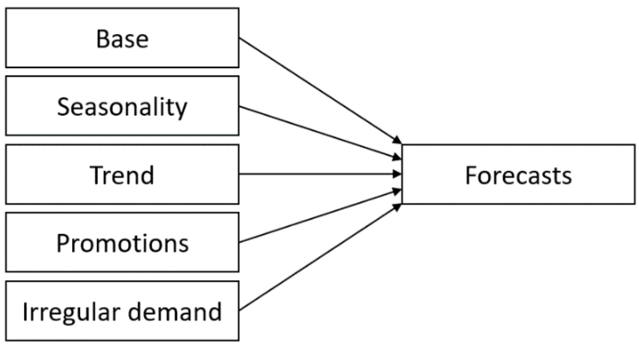

Figure 6: Bowersox et al. (2002) five components of forecasts

2.1.1 The base

The base is the number of products that are sold without a promotion. This is the number of products that are sold without any influence from the company(Fildes & Kolassa, 2019). The historical data should have been cleaned of the demand drivers, such as past promotions and weather (Fildes & Kolassa, 2019). This baseline forecast is adjusted for upcoming events, most often promotions (Fildes & Goodwin, 2007). It is crucial to note that, especially in the case of promotions, the accuracy of the baseline forecast can significantly impact the final forecast's overall accuracy. It is essential to consider the underlying demand drivers, such as seasonality and trend, to increase the accuracy of the baseline estimate (Fildes & Kolassa, 2022). To anticipate the baseline demand, various time series methods, such as exponential smoothing and ARIMA, can be utilized (Fildes & Goodwin, 2007). Additionally, it is crucial to monitor the baseline forecast and update it whenever new information becomes available since this might assist in increasing the final predictions' accuracy (Fildes & Goodwin, 2007).

2.1.2 Seasonality, calendar events & trends

Seasonality, calendar events, and trends can significantly impact the number of sales and thus cause levels of volatility (Fildes et al., 2019). Commercial time series are often seasonal due to the human behaviour they represent. It can be seen daily, weekly, monthly, or quarterly. Mostly on weekends, the sales are higher compared to workdays and the difference in sales between summer and winter. Seasonality is used to describe the predictable and regular patterns of activity that take place throughout the year. Understanding seasonality patterns is essential for predicting future trends, making wise business decisions, and efficiently allocating resources. It is a persuasive phenomenon that can significantly impact various fields.

Calendar events are significant days, weeks, or months noted on the calendar and frequently have political, social, economic, or cultural importance. Holidays, festivals, athletic events, and other significant dates acknowledged and honoured by people, groups, or nations can all be considered calendar events. Calendar events include special days like World Health Day and Mother's Day, and events like Black Friday. According to Huang, Fildes & Soopramanien (2014), the effect of the calendar event on sales is not the same for every product group. For example, IPL will sell more the days before and on Mother's Day, but this is not the case for the Male Grooming category.

Besides seasonality and calendar events, trends can be visible when plotting the data. The slow and enduring changes in behaviour, attitudes, or values through time are referred to as trends. A trend exists when there is an increase or decrease in the data over the long term. It does not have to be linear. Sometimes a 'change in direction' is called a trend, when it can change from an uptrend to a downtrend. For example, the rise of e-commerce and online shopping has led to a shift in how people make purchases, with more and more consumers choosing to shop online rather than in brick-and-mortar stores (Hays et al., 2005). Understanding trends is essential for companies and organizations to remain competitive and react to shifting market conditions.

Below in Figure 7 four types of trends and three types of seasonality are presented. The matrix provides us with an overview of the combinations between the types of seasonality and types of trends. When plotting the data, these patterns can be visible and traced back to the seasonality and trend type. Because seasonality, calendar events, and trends can significantly affect the forecast, they must be considered when making the forecast.

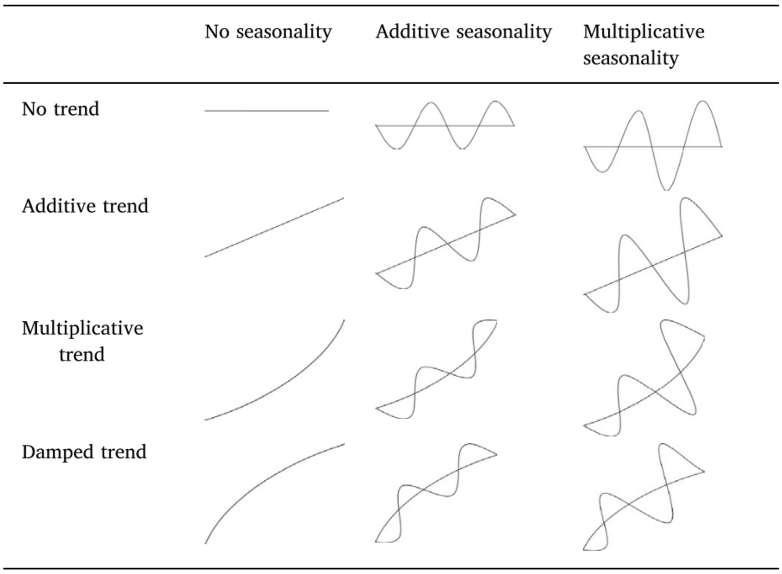

Figure 7: Data curves with the trends and seasonality (Liu et al., 2020)

2.1.3 Price and promotions

Besides the time-specific properties, price and promotions can influence sales, especially in the highly competitive environment where the case company is situated. Product promotion leads to substantially more sales (Ali et al., 2009). Retailers use various promotional strategies, such as discounts, coupons, and buy-one-get-one-free (1+1), to increase sales and attract customers. A study by Erdem et al. (2002) found that the impact of price promotions on consumer behaviour is influenced by consumer characteristics such as their level of price sensitivity. In line with this, a study by Macdonald & Sharp (2010) examined how product promotions affected consumer behaviour and discovered that they could lead to more product trials and repeat purchases. The authors contend that promotions are especially successful in attracting price-sensitive consumers and encouraging brand switching. The study emphasizes the importance of picking the proper promotion strategy to target particular customer categories, accomplish the intended marketing results, and sell more.

The sell-out, however, depends on various factors. Compared to ‘normal’ sales, promotion sales include some extra factors which make it more challenging to forecast the sales during a product promotion. The effect of a promotion depends on the size of the price discount (Cooper et al., 1999), the visualization of the promotions (Ailawadi, Harlam, César & Trounce, 2006), the advertisement type, e.g., folder advertisement, TV commercial, or newspapers (Sethuraman & Telli, 2002), and product category characteristics (Ailawadi et al., 2007). These characteristics are visualized in Figure 8. These are all positively affecting the sales performance. Price increases, however, will lead to fewer sales. Price increases are driven by inflation, more expensive production, or material costs (exploratory interview Sales leader Benelux) and negatively influence sales.

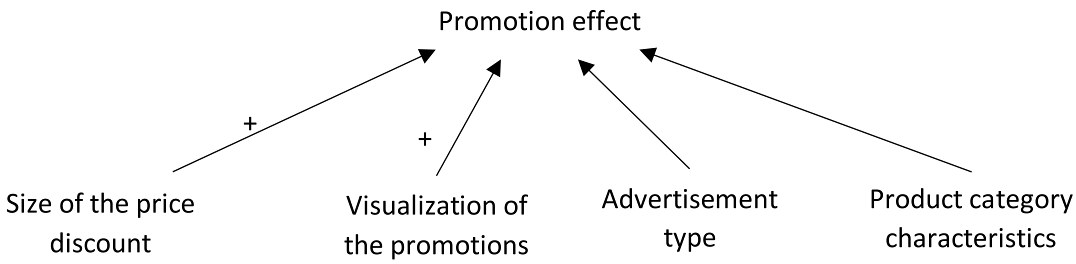

Figure 8: Factors influencing the promotion effectiveness

2.2 Three basic types of forecasting methods

There are three basic types of forecasts: qualitative techniques/judgmental forecasts, time series analysis and projection, and causal models (Chambers, Mullick & Smith, 1971). These three types of forecasts are visualized in Figure 9 below and will be discussed in the next sub-chapters.

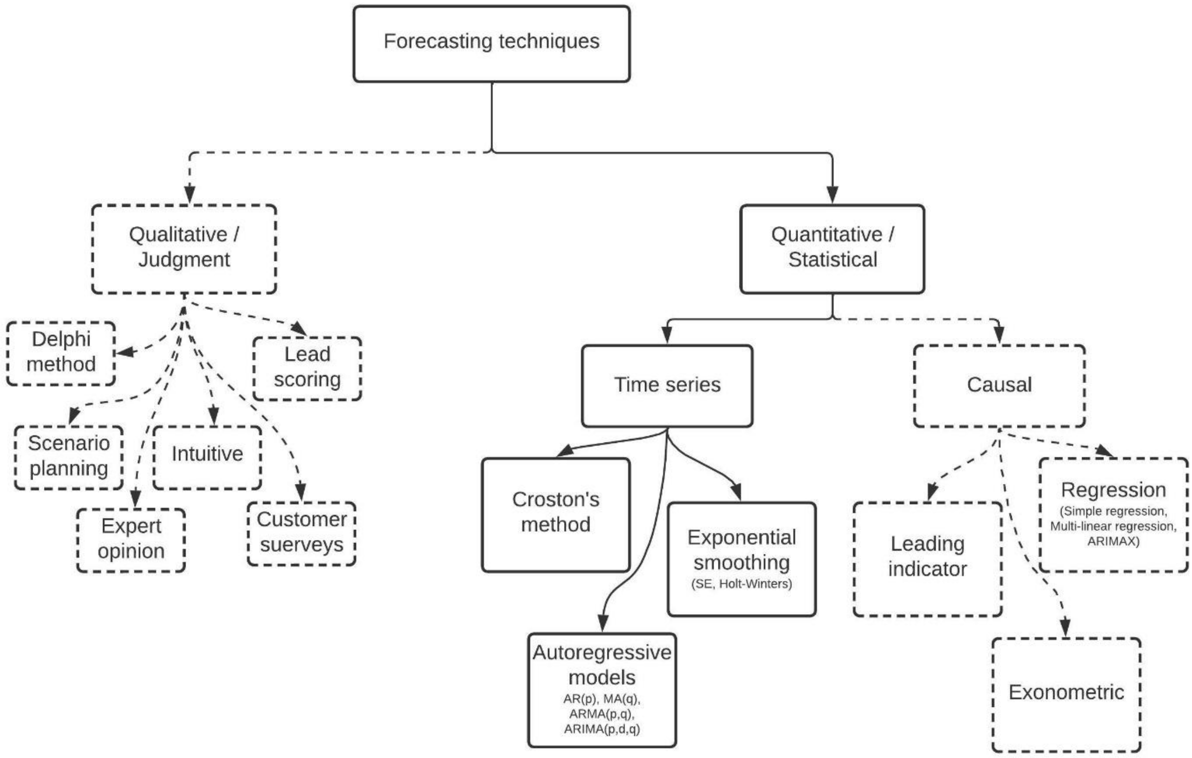

Figure 9: Classification of forecasting techniques

Note: Adapted from: Ungureanu, S., Topa, V., & Cziker, A. C. (2012). Deep learning for Short-Term Load Forecasting – Industrial Consumer Case Study. *Applied Sciences*, *11*(21), 10126. p.2

2.2.1 Judgmental forecasting

Judgmental forecasting is a method of forecasting that relies on human judgment rather than statistical models to predict future events. When there is a lack of historical data, a new product is being launched, a new competitor enters the market, or completely new and unique market conditions, judgmental forecasting is the only option to forecast the future (Hyndman & Athanasopoulos, 2018). This can also be the case when data is incomplete, or there is a significant delay in receiving the data. More generally, judgmental forecasting will be applied for three settings: (1) when there is no data, so it will not be possible to use statistical methods; (2) data are available, a statistical method is used whereafter it is adjusted using judgment; and (3) data are available and statistical and judgmental forecast are both used but independently from each other after which both outcomes will be combined to one forecast (Hyndman & Athanasopoulos, 2018). Especially in the first two settings, no complex calculations, software, or analytics have to be used to perform the forecast. This makes it simple, cheap, and easy to make a forecast. The objective of judgmental forecasting is to bring information and judgements related to the factors being estimated together in a logical, unbiased, and systematic way all information and judgements about the factors being estimated (Chambers, Mullick & Smith, 1971). Although this is the objective, and this forecasting method is relatively simple, cheap, and easy to perform, there are some limitations. This form of forecasting is subjective and can be inconsistent compared to statistical forecasts. For example, the limitation of human memory can cause the more recent numbers to be more important than they are (Hyndeman & Athanasopoulos, 2018). Another limitation can be that the forecast depends on the emotions or political agenda of the forecaster (Fildes & Goodwin, 2007b). Lastly, the effect of anchoring is an undesirable property commonly seen in judgmental forecasting. The forecast tends to converge to an initial familiar reference point, and thus the forecaster is influenced unduly by prior information (Hyndman & Athanasopoulos, 2018).

Recent research has been conducted to overcome the abovementioned restrictions and raise the accuracy of judgmental predictions. The effects of accuracy, confidence, and consensus in judgmental forecasting were assessed in a study by Bolger et al. (2011). The findings demonstrated that higher consensus among forecasters does not necessarily lead to higher accuracy and that the confidence level in the forecast significantly impacts its accuracy. The study emphasizes how critical it is to consider the sources of uncertainty in judgmental forecasts and incorporate these into the final result.

In conclusion, judgmental forecasting is an effective technique for making predictions in some situations, but it is crucial to be aware of its drawbacks. By taking into account the sources of uncertainty, incorporating pertinent feedback, and attempting to reach a consensus among forecasters, research has made significant strides toward increasing the accuracy of judgmental forecasts. The remaining shortcomings of judgmental forecasting must be addressed, and new methods must be developed to improve its accuracy.

2.2.2 Time series analysis and projection

'Anything that is observed sequentially over time is a time series' (Hyndman & Athanasopoulos, 2018, P. 14). Time series forecasting is used when data for a product or product line are available, and relationships and trends are both clear and relatively stable (Chambers, Mullick & Smith, 1971).

Time series analysis is a statistical method examining data collected at regular intervals over time. This analysis aims to find the data patterns, trends, and underlying structures that may be applied to predicting and making informed decisions. Estimating future values based on previous data and an awareness of the underlying patterns and trends is referred to in this context as time series projection (Shumway et al., 2000).

It uses historical data, which consists of a set of chronologically ordered points in time, to predict the current and the future. It helps to identify and explain: (1) any systematic variation in the series of data which is due to seasonality; (2) cyclical repeated patterns; (3) trends in the data; (4) growth rates of these trends (Chambers, Mullick & Smith, 1971).

A few techniques used in time series analysis include descriptive statistics, trend analysis, seasonality analysis, and modelling with time series models. The data are summarized using descriptive statistics, including central tendency and variability measures. Finding enduring patterns in the data, such as linear and nonlinear trends, is the goal of trend analysis. Finding recurring patterns within a single period, like monthly or quarterly patterns, is the focus of seasonality analysis (Hyndeman & Koehler, 2006). Time series models represent the underlying patterns in the data and forecast future values using mathematical techniques.

The autoregressive integrated moving average (ARIMA) model is a popular time series model (Box & Jenkins, 2015). A class of ARIMA models can accurately represent time series data's moving average and autoregressive components. Because they can be used with various time series data and have good forecasting capabilities, these models are frequently used in practice.

Two conditions must be satisfied to be able to use quantitative forecasting, according to Hyndman & Athanasopoulos (2018): (1) numerical information is available about the past, and (2) it is reasonable to assume that some aspects of the past patterns will continue into the future. Especially this last condition can be, at the same time, the limitation of using this method. Suppose time series does not appropriately capture the dynamics of the (business) context, for example, by excluding promotional activities or new product development. In that case, this statistical forecasting method based on historical sales data can produce inaccurate forecasts. As a result, using human judgement adds some value to the forecasts produced by quantitative/statistical models, making human expertise an essential component in sales forecasting (Arvan, Fahimnia, Reisi and Siemsen, 2019).

For understanding and projecting future values in time series data, time series analysis and projection are crucial approaches. The techniques employed in time series analysis, including time series modelling, trend analysis, seasonality analysis, and descriptive statistics, offer a comprehensive framework for comprehending and predicting time series data.

2.2.3 Causal models

Causal models are mathematical models used to study the relationship between variables and how one variable affects another. To create predictions and guide decision-making, causal modelling aims to understand the links between the variables of interest and the underlying mechanisms that drive changes in them. A causal model is the most sophisticated forecasting tool of the three models described. It expresses the causal relationships mathematically and may also directly incorporate the results of a time series analysis (Chambers, Mullick & Smith, 1971; Hlaváčková-Schindler et al., 2007). Causal models include models derived using segmentation, regression analysis, and the index method (Green & Armstrong, 2012). Forecasts from causal models are more accurate for situations where considerable changes are expected than forecasts derived from extrapolating the dependent variable (Armstrong 1985, p 408-409, Allen & Filders, 2001). This approach is suitable for determining the correlation between demands and estimating which business environment factors will predict future demands, for example, to assess the impact of price promotions on customer demand. It is most useful when (1) strong relationships exist, (2) directions of the relationships are known, (3) significant changes in the causal variables are expected, and (4) causal variables can be accurately forecasted and controlled (Green & Armstrong, 2012). If essential variables are missing from the causal method, judgmental adjustments can help improve the accuracy (Green & Armstrong, 2012). For example, when data is lacking, it may be necessary to make assumptions about some of the relationships and then track what is happening to determine if the assumptions are valid. Because of this, causal models are continually revised as more knowledge becomes available (Chambers, Mullick & Smith, 1971).

Causal models frequently employ experimental and observational data to determine the links between variables. Observational data reveal associations between variables without interventions, whereas experimental data reveal relationships between variables under the influence of interventions. These two forms of data may be combined with causal models to offer a complete understanding of the relationships between variables.

To sum up, causal models are mathematical representations that are used to investigate the connections between variables and the impact of one variable on another. These models have a variety of uses and can be depicted using equations or graphical representations. The links between variables and the effects of interventions are well understood when observational and experimental data are used in causal models. While causal models are suitable for forecasting aggregated sales for several items, it is not economically feasible to use these techniques to control individual item inventories (Chambers, Mullick & Smith, 1971).

2.2.3 Research gap

Forecasting is a critical component of decision-making in many different businesses and organisations. Managers can make informed decisions and prepare for probable outcomes when they have accurate projections of future events and trends. To capture complex and dynamic relationships in the data, classic forecasting methods like time series analysis have several drawbacks. As a result, systems of judgmental forecasting that depend on human skills, intuition, and experience to create forecasts have gained popularity.

In practice, judgment-based forecasting techniques are frequently employed, especially when data is limited or inaccurate (Fildes & Goodwin, 2007). To provide judgmental forecasts, these techniques use the expertise and information of specialists like the Key Account Managers for their retailers. However, there is still a gap in research on the usefulness and effectiveness of judgmental forecasting compared to traditional techniques. There is a growing understanding among academics that combining the two ways can result in more accurate forecasts, even though each methodology has advantages and disadvantages (Clemen, 1989). For instance, judgmental forecasting can be used to include external elements, such as changes in rules or market circumstances, that are not captured by previous data (Makridakis et al., 2018). Additionally, integrating the two methods might better comprehend the underlying causal process behind the data (Wang et al., 2022).

Despite this general agreement, integrating time series forecasting with judgmental forecasting is still a subject of resolved study in the literature. Little research specifically examines how well various ways to merge the two approaches work (Clemen, 1989). More study is also required to compare how well various forecasting techniques function when used with various data kinds and under different circumstances (Hyndeman & Koehler, 2006).

Using judgmental forecasting techniques in real-world scenarios has become increasingly prevalent (Rowe & Wright, 2001); however, their potential in conjunction with conventional methods remains limited. Given the potential benefits of combining time series forecasting with judgmental forecasting, additional study is needed to evaluate the applicability and efficacy of traditional techniques in real-world settings, where they can be used to complement and enhance judgmental forecasting.

There is still a research gap in the literature regarding integrating time series and judgmental forecasting and implementing the results in real-world applications. In particular, there is a lack of studies investigating the development of dashboards that can effectively communicate the effects of time series and judgmental forecasts to stakeholders in the forecasting process. This includes the people deciding on the planning and others who rely on accurate forecasting data to make informed decisions leading to more internal alignment regarding the forecast and decisions to be made (Siregar et al., 2017).

Therefore, there is a need for further research on the integration of time series forecasting and judgmental forecasting with the result of creating dashboards for stakeholders in the forecasting process. Such a study can increase forecast accuracy while allowing stakeholders to understand the findings clearly and better align the stakeholders involved in the forecasting process. As it will allow for better-informed judgments based on precise forecast data, this will have significant consequences for practitioners and policymakers across many fields.

3. Methodology

The constructed research question demands a two-pronged approach to identify the best forecasting method for The case company while considering the existing internal inconsistencies. This research methodology aims to develop a comprehensive action plan and improve the understanding of the most appropriate forecasting method by testing, implementing, and evaluating the best-suited method for enhancing the accuracy of the retailer sell-in prediction. The testing will be conducted using sell-in, stock and sell-out data from both the case company and The case company' retailers, followed by evaluating the most suitable method's impact on internal alignment between the stakeholders involved. The first stage will involve quantitative testing, including forecasting analysis and implementation, which will be presented as a dashboard. The second stage of the approach will involve qualitative data collection through semi-structured interviews and a focus group to assess the final design of the dashboard.

3.1. The model

This study aims to test the best forecasting method to forecast the sell-in of the retailer demand for The case company, whereafter a dashboard is built and evaluated. This aim requires a two-staged approach to be used.

In the first stage of the research methodology, the focus is on testing the best-performing forecasting method. To achieve this, quantitative techniques are employed, and the accuracy of the forecasted data is measured. This is accomplished by comparing the predicted and actual data using the Root Mean Squared Error metric.

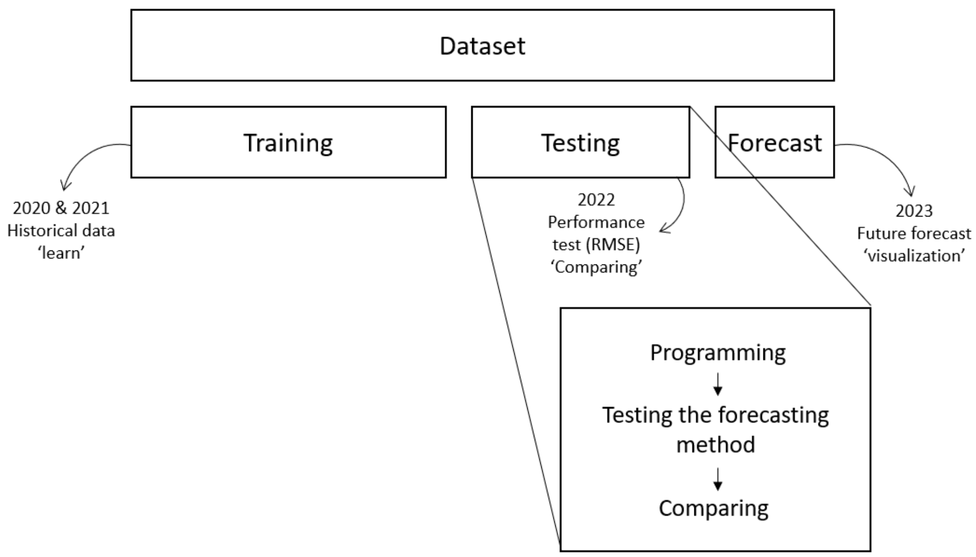

Figure 10: Stage 1 visualisation

To conduct the accuracy test, the dataset consists of data from 2020 to 2023. The 2022 sell-in data is utilized as the actual data, while the historical data of 2020 and 2021 are used to train the forecasting methods. The process of stage 1 is shown in Figure 10. To predict data obtained from the forecasting models are then compared against the actual data to measure the accuracy of the forecasting methods. This is the second step of the process. This step involves programming with Excel Solver or Rstudio, whereafter the methods will be tested and lastly compared to each other using the RMSE. The RMSE metric is utilized to measure the difference between the predicted and actual data, with a lower value indicating higher accuracy of the forecasting method. The RMSE is a commonly used indicator of predicting effectiveness (Hyndeman & Koehler, 2006; Makridakis et al., 2018). The fact that RMSE is in the same unit as the original data makes assessing the error's magnitude simple, which is one of its key advantages (Makridakis et al., 2018). The last step is visualizing the forecast for the next period for the case company. The best forecasting method is used to predict the data in the future for The case company.

Stage two has a qualitative approach. Figure 11 visualizes the set-up of this stage. Exploratory interviews ensure clear awareness of the problem and suggestions on how to tackle this. A proposal will be discussed, and a tentative design will be made. Subsequently, the development of the dashboard starts. This dashboard will be evaluated by the stakeholders using semi-structured evaluative interviews where the performance of the dashboard will be measured. The final evaluation will use a focus group with the stakeholders involved in the forecasting process, and lastly, the results will be discussed.

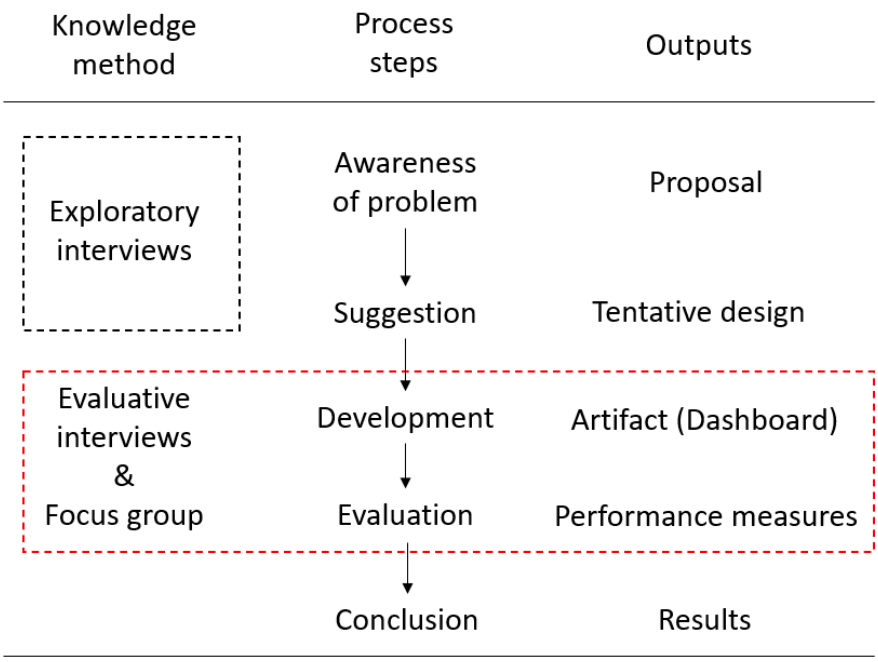

Figure 11: Stage 2 set-up flow model

The best-performing forecasting method is used to build a dashboard. This dashboard displays the historical and most recent sell-in, sell-out, and stock. Additionally, the predicted sell-out is given. The dashboard, which acts as an artefact in this study, is evaluated qualitatively. The qualitative evaluation consisted of semi-structured interviews, and whereafter improvements were made to the dashboard. Lastly, a focus group with the stakeholders involved in the forecasting process evaluated the final version of the dashboard.

3.2 Organizational approaches to forecasting

This chapter will discuss how forecasting will be used for the case company. It discusses the application of the literature to the case within the case company. The first sub-chapter will discuss the people involved in the forecasting process. The next paragraph covers the data components established by Bowersox et al. (2002) that are applied to the case company. The second paragraph will discuss different "types" of stock that exist within the case company and its distribution. The last paragraph covers the organizational learning of forecasting.

3.2.1 Internal forecasting

Two general approaches are suggested for developing forecasts for individual items in a family (SKUs): the top-down (TD) and the bottom-up (BU) approach (Gordon, Morris & Dangerfield, 1997). In the TD approach, which can be seen in figure 12, family data are used to develop a family forecast; whereafter it is disaggregated into individual items based on their specific historical fraction of sales. The BU approach has a different starting point for its forecast. For BU forecasts, a separate forecasting model is developed for each item in the family (for every SKU). The BU approach can be seen in figure 13. More specifically, within the case company, the TD approach will first look at the Male grooming category and make a forecast, whereafter, they look at a fraction of a particular SKU. A separate forecast is made using BU for every SKU within the Male grooming category. The BU approach is used within the case company. The stakeholders involved in the forecasting process deep dive into each SKU separately and work their way up. This is done for all categories except for MCC.

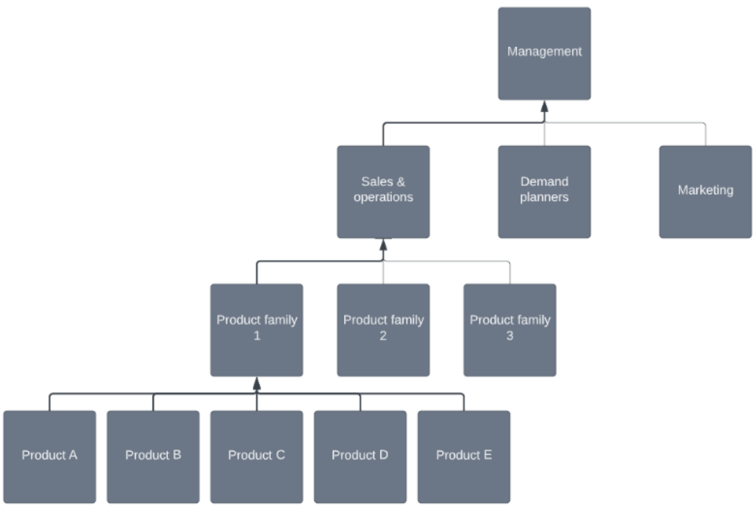

Figure 13: Bottom-Up forecasting approach

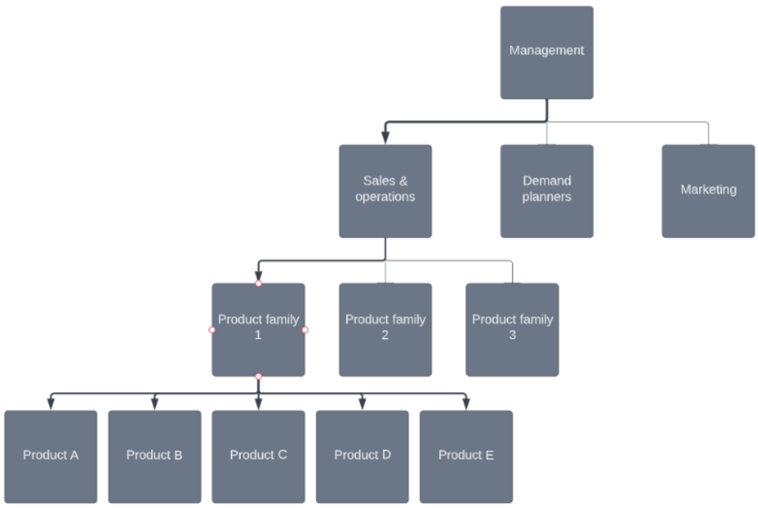

Figure 12: Top-Down forecasting approach

Within The case company the KAMs and the CDPs are the essential persons forecasting the demand of the retailer. The responsible KAM plans product promotions half a year ahead. When a product promotion comes close, the KAM looks at upcoming promotions and adapts its forecast to them. This forecast is done at weekly intervals due to these promotions. The KAM's weekly forecast differs from the CDP forecast, which has a monthly interval. The difference between time intervals concerns the warehousing and internal ‘competition’ for the stock between KAMs within the case company. The CDP orders SKUs monthly so that The case company can claim their part of the case company stock located in the case company distribution centre (DC) in ….., The Netherlands. This stock has to be claimed every month. This is in contrast to the stock the KAMs have. They have to divide the case company stock between each other's customers. This, combined with the product promotions, leads to a weekly forecast of the sell-in/sell-out. This whole process is visualised in Figure 14 below. As stated earlier, the CDP can assign a bit of the European stock to the Benelux zone. This is a centralised planning system. The European stock is allocated using a calculation, and the zones' CDPs

Figure 14: Timeline product promotion and stock allocation

can increase or decrease this a bit. After this allocation to the Benelux zone, the stock can be assigned to one of the KAMs clients. This process is decentralised. The KAM asks for stock to replenish its client, whereafter, the CDP will try to assign that stock to this KAM or client.

3.2.2 The case company five data components building a forecast.

As stated in Chapter 2.1, according to Bowersox et al. (2002), forecasts consist of five components. These include base, seasonality, trend, promotions, and irregular demand, as shown in Figure 6.

In the case of the case company SKUs, the base consists of historical data of last year (LY), which is 2021 data and 'last last year' (LLY), which is 2020 data. The most important data for the base to the case company is the sales data in quantities and triple net lease (NNN). The sales data in quantities are the number of products that are sold in the past period. This consists of both sell-in and sell-out. Thus, the same product in the same week can have a sell-in of 50 and a sell-out of 60. This means that the stock in the warehouse of the customer has declined by 10 (60-50) because the customer buys 50 products from the case company and sells 60 products to the consumer. The NNN is the recommended retail price (RRP) minus the tax, minus the discount, minus rebates, minus the folder contribution and promotion discount, as seen in the formula below. The RRP is a suggested price for which a manufacturer recommends a retailer to sell its products. The RRP is a guide for the retailer and helps establish the product's perceived value in the market. The actual price can be different from the RRP. The tax in the Netherlands is 21 per cent of the RRP. Discounts are reductions in the regular price of a product The case company pays for. Rebates, however, are refunds of a portion of the purchase price The case company pays back to its customer when they meet the case company' requirements.

$$NNN = RRP - Tax - Discounts - rebates$$

Seasonality refers to the fluctuations during the year based on seasons, while trend refers to a more general direction the forecast is going. Several combinations of seasonality and trends are visualized in Figure 7. Within The case company, this can be seen in spring and summer for products in the Beauty category. These products will be sold more compared to autumn and winter.

Promotions are activities that boost sales and are very important in the case of the case company. The product promotions provide spikes in demand compared to the baseline. Most of the products in their markets are highly driven by product promotions. Some are more than others based on a product's competition in a specific market. This, however, is a crucial factor in the sales of The case company products and thus influences the forecast.

The last component is irregular demand which is for some product season based as well. For The case company, two different types of demand are important. The demand of their retailers, ordering products on pallets goes to the retailer's distribution centre, called sell-in. And the demand of the customers buying products from the retailers is called a sell-out. Due to the bullwhip effect, the sell-in demand shows more fluctuations than the sell-out for base-line products. This is due to the irregular ordering of the retailer compared to the more gradual demand of the consumers in the shops (sell-out).

3.2.3 Stock

Stock is an important aspect of the retail industry's supply chain. Products cannot be sold without stock, but too much stock in the warehouse leads to high costs. Retailers and their suppliers are thus always looking for an optimal amount of stock. Replenishment is commonly based on a policy of ordering up to a certain number of weeks' stock cover. Mostly one week's stock cover is the forecast demand for the coming week, with replenishment frequencies built around delivery schedules. The warehouse fill rate can measure the stock against the orders for a company. It refers to the percentage of demand that immediate stock availability meets without backorders, stockouts, or lost sales (Quickbooks, 2017). Managers strive for a fill rate of 100%. More than 100% means inventory is not being purchased or managed efficiently, and less than 100% means there are more orders than stock to fulfil.

The case company keeps track of two critical targets concerning their stock. The stock can be allocated in four categories based on the two characteristics described below in Table 1.

Table 1: Excess and Aging stock definition

Characteristic	**Definition**
Excess stock	The next 10 weeks are not in plan
Aging stock	Longer than 3 months in the warehouse

The matrix with four categories is plotted in Table 2, which is shown below.

Table 2: Excess and Aging stock matrix

	Aging	No aging
Excess	(1)	(2)
No excess	(3)	(4)

No aging & no excess is 'healthy stock' (4). The remainder is covered as 'unhealthy stock' (1, 2 & 3). This unhealthy stock is the first of the two critical measurements of the case company' stock. It can be calculated by: $\frac{Unhealthy\ stock}{Total\ stock} * 100\%$. A percentage target is set within the case company, and they closely track this number. The second measurement is keeping track of the Excess & Aging stock (A&E). This is stock which meets both excess and ageing characteristics and can be calculated by: $\frac{Excess\ \&\ Aging\ stock}{Total\ stock} * 100\%$.

The case company had two distribution centres in Europe, one in Northern and one in Southern Europe. At this moment, the case company is closing the Southern DC and is selling its stock to retailers. Stock that is left in this DC will be moved to the Northern DC. Because of this, the case company has less stock capacity because it can only use the Northern DC in ….. All stock of the case company will be located here. Because of this, the case company is more strictly managing their

Unhealthy stock and E&A targets. The percentages are lowered, meaning the stock should be healthier and shorter within the DC of the case company. From this DC, the CDPs from all 7 European areas of the case company can claim part of this stock. From there, the product will be directly transported to the DC of the customer, who will supply it to their own shops.

3.2.4 Forecasting and inventory management at the case company

Within The case company, there is a lack of consistency with the numbers used and the data gathered. The KAMs look and plan at weekly data while the CDPs plan on a monthly basis. These forecasting methods discussed above will be tested on the LY (and LLY) data of The case company for the retail. The most accurate method will be used to implement and therefore be able to forecast the demand of the retailer for the case company. This way, one consistent forecasting method exists for both KAMs and CDPs. The CDPs use this data to see the stock within the retailer warehouse, the sell-in to see how much we expect the retailer to buy next month, and the sell-out to see the number of products sold from the retailer to the customer. With these three data measurements and the forecast that is made, we get a good insight into the flow of products from the case company to the retailer's warehouse and to the consumer. If the sell-out is lacking behind the sell-in, we know the retailer stocks will rise in the future, whereafter the retailer will lower their sell-in for the next period. Thus, this forecast will be used to see what the forecast method thinks the sell-in will be of the retailer in the next period, for example, by looking at seasonality, trend, and some other parameters. After this forecast, the CDPs and KAMs can discuss the next period by looking at the stock and sell-out. They can adapt the forecast and predict a more accurate sell-in for the next period. By doing this, the case company warehouse will be less packed so that there is more healthy and less unhealthy stock in the warehouse. This will reduce costs and improve the reliability of delivering on time from the case company to their retailers/customers.

4. Stage 1: Forecasting method selection and techniques

Stage one covers the quantitative technique to find the best-performing forecasting method. In this section, we will explore the selection of forecasting methods, highlighting the factors that influence the choice of method. The choice made choosing Time series forecasting over causal models will be discussed, and the details of well-known techniques, including Holt-Winters' approach, (S)ARIMA, and Croston's method, will be examined. Lastly, the modelling software will be discussed.

4.1 Data collection analysis

In this research, several types of data will be gathered. Because this research includes both quantitative and qualitative approaches, three different types of data will be gathered. First, the forecasting model will be analysed. Three different forecasting techniques will be tested, and the best forecasting technique applied to the case company for the retailer will be chosen and implemented. This will be done by using a big data dump; whereafter it will be possible to test those forecasting methods.

4.1.1 Forecasting analysis

The three forecasting techniques will be tested on the LY (and LLY) data. The LLY data will be used to forecast the LY data, which can be adapted to the real sell-in values. The three forecasting techniques can be used to predict the next period in the current. Depending on the forecasting technique, this will use LY and LLY data with a weight included. The best-performing forecasting technique using the LY, LLY data, and CY data will be chosen to predict the sell-in of the next period. This method will be implemented whereafter the interviews will take place. The old and new methods will be discussed during these interviews regarding the collaboration between the CDPs and KAMs.

The case company receives data from a third party. This company collects data from many companies and combines them. It has an online platform where data is visible to employees of the case company. This tool provides us data about all retailers which are clients of the case company, CY, LY, and LLY data with dimensions like Week number, Product ID and measures like the sell-in quantity, the sell-out quantity and the stock quantity. The used dimensions and measures will be elaborated in more detail below.
The dimensions Month(/Week), BG, Category, MAG, AG, Product_ID, and Banner_Name are selected to get the correct data for this study. Month and week provide us for every SKU (product_ID) the data. The Banner_Name is Watsons, which is the retailer this study is about. The data of other retailers is irrelevant and not included in the data overview. BG, Category, MAG, and AG are additional dimensions for accommodating the SKUs. From biggest to smallest are BG, Category, MAG and AG, whereafter the Product_ID / SKU is given. For example, SKU …. is part of the AG Beard trimmers, which is part of the Grooming MAG, part of the Male Grooming Category and within the Grooming and Beauty BG. Due to these dimensions, the product can be classified very easily. This can be important in distinguishing product groups from each other. For example, a beauty product is more likely to show more sell-in and sell-out during spring and summer than autumn and winter (Seasonal). This will be less the case for the Oral Healthcare product group. The Measures selected are Sell_In_Qty, Sell_Out_Qty and Stock_Qty. These measures will be provided for CY, LY, and LLY, giving us nine columns of data and hundreds of rows (For every SKU per week, a new row of data).

This study focuses not on all SKUs within the case company portfolio. The retailer alone, as a customer of the case company, already has an assortment of 206 SKUs (based on the output '*Name of de document*', which can be seen in Appendix 9.3.2). Thus, focussing on five key SKUs within this assortment. To get these five SKUs, the NNN value in Euros of the sell-out value of the SKUs in 2022 until week 50 for the retailer is looked at. This data is exported and ordered at their sell-out value (high-to-low). This export (Appendix 1) and order mark five key SKUs listed in Table 3.

Table 3: Top 5 Key SKUs' the retailer

Category	MAG	SKU	Sell-out NNN CY
[redacted]			

The SKUs listed in Table 4X are the top 10 most important SKUs according to the sell-out value at the moment and, thus, the most important SKUs for the KAM to perform an analysis on. However, the forecast will be tested on data from week 15 in 2020 until week 15 in 2022. To be able to test the performance best, all data must be available. Missing weeks will decrease the forecast accuracy and ability to evaluate the methods against each other. The forecasts will be tested on the top 5 SKUs without missing data. The top five SKUs are chosen based on their importance according to Participant 1 and the availability of the data. Once the forecasting method is tested on a smaller number of SKUs, it can easily be scaled up to a more extensive set of SKUs. This allows us to refine the methods and ensure accuracy before they can be applied to a larger dataset. All SKUs have complete data except the fourth SKU. This SKU has missing data in 2021 and 2020. Especially in 2020, many weeks are missing. This SKU, therefore, will be replaced by another SKU. The fourth SKU is a Beauty product and will be replaced by a Beauty product to have coverage of all Categories sold by the retailer on the SKU level. The MCC category is not planned on SKU but on AG level. The ninth SKU has missing data as well. Thus, the tenth SKU will be used to replace the fourth SKU. An overview of the most sold products and the data availability can be seen in Table 4.

Table 4: Overview of most sold products & data availability

SKU	MAG	Category	Sell-out NNN CY	Missing Data
[redacted]				

We now have a data dump which can be downloaded. The downloaded data dump is not in the correct form to use for forecasting due to its format and layout. A new layout is made in Excel, considering the layout for forecasting the demand and the ability for the KAM and CDP to 'read' the layout with data quickly. Readability is an essential aspect of the KAM and CDP. They want to be able to perform a deep dive on a particular SKU to see conveniently what is going on with the demand or stock of that SKU in a particular period. This process is executed iteratively. We planned a meeting with the KAM responsible for that client and me twice a week. The CDP joins the meeting biweekly to give his input on the layout and model.

4.2 The selection of forecasting methods

This section discusses why to use time series, the factors used to select the time series forecasting methods, whereafter the three types of forecasting techniques will be explained to analyse the demand of the retailer.

4.2.1 Time series forecasting over causal models

Quantitative forecasting methods consist, next to Machine Learning methods, of two main 'categories' of forecasting techniques, namely: time series and causal models (Apuke, 2017). Time series forecasting is created expressly to identify patterns and trends in time series data, such as sales data. The foundation of time series models is that a variable's previous behaviour is a reliable indicator of its future behaviour. In order to find trends, seasonality, and other patterns that may be utilized to create forecasts, these models use historical data (Athiyarath, Paul & Krishnaswamy, 2020). Contrarily, causal models are predicted on the idea that the variable being projected (such as sales) and one or more other variables have a cause-and-effect connection (e.g., price, advertising, economic indicators) (Morgan, 2013). To provide projections, causal models try to locate and quantify these links. However, in reality, managing these models may be time-consuming and challenging due to their complexity and need for expensive feature engineering and data pre-processing.

Time series models are frequently used over causal models for sales forecasting due to the difficulties with causal models. For instance, research by Makridakis et al. (2018) indicated that time series models outperformed other forecasting techniques, including causal models for short-term forecasting horizons. The study discovered that time series models could produce precise forecasts with relatively little data and were particularly good at capturing the patterns and trends in time series data. Similarly, time series models were shown to be more accurate than causal models for anticipating sales demand in the retail industry in research by Chu & Zhang (2003). The study discovered that time series models could accurately estimate even when there were significant changes in the data and could capture seasonal patterns and trends in sales data. Time series are suitable for practical applications due to their accuracy and ease of implementation and interpretation. Time series models are frequently chosen for sales forecasting due to their simplicity and ease of implementation, according to a review by Hyndeman et al. (2008). The analysis discovered that time series models were useful for many commercial applications because they could produce precise forecasts with comparatively little data.

It can be concluded that time series are preferred in this study over causal models based on empirical data and the practical reasons covered above. For short-term forecasting horizons, time series models have been found to be more accurate than causal models in capturing patterns and trends in sales data. The definition of short -term forecasting horizons can vary depending on the context and industry. However, in general, short-term forecasting horizons refer to a period ranging from a week to a few months. Time series models are useful for real-world applications since they are also reasonably easy to build and comprehend.

4.2.2 Factors selecting the forecasting method

Due to the increasing variety and complexity of managerial forecasting problems, many forecasting techniques have been developed. Which one to select depends on different factors such as the context, relevance and availability of historical data, degree of the accuracy, time period to be forecasted, cost/benefit, and the time available for making the forecast (Chambers, Mullick & Smith, 1971). Below, the five factors will be discussed:

1. <u>Context</u>
   The forecast will be used to receive a more accurate prediction about the sell-in. The sell-in refers here to the weekly order of the retailer for a The case company product to ship from the case company warehouse to the central warehouse of the retailer in the Benelux. The forecast will be used in addition to the judgmental forecast the KAM and CDP already make. The KAM and CDP have insights into previous years, customer experience, and order patterns. They still use this knowledge to forecast demand. Nevertheless, the quantitative forecasting technique can add value to the predicted sell-in with historical data. The KAM and CDP can use the insights of this forecast for their judgmental forecast as an input of the starting-off point.

2. <u>Relevance and availability of historical data</u>
   The case company receives data from a third party. This company has a platform from which the case company can export relevant data. This can be data for a particular retailer, for a particular week, or for a particular SKU. However, it can also consist of a data dump with the data of the previous and current year for one retailer and all (four) categories of products The case company has. The third company weekly updates this data, which is also the data interval. Day data is not available. The smallest timestamp is weekly data. There are some exceptions for online clients of the case company, such as Bol.com and Coolblue, which deliver (by themselves) the data every week with the day data for that particular week. This is not the case for the retailer. The data of the retailer is received from a third party. The case company has a license to receive this data for all its clients via this third party.

3. <u>Degree of accuracy time-period to be forecast</u>
   This forecast will be used to predict the next period. This next period will be the next month. The sell-in should be forecasted based on the sell-in, sell-out, and stock level data. It can be

the case that some SKUs are not available for the full quantity in the warehouse. The factory then must produce the SKUs and ship them to the central warehouse in Europe whereafter they can be planned by the CDP to ship to the retailer warehouse. Because of this, the forecast should be accurate for the next three months. The forecast has to be made on the SKU level (except for MCC products which will be planned on MAG or AG level) and should be accurate. Not a very long timeline, but accuracy is essential to make sure unhealthy stock will be reduced.

4. <u>Cost/benefit</u>
   The forecasting methods proposed in this study can be used instead of or used in addition to the judgmental forecast that every CDP and KAM made until this study. Because this forecast should be easily implemented for every CDP and KAM, and a forecast for every retailer or KAMs portfolio has to be made, the forecast budget is not high. This factor includes the value of the forecast for the company. The interpretability and execution should be made simple, giving the forecast the most value for the case company team. The forecast can help to estimate the sell-in of the particular retailer accurately. The more accurate this is, the better the CDP can order the SKUs from the factory or warehouse, thereby reducing unhealthy stock in the warehouse. This is a crucial aspect of cutting costs concerning the supply chain, but we have to take into account that this forecast has a limited and indirect effect on the unhealthy stock, and therefore the costs should not be too high to hit the break-even point or above. Besides the costs alone, this forecast does, however, help to lower the inventory level in the case company warehouse, leading to more healthy stock coming in the warehouse and thereby improving the overall supply chain and percentage delivered to the client. This is measured as the fill rate.

5. <u>Time available for making the quantitative forecast</u>
   The quantitative forecast has to be made by the KAM, CDP, Channel Manager, or an intern within the Sales Retail team. This is an additional task to contribute to a more accurate final forecast. Due to this fact, little time is available for making the forecast. Complex modelling cannot be executed due to time and knowledge limitations. More straightforward methods should be used in this context to implement the forecasting technique in the team so that it can be used weekly.

4.2.3 Holt Winters' method

The first forecasting method is the Holt-Winters' seasonal method. This method is constructed by Holt (1957) and Winters (1960). The goal was to develop a high-accuracy and low-cost forecasting model to integrate with the existing system (Da Veiga et al., 2014). In 1957, Charles Holt showed that the most widely used forecasting method at the time, the exponential weighted moving average method, could be used not only to smooth the level of variable but also to smooth trends, seasonality, and other components of a prediction (Holt, 2004). It can control multiplicative and additive seasonality, additive and multiplicative trends and standard errors (Da Veiga et al., 2014). Besides that, this method was quick, easy to program, required minimal data storage, used simple initial conditions and robust parameters and allowed automatic adaption (Da Veiga et al., 2014).

In addition to the utilization of a smoothed estimated and a smoothed trend, this forecasting technique utilizes a multiplicative seasonality factor to account for seasonality associated with the particular SKU. This method comprises the forecasting equation and three smoothing constants (Hyndman & Athanasopoulos, 2018).

The Holt-Winters method is a sophisticated extension of the exponential smoothing method. This method is used to deal with trends and seasonality. To do so, it considers α, γ, and δ as the three smoothing parameters, and *p* denotes the number of observations per seasonal cycle (Hyndman, Ord & Snyder, 2008). It is the same as the linear method except for the additional equation to deal with seasonality. The component form for the multiplicative method can be written as:

$$F_{(t)} = \alpha\left[\frac{A_{(t)}}{c(t-N)}\right] + (1-\alpha)[F_{(t-1)} + T_{(t-1)}]$$

$$T_{(t)} = \beta\left[F_{(t)} - F_{(t-1)}\right] + (1-\beta)T_{(t-1)}$$

$$c_{(t)} = \gamma\left[\frac{A_{(t)}}{F_{(t)}}\right] + (1-\gamma)c(t-N)$$

$$f_{(t+\tau)=[F_{(t)}+\tau T_{(t)}]c(t+\tau-N)}$$

$$t+\tau = N+1, \dots, 2N$$

Where:

$F_{(t)}$ = the smoothed estimated at time *t*

$T_{(t)}$ = the smoothed trend at time *t*

$C_{(t)}$ = the multiplicative seasonality factor at time *t*

α = a smoothing constant ranging from 0 to 1

β = a smoothing constant ranging from 0 to 1

γ = a smoothing constant ranging from 0 to 1

$A_{(t)}$ = the demand in time period *t*

$F_{(t+\tau)}$ = the forecast for τ periods ahead of *t*

τ = # of forecasting periods ahead of the current time period

N = # of forecasting periods in a season

A downside of this forecasting technique compared to exponential smoothing and exponential smoothing with a linear trend is that it requires a complete data cycle before it can start calculating the forecast due to the seasonality effect. This means that when the seasonal effect is repeated every year through weather seasons, the historical data must be at least full years of data. When more data is available, the better the forecast can be made. The seasonal effect can then be analysed from more than one cycle.

4.2.4 (S)ARIMA

The second forecasting technique that can be applied to forecast sell-in within a supplier-retailer environment is the SARIMA technique. This is a variation on the ARIMA model, which is an acronym for "Auto-Regressive Integrated Moving Average" with the parts AR, I, and MA discussed below.

<u>The Autoregressive component – AR (p)</u>

This part of the ARIMA model is represented by:

$$y_t = c + \sum_{n=1}^{p} \alpha_n y_{t-n} + \epsilon_t$$

We will discuss three parameter options. If we set the parameter p to 0 (AR(0)), no autoregressive terms exist. This time series is called 'white noise' (Brendan, 2022). Each data point is sampled from a zero mean and sigma-squared variance distribution. This results in an unpredictable sequence of random numbers. This is useful because it can serve as a null hypothesis and protect our analyses from accepting false positive models (Brendan, 2022). When we set the parameter p to 1 (AR(1)), this is called random walks and oscillations. AR (p) assumes that the previous timestamp has been adjusted by a multiplier and adds random noise. A multiplier of 0 results in white noise, and a multiplier of 1 result in a random walk. If the multiplier is between $0 < \alpha_1 < 1$, the time series exhibit mean reversion. This means the values hover around 0 and then return to the mean after regression (Brendan, 2022). If the parameter is increased further (AR(p)) this is called higher-order terms and adds more timestamps adjusted by their own multipliers. When going further back, it is more likely that we should use additional parameters such as the Moving Average (MA) (Brendan, 2022).

<u>The Moving Average – MA(q):</u>

q is the number of lagged forecasting error terms in the prediction. When MA(1), the forecast is a constant term plus the previous white noise term times a multiplier, added with the current white noise term (Brendan, 2022).

Seasonal ARIMA (SARIMA) decomposes the components of trend, seasonality, and residuals. The moving average will look at a 12-month period to capture the seasonality during the year. Because of peak sales at the end of the year, it can be expected that the trend index will be higher in the last month(s) than the other months for the case company.

To better understand the SARIMA, we first start with the autoregressive models. Autoregression refers to the fact that it is a regression of the variable itself (Hyndeman & Athanasopoulos, 2018). This model forecasts the variable of interest using a linear combination of past values of the variable. The autoregression model of order *p* can be written as:

$$y_t = \mathrm{c} + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

ε_t refers to the white noise. It is like a multiple regression but with lagged values of y_t as predictors. Hyndeman & Athanasopoulos (2018) refer to this as an AR(*p)* model, so an autoregressive model of order *p.* For a model where *p* = 1, so AR(1) hold:

- When $\Phi_1 = 0$, y_t is equivalent to white noise;
- When $\Phi_1 = 1$, and $c = 0$, y_t is equivalent to a random walk;
- When $\Phi_1 = 1$, and $c \neq 0$, y_t is equivalent to a random walk with drift;
- When $\Phi_1 < 0$, y_t tends to oscillate around the mean.

Moving average models need to be understood to take a step further in SARIMA. This model does not use past values but instead of that uses past forecast errors. This gives the following formula:

$$y_t = \mathrm{c} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_q$$

This is the MA(*q*) model, so a moving average model of order *q*. For each y_t, a weight can be added to the previous forecast errors. In this model, similar to the AR model, the variance of the error term ε_t will only change the scale of the series and not the patterns (Hyndeman & Athanasopoulos, 2018).

Combining the differencing with autoregressive and a moving average model gives us the ARIMA (AutoRegressive Integrated Moving Average) model. This model can be written in the following formula:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Where y'_t is the differenced series. The 'predictors' at the right side of the formula include the lagged values of y_t and lagged errors. Hyndeman & Athanasopoulos (2018) call this an ARIMA (*p, d, q*) model where:

- *p* = the order of the autoregressive part.
- *d* = the degree of first differencing involved.
- *q* = the order of the moving average part.

Hyndeman & Athanasopoulos (2018) distinguish some exceptional cases of the ARIMA mode as shown in Table 5.

Table 5: ARIMA modes

White noise	ARIMA (0,0,0)
Random walk	ARIMA (0,1,0) with no constant
Random walk with drift	ARIMA (0,1,0) with a constant
Autoregression	ARIMA (*p*,0,0)
Moving average	ARIMA (0,0, *q*)

The constant *c* has an essential effect on the long-term forecasts obtained from these models:

- If *c* = 0 and *d* = 0, the long-term forecasts will go to zero.
- If *c* = 0 and *d* = 1, the long-term forecasts will go to a non-zero.
- If *c* = 0 and *d* =2, the long-term forecasts will follow a straight line.
- If *c* ≠ 0 and *d* = 0, the long-term forecasts will go to the mean of the data.
- If *c* ≠ 0 and *d* = 1, the long-term forecasts will follow a straight line.
- If *c* ≠ =0 and *d* = 2, the long-term forecasts will follow a quadratic trend.

d has an essential effect on the prediction intervals. The higher the value of *d*, the more rapidly the prediction intervals increase in size (Hyndeman & Athanasopoulos, 2018).
Some products can be sensitive to seasonal effects, as discussed earlier. The seasonal effect is repetitive and can cause higher or lower forecasts for a particular period in time. Considering this seasonal effect when making a forecast is essential. SARIMA is the better choice to forecast products with seasonality than ARIMA because the SARIMA method considers the repetitive seasonal effect.

ARIMA $\underbrace{(p, d, q)}_{\text{Non-Seasonal part of the model}}$ $\underbrace{(P, D, Q)_m}_{\text{Seasonal part of the model}}$

Where m is the # of observations a year. The seasonal part of the model is similar to the non-seasonal part but involves backshifts of the seasonal period. Hyndeman & Athanasopoulos (2018) give the following example: an ARIMA $(1,1,1)(1,1,1)_4$ model (without a constant) is for quarterly data (*m* = 4) and can be written as:

$$(1 - \phi_1 B)(1 - \phi_1 B^4)(1 - B)(1 - B^4) y_t = (1 + \theta_1 B)(1 + \Theta_1 B^4)\varepsilon_t$$

The additional seasonal terms are multiplied by the non-seasonal terms.

4.2.5 Croston's method (CR)

There are always fluctuations in demand, but when there are also a lot of zero demands, it is called intermittent demand. Intermittent demand is characterized by a high portion of zero values and is a common phenomenon in the real environment (Tian, Wang & Erjiang, 2021). This is common in the military, aerospace, and automotive industries, but also applies almost universally to the retail sector (Babai et al., 2019). Although many products are exhibiting intermittent demand (Babai et al., 2014), this has not been the subject of much research in the area of retail forecasting (Filders et al., 2019).

The first method for forecasting intermittent demand was proposed by Croston (1972) with corrections by Rao (1973). It splits the intermittent demand chain into two series:

1. Non-zero demand sizes,
2. The time interval between successive non-zero demands.

Each of these is predicted separately by using simple exponential smoothing. The final forecast is the ratio of the size of the forecast to the forecast period. When non-zero demand occurs, forecasts of size and duration are updated.

The assumptions of this method include static process, geometrical distribution of interval, normal distribution of demand size, and independence between size and interval (Li & Lim, 2018). With the first two assumptions, a stationary demand process of the following form is assumed:

1. A process of demand occurrence with a constant probability of demand occurrence.
2. Normally distributed demand sizes, with constant mean and variance.

According to Syntetos & Boylan (2021), the geometric has two distinct roles in intermittent demand modelling. It can represent the times between demands, but it can also represent the sizes of the demand. In addition to the first two assumptions, Croston (1972) made the following implicit assumptions:

3. Independence between the demand sizes and the inter-demand intervals. This means that the length of the demand intervals is not related to the magnitude of the demand sizes (Syntetos & Boylan, 2021).
4. Independence of successive demand sizes. A demand size is not related to previous demand sizes.

Croston (1972) found that using a simple exponential smoothing technique for forecasting lumpy demand results in a bias in demand estimates and too high stock levels. Croston's (1972) technique estimates not only the size of the demand but also the inter-arrival times. It forecasts the time between consecutive transactions p_t and the magnitude of the individual transactions z_t. At the review period of *t*, if no demand occurs in a review period, then the estimates of the demand size and inter-arrival time at the end of time *t,* $\hat{z}_t$ and $\hat{p}$, respectively, remaining unchanged (Croston, 1972). If a demand occurs so that $z_t > 0$, then the estimates are updated by:

$$\hat{z}_t = \alpha z_t + (1 - \alpha)\hat{z}_{t-1}$$

$$\hat{p}_t = \alpha p_t + (1 - \alpha)\hat{p}_{t-1}$$

Where α is a smoothing constant between 0 and 1 (Teunter & Sani, 2009, p. 178), the forecast of demand per period at time *t* is given as:

$$C_t = \frac{\hat{z}_t}{\hat{p}_t}$$

There are other variations to Croston's intermittent demand forecasting method, but none of them performs significantly better than Croston's except the greedy aggregation-decomposition method (Li & Lim, 2018). Li & Lim (2018) state that the greedy aggregation-decomposition approach is another suitable intermittent forecasting method. This method combined hierarchical demand forecasting and the idea of Croston (1972) to divide the intermittent series into two series of sizes and intervals. This method consists of three parts: (1) forecasting the daily demand by a revised seasonal Holt-Winters exponential smoothing, (2) forecasting the demand size and interval by simple exponential smoothing for each intermittent demand series, and (3) greedily allocating the total demand to each SKU at each store based on the forecast generated in (1) and (2) (Li & Lim, 2018). Due to the complexity of this process and the moderate improvement over Croston (1972), which take already into account the intermittent pattern, Croston's method is chosen over the greedy aggregation-decomposition method.

Due to its characteristics, Croston's method will make use of different data than the other two methods. Croston performs well on intermittent demand and predicts a gradual spread of the peaks over the following periods. Thus, this method will be tested on the sell-in data instead of the sell-out data on which the SARIMA and Holt-Winters methods are trained. Croston's method will use the sell-in data of the same SKUs and predicts the sell-out data, which is the same output to be predicted as the other methods.

4.2.6 Modelling software

The software required to test and make the forecast does not need to exceed the goal of a proof concept. The results have to be presented in a model that can be widely understood by all stakeholders and can be extended. Therefore, two tools were used. Microsoft Excel using Excel Solver is used for both Holt-Winters and Croston, and Rstudio is used to test the performance of SARIMA.

Excel is a widely used tool within the case company, especially within the sales and planning teams. The Excel Solver is a computational tool used to optimise issues in mathematical modelling. It works with the Microsoft Excel spreadsheet application. Since the goal is to minimize the error, our objective is to set the RMSE to be minimum by changing the values of the coefficients. The values of α, β, and γ should be between 0 and 1; thus, a constrain is added: $0 \leq \alpha, \beta, \gamma \leq 1$. For this study, the GRG Nonlinear solving method is used. This method is used because of its ability to handle a wide range of optimization problems, including problems with nonlinear objective functions and constraints. The robustness is another benefit. The GRG can still identify solutions when the objective function and constraints are not smooth or have several local minima or maxima. The forecast output cannot be below 0, because a sell-out below 0 means that products are returned. We assume this will not happen. To make the outcome meaningful, the values of the decision variables should be non-negative. The solver is now able to minimize the RMSE by optimizing α, β and γ.

R-studio is used for testing and forecasting the SARIMA model. This tool is chosen due to its ease of use, understandability and ability to combine unit root test and minimisation of the AIC and MLE with the *auto.arima()* function. Below in Table 6 is the default behaviour of the *auto.arima()* function.

Table 6: Auto.arima() default behaviour. Reprinted from: Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: principles and practice. OTexts.

Hyndeman-Khandakar algorithm for automatic ARIMA modelling
1. The number of differences $0 \leq d \leq 2$ is determined using repeated KPSS tests.
2. The values of *p* and *q* are then chosen by minimizing the AICc after differencing the data *d* times. Rather than considering every possible combination of *p* and *q*, the algorithm uses a stepwise search to traverse the model space.
a. Four initial models are fitted: • ARIMA(0,*d*,0), • ARIMA(2,*d*,2), • ARIMA(1,*d*,0), • ARIMA(0,*d*,1). A constant is included unless *d* = 2. If *d* ≤ 1, an additional model is also fitted: • ARIMA(0,*d*,0) without a constant.
b. The best model (with the smallest AICc value) fitted in step (a) is set to be the “current model”.
c. The variation in the current model are considered: • Vary *p* and/or *q* from the current model by ± 1; • Include/exclude *c* from the current model. The best model considered so far (either the current model or one of these variations) becomes the new current model.
d. Repeat step 2(c) until no lower AICc can be found.

Two packages must be installed to use R-studio for forecasting and testing the dataset. The packages installed are: (1) the ‘forecast’ package and (2) the ‘tseries’ package. The forecast package enables us to fit ARIMA models and estimate the model's parameters. This can be done with the *auto.arima()* function. Another useful function of this package is the ability to visualize the forecasts by generating plots of the observed data and the forecasted values. The tseries package decomposes the data into its trend, seasonal, base and residual components. A step-by-step explanation of each step of the R-studio ARIMA modelling process can be seen in Appendix 9.4.1.

5. Stage 2: Implementing and evaluating the forecasting dashboard

When the best forecasting method is implemented, semi-structured interviews will be conducted. Stage 2 is the qualitative part of this research, where the goal is to get insight into the possible improvements of internal alignment due to the applied forecasting techniques to predict the retailers sell-in demand using the sell-in, sell-out, and stock data.

This section will discuss the key elements of implementing the forecasting dashboard, including the importance of exploratory interviews to understand stakeholders' needs and requirements. The specifics of the forecasting dashboard will be explored as a tool that can help the stakeholders with forecasting and collaboration in this process. Additionally, the evaluation will be examined, which involves assessing the usability of the dashboard. The benefits of using semi-structured interviews and focus groups to gather stakeholder feedback and refine the dashboard will also be discussed. By understanding the implementation and evaluation stages of the forecasting process, organizations can develop and implement effective forecasting dashboards that drive informed decision-making.

5.1 Implementation

This chapter will cover the process from the beginning of my internship until the outcome, which can be evaluated by the stakeholders within the case company. Exploratory interviews are conducted to understand the problem and gather solutions. A preliminary design is developed and initiated, whereafter the dashboard is evaluated by the stakeholders involved in the forecasting process using semi-structured interviews and a focus group.

5.1.1 Exploratory interviews

The sales team of the case company faces some challenges. The challenge of getting a deeper insight into the data to be able to forecast the sell-in better became a priority for me. This was discussed before and during the internship with the KAMs guiding me. Before my internship, we discussed de setup of the internship and the possibilities of reaching the goal to forecast the sell-in better.

During the first weeks/months, I had a meeting twice a week with my main supervisor (participant 1) from the case company and weekly with another KAM (participant 1.2), who was my second supervisor from the case company. We discussed how data could improve the forecast accuracy for them separately. They have different accounts, and it turns out my project was best applicable to my main supervisor. My second supervisor was participant 1.2. These were small clients and are not marked as 'a particular status' or 'another status, but as 'lower status', meaning these clients have a lower priority for the case company.

Twice a week, participant 1, I and bi-weekly, the involved CPD discussed the ability to collect the data and the possibilities we had with these data. We concluded that we were able to collect the data from the third party as mentioned in section 3.3.1, and aimed to build a dashboard in collaboration with the KAM and CDP to be able to visualize the sell-in, sell-out, and stock.

5.1.2 The dashboard

The final practical outcome is to deliver a dashboard for the stakeholders in the forecasting process of The case company. This dashboard will use the best of the three forecasting techniques. Historical data will be visualized in the dashboard that will be made in Excel. Part of this dashboard is shown in

Figure 15 and calculations can be found in Appendix 9.3.1. The SKUs can be seen in the Figure in column G, where column H specifies the SKU into the different measurements including the SARIMA forecast. This forecast is only available for weeks 50, 51 and 52 because the model is trained with the data till week 49. According to the feedback from the stakeholders involved in the forecasting process, the stock CY is colour coded. The utilization of color coding was suggested by Participant 1 to provide the stakeholders with a visual indication of the current stock status, specifically regarding its levels of abundance or depletion. As such, the color red has been assigned to represent high stock levels, while green has been designated to denote low stock levels. The rationale behind this decision by Participant 1 was based on the premise that in instances where the retailer is perceived to possess high stock levels, a subsequent order of that particular SKU would be deemed unlikely in the immediate future. Consequently, it would be necessary to decrease the forecast to prevent an increase in the stock levels of the case company.

The dashboard aims to provide the stakeholders with better information about the next period. The sell-in of the next period is essential for the stakeholders to use their stock efficiently. Therefore, the forecast of the sell-in for the next period will be visualized as well. A predicted sell-out will be given in the dashboard to the stakeholders. The KAM and the CDP will use this dashboard most frequently and discuss the stock allocation every week. They will evaluate this dashboard on usability for their weekly meeting about the allocation of the stock. The TSM and Channel Manager will look into this dashboard less frequently. The TSM will look at this dashboard when a listing (a place where the product is displayed in the shop) is added or removed, when a new product is introduced, or when a product sell-in or sell-out shows unnatural behaviour. The Channel Manager will be involved and use the dashboard when there are exceptional sell-in or sell-outs, or a product should be looked at in detail due to an event in the future. The TSM and Channel manager thus will evaluate the dashboard thus differently. They focus on the detail of the historical data and forecast to look more closely at one SKU's behaviour to get a deeper understanding of the sell-in in the (near) future.

5.2 Evaluation

The evaluation phase is the last phase of this study. The forecasting method is used to make the dashboard which will be evaluated in this phase.

The evaluation will be conducted using semi-structured interviews as an alpha test and a focus group as a beta test. The semi-structured interviews will be used during the building process of the dashboard to test and guide the process. This parallel process will try to avoid implementing the wrong components in the dashboard. A final dashboard version will be made, whereafter, the focus group will evaluate this end result.

5.2.1 Semi-structured interviews

This part has a more qualitative approach. The status quo of the case company will be discussed, where questions will be asked about how the forecasting process went before, and the role of every stakeholder involved in the forecasting process for the retailer. The semi-structured interviews will be constructed as a funnel. Initially, general inquiries are posed to avoid erroneous presumptions regarding the organization and its procedures. Subsequently, more specific questions will be asked. The company's structure, job descriptions, and tasks within the case company are the more general questions. Following the preliminary stage of general inquiries, the focus of the investigation will shift towards examining the specific process, which encompasses gathering and analysing data, forecasting future patterns, and observing ordering behaviours. Acquiring a comprehensive understanding of the whole process and the persons involved is crucial. Internally as well as externally. This step aims to get insights into the company's current activities regarding the forecasting demand within the case company. The objective of these interviews is to gather data to gain the knowledge required for the design process of the dashboard. Using semi-structured interviews will allow us to funnel the questions without making wrong assumptions. Subsequently, the interview can get deeper into the forecasting topic. The possibility to ask sub-questions and additional questions enables it to learn more about a complex problem.

Interviews will be conducted with KAMs, the Customer Collaboration Manager, Customer Demand Planner, and Channel Manager. The KAMs are the people within the organization with their own accounts (clients). These people have the shortest distance to the clients and have the most information about their particular clients, the negotiations, agreements with the clients and their demand pattern. KAMs exist in three 'groups' within the case company. For online, chains, and …... The retailer is a client of the last group, so all the KAMs of this last group will be interviewed to gather information about this channel, their own clients, and how they order from the case company. A KAM from the other group will be interviewed to get a perspective from a slightly different market. Different clients, different management, and different gathering of data can make the forecast differ from another channel. The channel manager manages the KAMs within his or her channel, has an overview, and has to report the sales to higher management. Getting better insight from their perspective can contribute to the overall insight in the process. The Customer Collaboration Manager manages the fill rate and stock, which is highly interwoven with the forecasts and performance of the sell-in, sell out, and stock. This is one person for the case company who is included in the interviews to get the perspective of the stock within the case company. Lastly, the customer demand planner will be interviewed. This is one person within each channel. The Customer Demand Planner of the … channel will be interviewed to get the perspective of the planning for the next month for the particular clients. The results from all semi-structured interviews will be acquired by transcribing and processing them with open coding software.

5.2.2 Focus group

This study will use a focus group to evaluate whether the final solution created the expected outcomes. The Dashboard will be presented to the stakeholders of this team within the case company, consisting of Participant 1, the CDP, the Channel Manager, and the TSM. The dashboard will be evaluated on certain criteria. For example, the dashboard's usability and visibility/readability will be discussed. This Focus Group has a second aim to look at how this dashboard can be applied in the other teams within the case company. Two more teams are very similar to the …. team but have other retailers. These retailers may have other ordering patterns or intervals.

The focus group will be conducted offline. Organizing the focus group in person at a specific location can offer several advantages over hosting it online. First, gathering the stakeholders physically can foster a sense of community and encourage more open and honest discussion among group members. Secondly, it is harder for them to be distracted or to leave the focus group. Lastly, the participants can be observed and evaluated in their natural environment, which can provide valuable insights into how they interact when they are discussing forecasting in a meeting at home or the office. When possible, the focus group will be recorded. This allows for a more accurate and detailed record of the discussion and can be used for later analysis. Additionally, video recordings can be used to evaluate nonverbal cues and body language, providing valuable insights into the stakeholders' opinions and reactions. When video recording is not allowed, the focus group will be audio-recorded to be able to transcribe and analyze it.

6. Empirical analysis

6.1 Analysis of the models (stage 1)

The following section presents an overview of the plots, and the intermittent demand, stationarity and heteroscedasticity will be discussed. Subsequently, the results and performance of each forecasting technique will be discussed. Lastly, the forecasting techniques will be compared to each other to determine which technique performs the best on the five SKUs. This comprehensive analysis provides insight into the most suitable forecasting method for these SKUs and can be implemented into the dashboard.

6.1.1 Overview

The following section presents an overview of the plots depicting the sell-out quantity data for the five selected SKUs. These plots provide visual insight into the demand patterns over time. The plots are displayed below in Figures 16, 17, 18, 19, and 20, to provide visual insight into the demand patterns over time. Following the graphical representation of the data, the next section will discuss the data's intermittent demand, stationarity, and heteroscedasticity.

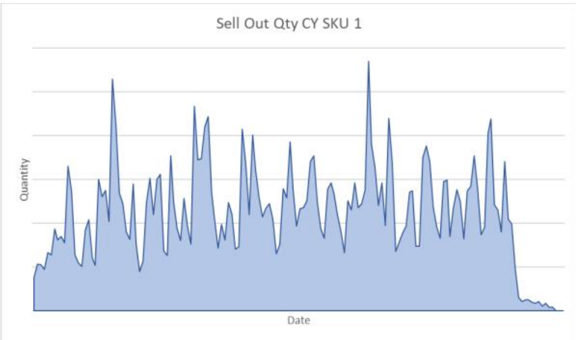

Figure 17: Historical data SKU 1

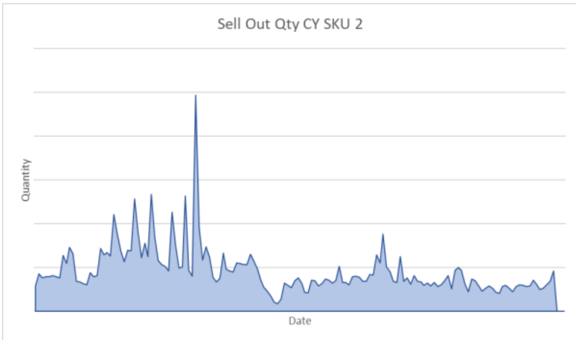

Figure 15: Historical data SKU 2

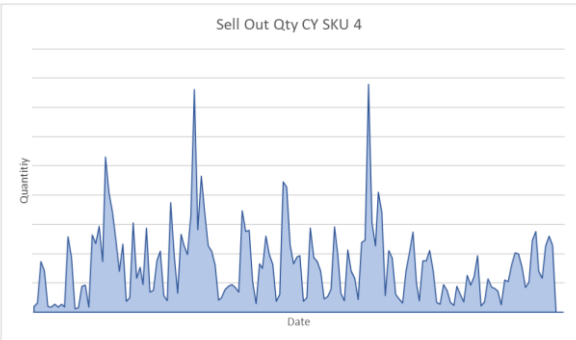

Figure 18: Historical data SKU 3

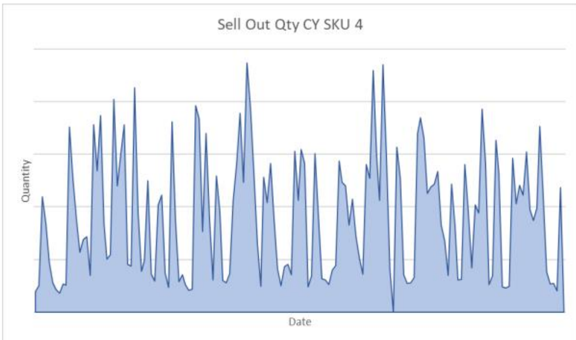

Figure 16: Historical data SKU 4

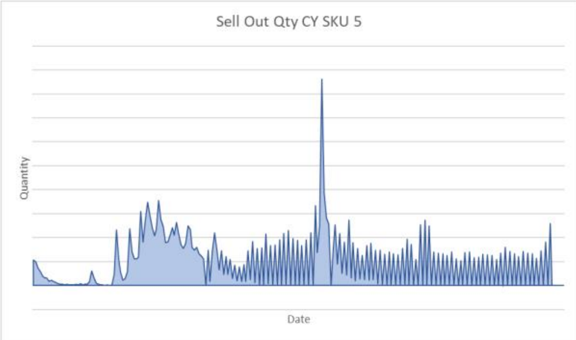

Figure 19: Historical data SKU 5

As shown in the Figures above, the graphs show highs and lows, making it a jagged line visualising the sell-out quantity. These characteristics indicate strong intermittent demand. The only outlier in this is SKU 2, which shows a smoother line in 2021 and 2022. According to Respondent 1, price promotions are the main factor for this intermittent demand. Besides the intermittent demand, the SKU's sales data show a slight upward trend in 2021 and 2020. This upward trend, however, does not continue into 2022, according to these plots. Seasonal cycles are difficult to see in these plots due to the jagged line with a couple of weeks with high demand followed by a few weeks with low demand, which can be seen the best in Figure 17. This suggests the price promotion of that particular product in those weeks with high sell-out and the weeks between these price promotions with a low sell-out.

To test whether the data is non-stationary, we use the ACF, PACF, and the ADF test.

According to the Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots, the vertical lines exceed the critical values. The blue dotted horizontal line visualizes these critical values in the plot. Exceeding this line indicates the presence of a unit root and non-stationarity in the time series. This hold for every SKU tested, and thus all SKUs are non-stationary.

The Augmented Dickey-Fuller test is used in addition to the ACF and PACF plot to test for stationarity (Clements & Hendry, 1998). The null hypothesis of the ADF test is that the series is non-stationary, while the alternative hypothesis is that the time series is stationary. According to this test, all the SKUs are stationary.

Heteroscedasticity refers to the presence of unequal variance in a time series. The ACF and PACF both show a peak at the first leg but do not show any form of seasonality. No repetitive cycle can be found in all the plots; thus, seasonality is unlikely. When looking at the residuals' ACF and PACF plots, we neither see a pattern in the peaks, thus indicating non-heteroscedasticity for all SKUs.

6.1.2 Performance of Holt-Winters model

Table 7 below shows the results of the Holt-Winters forecast performance on the five SKUs. The Alpha, Beta, and Gamma weights are given, as well as the periods the forecast is tested the performance on and lastly, the RMSE is shown which is the performance result.

Table 7: Holt-Winters results

	SKU 2	SKU 1	SKU 3	SKU 4	SKU 5
Alpha	0,960827	0,955685	0,988048	0,948813	0,932176
Beta	0,96883	0,240553	0,145775	0,147	0,10955
Gamma	1	1	1	1	0,050874
Periods	153	134	153	153	119
RMSE	14,92301	90,28929	57,65482	186,1949	308,8603

The Alpha, Beta, and Gamma are optimized to minimize the RMSE. This Root Mean Squared Error measures the differences between the forecasted and actual values. This is used to benchmark the forecast's quality and compare the performance against the other forecasting methods used. The lower the RMSE, the better the forecast will be. Thus, the forecasting method with the lowest RMSE, in general, will be chosen to be implemented for the case company. The RSME performs best on the SKU 2 SKU and worst on SKU 4. SKU 4 is an outlier. There is a middle and lower sector as well. The middle sector has values of 143 and 170, and the lower sector has values of 28 and 53.

The Alpha controls the smoothing of the level component, which determines the weight given to the most recent observations when updating the level component for every forecast. The larger the Alpha, the more weight is given to the recent observations. Each parameter can have a value between 0 and 1. Upon reviewing the results, it can be inferred that the most recent observations have been given significant weight in the analysis. This is evident by the values of Alpha, which are found to be close to 1, indicating a high degree of emphasis on recent observations. The Beta parameter refers to the smoothing parameter used for the trend component of the forecast. It is a measure of the direction the time series is moving in. This can be any upward or downward trend in the historical data. Like the Alpha parameter, the Beta determines the weight given to the most recent observations, but then for the trend component. The Beta results differ a lot when looking at the SKU results. All SKUs show a low Beta reaching from 0.13 to 0.23.

Gamma is the smoothing parameter for the seasonal component of the forecast. This captures the recurring patterns in the time series, which can be weekly, monthly, quarterly, or yearly patterns. Regarding the value of the results and weight given to the most recent observations, the principles applicable to Gamma are analogous to those that apply to the other parameters. The results show for every SKU except SKU 5 a value of 1. This means that the highest weight is given to the most recent observations, and no weight is given to older observations. The forecasted seasonal component will be the same as the observed seasonal components for future time points. For SKU 5, the value is 0.051.

The number of periods is inconsistent across the products. This is due to phase-in and phase-out products. Every 2 to 4 years the case company replaces its products thus, we see the number of periods from 119 till 155. This study is not about comparing the difference in forecasts for different SKUs but different forecasts testing on the same 5 SKUs. Thus, the number of periods will stay the same for every forecasting technique used to test and forecast for that particular SKU. Overall, the Alpha values are relatively high, indicating that this component (level) strongly influences the forecast. The RMSE results indicate that the Holt-Winters method can be a valuable tool for forecasting, but the performance depends highly on the product.

6.1.3 Performance of the SARIMA model

As shown in Table 8, in the KPSS test, the p-value > 0.1 for all SKUs. The significance level for all SKUs is 0.05. This means we fail to reject the null hypothesis that the data is trend stationary. This is in contrast with the results of the ADF test where the values are <0.01 and thus conclude that the data should be stationary. Although the results are different, we need to keep in mind that the ADF test is more powerful than the KPSS test. We thus conclude that the data is stationary. We used the auto.arima function in Rstudio, which uses a combination of techniques to determine the lag order of the model. It starts with (1) separating the time series into its trend, seasonal, and residual components. Thereafter (2) AICc and BIC are used to compare different models with a penalty for the number of parameters in the model. Then (3) tests combinations of the p,d,q and P,D,Q to find the optimal model for the data.

Table 8: SARIMA results

	SKU 2	**SKU 1**	**SKU 3**	**SKU 4**	**SKU 5**
ARIMA	(5,0,2)(1,0,0)	(3,0,2)(0,0,2)	(4,0,4)(2,0,0)	(3,0,2)(1,0,1)	(5,0,2)(1,0,0)
Periods	153	134	153	153	119
RMSE	17,62	14,21	18,08	42,76	19,98

To measure the performance and compare this to the other two forecasting methods tested on the data, RMSE is used. The RMSE value is calculated by the root of MSE. The MSE is, in turn, calculated using the following formula:

$$MSE = \frac{1}{n} * \sum_{i+1}^{n} (A_t - Y_t)^2$$

Where:
N = number of periods
A_t = The actual value at time t
Y_t = The forecasted value at time t

The RMSE values are similar except for the value for SKU 4. This value is significantly higher than the other RMSE values. The other values are between 14.21 and 19.98.

Overall, the results of the MSE and RMSE values indicate that the model has a relatively low error for all the series. The results suggest that the SARIMA model is suitable for forecasting these time series.

6.1.4 Performance of Croston's model

Table 9 shows the values and performance of Croston's model. The same data is presented as Holt-Winters results except for Gamma. This is because the intermittent demand does not exhibit a clear pattern or seasonality, as the demand occurrences are sporadic and irregularly paced.

Table 9: Performance Croston's forecast

	SKU 2	Sku 1	SKU 3	SKU 4	SKU 5
Alpha	1	1	0,3868893	0,07014869	1
Beta	0,038035	0,0190186	0,0248666	0,006676249	0,23847342
Periods	153	134	153	153	119
RMSE	490	372	446	1239	298

Croston performance results are based on the alpha and beta, determining the weight, the number of periods, and the RMSE to compare the performance against the other forecasting methods.

The Holt-Winters method is not the only forecasting method that utilizes the concepts of smoothing factors, as Croston's method also employs the use of alpha and beta parameters to achieve a more accurate forecast. Croston's method uses the alpha parameter to control the weight given to the historical demand when forecasting. The Beta parameter adjusts the average demand rate between high and low demand periods. The alpha values are 1 for three of the five SKUs, which can be seen in Table 9, meaning that the forecast will rely heavily on the recent history of demand and less weight to the historical average demand. The other two SKUs have a lower value; thus, less weight is given to the recent history of demands. The Beta values are all particularly small except for SKU 5, so for this SKU, high demand is more likely to occur soon. The other SKUs have a peak at 0.038, and the lowest value is 0.0057, which is extremely low. The low values indicate that the model presumes a low probability of demand occurrence, resulting in a corresponding decrease in the expected average demand rate.

One RMSE value is an outlier compared to the other SKU RMSE values. SKU 4 has a significantly higher RMSE value than the other SKUs. The other four SKUs have an RSME value range between 298 and 490, whereas the SKU 4 has a value of 1,239. These results suggest that the Croston model may not be suitable for forecasting these time series.

6.1.5 The comparative performance of forecasting models

In this chapter, we will evaluate the performance of the three chosen forecasting methods: Holt-Winters, SARIMA, and Croston. These methods are applied to forecasting the demand for five the case company SKUs with the highest sell-out for the retailer.

The Holt-Winters method combines exponential smoothing and moving averages and is widely used for forecasting time series data. It considers both the level and the trend of the data, making it a widely used forecasting method. The SARIMA method, on the other hand, is a class of models that combines the concepts of seasonal decomposition and ARIMA modelling in order to analyse and forecast time series. It is particularly useful for forecasting time series data with a seasonal component. Lastly, Croston's method is explicitly designed for intermittent demand forecasting and is suitable for situations where the demand is sporadic, with long periods of low or zero demand and occasional spikes of high demand.

The forecasting performance is measured using the RMSE. The results for every SKU using the three methods are given in Table 10 below.

Table 10: : Comparative performance measured by RMSE

SKU	HW	SARIMA	Croston
SKU 2	27,93	17,62	490
SKU 1	170,22	14,21	372
SKU 3	142,62	18,08	446
SKU 4	409,48	42,76	1239
Sku 5	53,02	19,98	298
Average:	160,65	22,53	569

Upon examining Table 10, the average RMSE value for each forecasting method across all SKUs reveals that SARIMA exhibits the most optimal performance on the given dataset. The average value is far less than the two other methods. SARIMA (22.53) is followed by Holt-Winters (160.654) method and, lastly, Croston's method (569). Upon further investigation of the data, it can be inferred that SARIMA consistently performs better than the other forecasting methods because SARIMA has the lowest RMSE. However, we need to mark that the Holt-Winters and SARIMA models are trained on the sell-out, whereas Croston's method is trained by the sell-in data for every SKU. The reason for this is because of the characteristic of Croston's method is renowned for its proficiency in handling intermittent demand. The sell-in data is a couple of days earlier available for the case company due to their clients' fixed order data for this particular client. The sell-out data will be available the Monday after the week's data. This can lead to a slightly better judgmental prediction because the data is 'newer'. However, this is disproportionate to the more accurate predictions of the other two forecasting methods. Thus, it can be concluded that the SARIMA forecasting method will be implemented in the dashboard.

6.1.6 Future predictions of the forecasting methods

The three alternative forecasting methods are used to forecast the next period. This subsequent period contains the next month, which is the next four to five weeks ahead. These numbers will be implemented into the dashboard to support the stakeholders involved in predicting the sell-in of the retailer. Figures 21 to 25 show the forecast for every forecasting technique visualised in a graph plotted against the actual sell-out. The green (solid) line corresponds with the real sell-out data. This line starts in t = -10, ten weeks behind making the forecast, until t = 5, five weeks into the future. The yellow (two-striped), blue (small dotted), and grey (small striped) lines represent the forecasting techniques forecasting the sell-out. The yellow line represents the Holt-Winters forecast. The blue line represents SARIMA, and the grey Croston. It should be marked that the green line between from t = 1 till t = 5 is data the forecasting method did not 'know'. This data is added after making the forecast to visualize how the forecasting techniques are performing against the actual data.

When analysing the graphs, the flat line of Croston immediately stands out. Croston's method consists of two equations: (1) estimating the average inter-demand interval and (2) estimating the average demand level when there is non-zero demand. These two estimations are multiplied to provide the prediction. The prediction with zero demand is always zero. For periods where demand is non-zero, the prediction is a constant value which is equal to the estimated average demand level. The projection will thus be a straight line of zeros if the intermittent demand data shows extended periods of zero demand. The projection will be a straight line of constant values if the data contains rare instances of non-zero demand. The forecast for t = 1 will thus be the same for every t into the future until new data is available.

Additionally, Holt-Winters exhibits a diminishing accuracy as the forecasting horizon increases compared to SARIMA. The former method relies on the time series' level, trend, and seasonality. While the later incorporates autoregressive, differencing, and moving average terms, which capture a more comprehensive range of data patterns and trends and are capable of modelling seasonality. Thus, SARIMA may be a more appropriate choice for predicting future values further into the future (four to five weeks ahead), as it is capable of capturing more complex patterns and trends.

Lastly, while it should be noted that the visualizations presented may not accurately assess the forecasting techniques' performance, according to the visualisations, SARIMA is the most effective method, followed by Holt-Winters, with Croston displaying the least favourable performance.

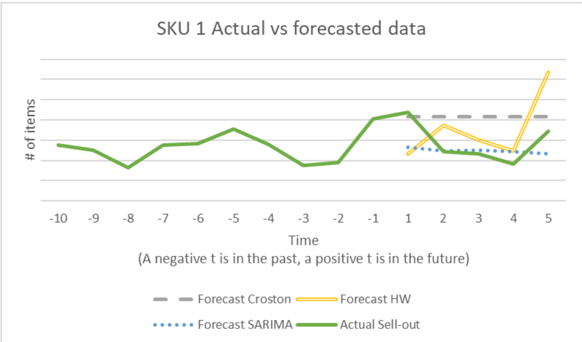

Figure 20: Forecasted versus actual values SKU 1

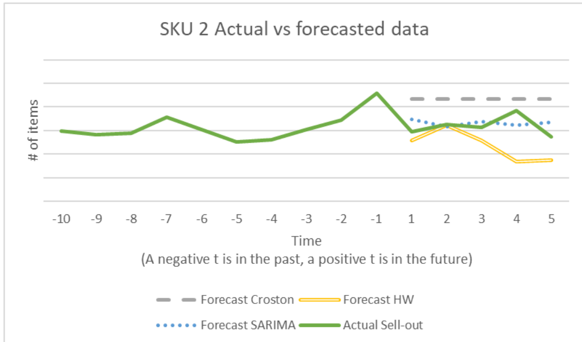

Figure 23: Forecasted versus actual values SKU 2

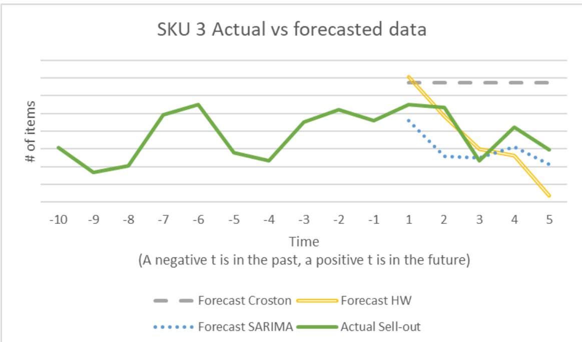

Figure 22: Forecasted versus actual values SKU 3

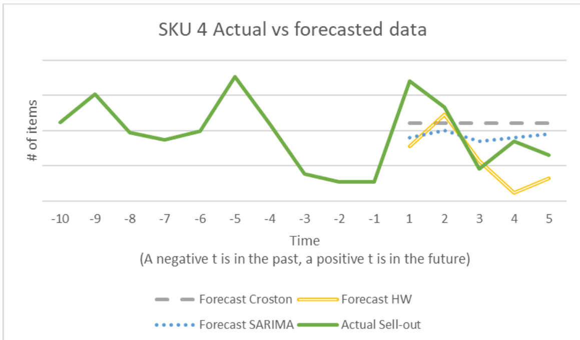

Figure 21: Forecasted versus actual values SKU 4

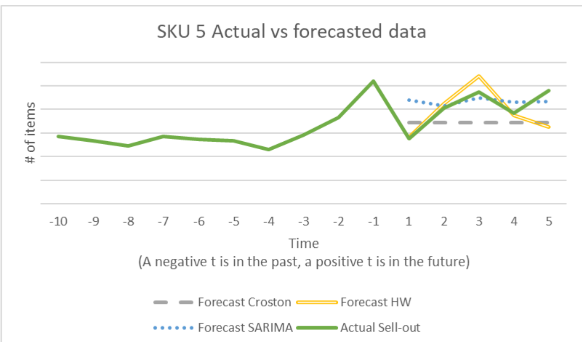

Figure 24: Forecasted versus actual values SKU 5

6.2 Analysis of the evaluation (stage 2)

In the previous section, the forecasting methods are tested. The SARIMA method performed the best and is implemented in the dashboard. This section is qualitative and consists of the evaluation of the created dashboard. Five interviews are executed as evaluative interviews, and a focus group is conducted to get the final result.

The methodology and data analysis will be discussed, whereafter, the results of the evaluative interviews and the focus group will be given. Lastly, the results will be analysed and summarized, and a conclusion will be given.

6.2.1 Overview of the methods

The purpose of stage 2 was to evaluate the dashboard, its application, and how it can add to the internal alignment between the stakeholders within the case company. Exploratory interviews were conducted to gather data and first insight into the forecasting process, what data was available, and what is needed to improve this process. After that, evaluative interviews were conducted with six stakeholders, of which five were directly related to the forecasting process within the …. channel and one from another channel. Lastly, a focus group is conducted with the five stakeholders from the ….. channel to finalize the evaluation of the dashboard and its applicability. These five stakeholders are part of the stakeholders who participated in the interviews which can be seen in Table 11. In this session, the final result of the dashboard is shown and evaluated for the last time. The dashboard is thoroughly demonstrated and critically evaluated. The pros and cons are given by the participants and written down. The goal of the focus group is to finalize the dashboard so that it can be used to forecast the upcoming sell-in of Watsons.

6.2.2 Methodology

The methodology used in this research included exploratory interviews with 12 stakeholders. These were mostly informal conversations and meetings with the aim of gaining an insight into the challenges of the teams within the sales department. Five of the 12 stakeholders participated in the evaluative interviews and a focus group is held with four out of the five stakeholders. This is visualized in Table 11 below. is

In order to gain an understanding of the forecasting issue within the case company, a series of exploratory interviews were conducted. The interviews were aimed at obtaining insights and experiences from a diverse range of employees regarding the sell-in forecasting process for retailer demand. A total of 12 stakeholders participated in the initial phase of the research to explore the problem within the organization.

Participants for the evaluative interviews were chosen based on their direct involvement in the forecasting process on a weekly or monthly basis or when an event occurs. The five stakeholders were picked to conduct the interview. One out of the five stakeholders is involved in the forecasting process. However, this stakeholder works in another channel and is interviewed to test the applicability of the forecasting dashboard created in another channel. This interview has different questions than the other interviews. The questions of the interviews for the five stakeholders from the …. channel are very similar except for some specific questions about their role in the channel. The stakeholders involved are between 27 and 54 years old, one woman and the rest men. The participants were recruited by asking them in the office; invitations were emailed, and the interviews were conducted online and offline. Stakeholder characteristics who participated in this study are presented in Table 11 below.

Table 11: Stakeholder characteristics

Participant number	Position / Role	Age	Gender	Exploratory Interview	Evaluative interview	Focus group
1	[redacted]			X	X	X
2	[redacted]			X	X	X
3	[redacted]			X	X	X
4	[redacted]			X	X	X
5	[redacted]			X	X	
6	[redacted]			X		
7	[redacted]			X		
8	[redacted]			X		
9	[redacted]			X		
10	[redacted]			X		
11	[redacted]			X		
12	[redacted]			X		

Each evaluative interview lasted around 40 minutes. Four interviews were conducted online via a Teams meeting, and one was conducted in person in a meeting room in the office at HTC. The type of interviews is semi-structured. This type of interview allows for some improvisation and exploration during the interview but still follows a general outline or set of questions (Magaldi & Berler, 2020). The questions were sent a week before the interview. So that the interviewee knows the subject of the interview, can read it through, and prepare if needed. The questions focused on the data needed, the availability, the forecasting process, and the influence of the dashboard in the forecasting process. For every specific role, some additional questions are asked, which can be found in Appendix 9.1.1.

The focus group took place in a meeting room in the office. The focus group was held on a Monday because this is the mandatory office day for everyone in the team. This made it possible to conduct the focus group offline with all stakeholders needed. The focus groups were led by me and took around 64 minutes. I was leading the focus group by first presenting the dashboard whereafter questions could be asked about the dashboard's functionality. Lastly, the stakeholders were asked to provide their opinions on the dashboard and how it affects or affected their forecasting process. To ensure a thorough record of the debate, I mediated the group discussion, and a colleague intern took the notes. This made it possible to focus entirely on the debate.

6.2.3 Data analysis

Thematic analysis was used to assess the data gathered from the evaluative interviews (and focus group). Based on the experiences and viewpoints of the participants, themes were found and grouped in the transcripts of the audio recordings and the notes made during the sessions.

NVivo was used as a qualitative data analysis tool to assist with the analysis. After importing the transcripts into NVivo, the transcripts were coded using a combination of open and axial coding methods. The themes that resulted from the codification of the codes were utilized to address the study question and goals.

Several significant themes that arose from the data were discovered using thematic analysis. These topics include the usability of the dashboard, its benefits, and possible improvements.

It is important to note that the data analysis procedure has several limitations. For instance, the extent to which the data was obtained may have been influenced by certain participants' reluctance to disclose their experiences. By asking open-ended questions and allowing participants to take their time replying, I tried to remedy this.

In conclusion, the data analysis provided insightful information on the viewpoints and experiences of participants. The topics established give a thorough knowledge of the effect of the dashboard on the forecasting process. The dashboard allows every stakeholder to see the same data in the same format leading to more internal alignment within the forecasting team according to the stakeholders. This will be discussed in more detail in the next chapter.

6.2.4 Results from evaluative interviews

The findings of this study were organized into four themes based on the participants during the evaluative interviews. These four themes are the most important themes. The full coding can be found in Table 12.

Table 12: Final coding scheme

Category	Level	Dimension	Empirical indicators
Usability	Dashboard usability (external from channel)	Usability dashboard for clients or channels	• It depends on the client • For similar clients it is useful • In the online channel it can be valuable • Everything is in here, so anyone can work with this • When the retailers' data is available, it can be applied to every client
	Dashboard usability	Usability of the dashboard	• Has to be a reason to have a look at the dashboard • Weekly using it • KAM and CDP use it the most • Can fit within my workflow processes
		Usefulness of the dashboard	• Strength is ease to see what is going on at SKU level • Easy to interpret data and helps in visualizing it • Transparency • Contributes to preventing unhealthy stock • Gives more structure to the forecasting process
Advantages	Intention	Reason to use the dashboard	• When a KPI is not performing well • When the KAM asks me to do • To have extra information or deep-dive into a SKU • To check how a promo performed
	Dashboard insights	Most valuable features	• Overall ability to have a quick look at what is going on (the overview) • The visibility and availability of the data • The consistency of the format • Three dimensions (Weekly, Monthly and Quarterly data) • The comparison with last year • Faster and more clear data
		Insights from the dashboard	• Insight in logistical data (whole pallet or pallet layer) • Understanding ordering patterns • Identify trends
		Example where the dashboard can help with	• Prevention of out of stocks • Getting insights into the ordering of the client • Explanation with insights into how SKU sales perform • Data-based supporting decisions • Logistical insights (ordering per pallet or per pallet layer) • Insights into how a promo performed

Stakeholders	Involvement	Involvement different stakeholders	• TSM and Channel manager are involved when asked or when there is a need • Every stakeholder looks at the data from a different perspective • KAM and CDP are involved weekly
	Information sharing among stakeholders	Organize data across stakeholders	• Seeing the same data across all stakeholders • Helps forecasting • Getting insights into why patterns occur • The main source of data used by CDP and KAM
Implementation	Dashboard implementation (technical)	Integration of the dashboard	• Does not integrate with systems or tools • Not linked automatically • Within The case companywe work with a lot of systems in parallel
	Dashboard implementation (external channel)	Implementation online team	• Can be adopted • Very easy to implement
	Dashboard implementation (strategy)	Alignment with the business strategy	• Is in line • Most important alignment is decreasing the stock • Unhealthy stock challenge aligned perfectly • Is an important KPI
Improvements	Improvements to be made	Improving the dashboard even further	• Visualisation • Colouring • Refreshing speed improvement • Reliability • Translation of the data into insights • Updatability when the owner is gone
	User improvements	Improvements using the dashboard	• Unhealthy stock has decreased • Forecasting accuracy increased • Keeping the stock at a good level • Save time
		Forecast improvements due to the dashboard	• Not based on the data, but the Channel Manager sees improvement • Outperforming last year with sales accuracy and stock allocation • Less out of stocks and European stocks declined • Take time to better measure the effect
Challenges	Dashboard input	Inputs needed for dashboard online channel	• Weekly (more recent data) • Order data should be added
	Dashboard challenges	Different time-stamp forecasting	• Moved away from weekly planning the sell-in due to confidence in the dashboard
		Issues with the dashboard	• The autosave takes time • Dashboard was not updated • Changing delivery dates may be a problem
	Training	Training or support	• The stakeholders who use it know how to use it • It is important that everyone in the team knows about the dashboard and its functionality
Way of working	Forecasting	Forecasting sales	• Use information to estimate what we will sell next week
		Forecasting across teams	• It is already multi-disciplinary and it could be used by multiple teams
		Forecasting	• One month in advance • CDP plans according to the latest view based on the dashboard • TSM does not forecast
	Difference in channels	Difference online channel vs …..	• Online channel works further ahead • Ordering pattern and distribution is different • Irregular demand for the …. channel
	Targets	Sales targets	• Every quarter new targets • Crucial to achieve/reach the targets
Communication & Collaboration	Collaborative forecasting	Collaborative forecasting with clients	• The case company is too small as a supplier • The case company is not at that level yet • Try to discuss during the meetings with the client • Unfortunately, do not collaborative forecasts with clients • No supporting systems
	Communication and Collaboration (external channel)	Dashboard affecting communication and collaboration with	• leads to more visibility and consistency • Internally it does, not externally • Leads to more alignment • One source of truth of data

		other external stakeholders	
	Communication and Collaboration (internal)	Dashboard affecting communication and collaboration with internal stakeholders	• Everyone has access to and sees the same data • Collaboration frequency and quality increased between KAM and CDP • Supports discussing the sell-in between stakeholders • Frequency of communicating increased
	Support Decision making	Dashboard influencing decision-making	• Sometimes it does • Strategically (annual review with the client) • Logistical decisions
	Discussing forecast	Conversation using the dashboard	• Always with the responsible KAM • Sometimes with the CDP

The themes were: (1) the benefits of the dashboard and reason to use it, (2) the effect on communication and collaboration with internal and external stakeholders, 3) the possible improvements, and (4) The overall satisfaction and most valuable features of the dashboard.

1. The benefits of the dashboard and reason to use it: The participants reported several benefits associated with the dashboard, including insights into the stock and coverage, visualisation of data, consistency in format and faster and more clear information. For example, participant 1 stated, 'I really like that there is a kind of three dimensions in it. We can look at a weekly, monthly, and quarterly level. We can even look at a yearly level.' The Channel Manager said: 'The consistency of the format is crucial' and 'The overall ability to have a quick look at what is going on'. The dashboard is a vital tool for the CDP, as it can provide logistical data for numerous clients, each with multiple SKUs. The CDP does not have the logistical information for every SKU and retailer, but the dashboard provides an overview of each SKU's order quantity, whether it is ordered per pallet, half pallet, or pallet layer. This information is critical for the efficient supply of the case company' clients. The participant 1 and TSM reported that the dashboard provides them with insights into how promotions are performing. After stacking the sell-in, they can quickly determine the uplift in sell-outs, allowing them to identify which promotions are successful and which are underperforming. The TSM further added that the dashboard brings structure to the forecasting process. According to the stakeholders, the dashboard can be applied as a generic template for almost every KAM client, provided that the retailers' data is available.
2. The effect on communication and collaboration with internal and external stakeholders: While external stakeholders are not involved in the forecasting, the participants reported that the internal stakeholders are more aligned with each other because all team members are looking into the same data, the dashboard makes it easier to talk about the forecast, and the dashboard increased the ease and frequency of forecasting with the internal stakeholders. The dashboard supports discussing the forecast among the stakeholders involved in the forecasting process and provides 'one source of truth'. The TSM even stated that 'it can eventually maybe lead to less frustration or disagreements.' Participant 1 underlines this by stating that they work with it more internally, 'and again, internally, we can use this very well!' In the case of the retailer, external stakeholders are not involved in the forecasting process, as previously mentioned. The stakeholders have noted that the retailer is not inclined to engage in collaborative forecasting with the case company. The Participant 1 have suggested that this reluctance may be attributed to the relatively small size of the case company in the retailer's assortment. Furthermore, the participant 1 opined that the case company may not have reached the level required for collaborative forecasting, a sentiment supported by the CDP, who expressed that the systems at The case company may not yet support this approach.

3. The possible improvements: the dashboard has been identified as an area for improvement in several aspects, including the incorporation of colours to differentiate good and bad results, the enhancement of document efficiency, and the improvement of reliability and collaboration between the forecast and plan files of the CDP. During the interview, participant 1 reported experiencing slow performance and occasional dashboard malfunctioning when the ‘automatic refreshing’ feature is enabled. The Channel Manager repeatedly emphasized to ‘add colouring to make it easier to see what is happening’. He marks the need to incorporate colour coding to facilitate data interpretation. Lastly, the TSM stressed the criticality of improving the dashboard’s updateability.
4. The overall satisfaction and most valuable features of the dashboard: The stakeholders have expressed their contentment with the dashboard, although they have also suggested potential areas for improvement. The capacity to obtain a rapid overview of the data and its presentational format is a primary source of satisfaction for each participant, as they have mentioned consistently. However, their overall outlook remains positive, particularly among the KAM and CDP, who frequently utilize the dashboard. Participant 1 commented, ‘This should definitely start contributing to preventing unhealthy stock’.

6.2.5 Results from the focus group

The focus group was held in the office at HTC in Eindhoven with the stakeholders involved in the forecasting process of the …. channel. All these stakeholders were involved in the evaluative interviews as well.

First, I presented the dashboard. After that, the stakeholders were given the possibility to ask questions about the dashboard and its functionality. Lastly, the stakeholders were asked to give their opinion about the final version of the dashboard created. The focus group was conducted to evaluate the dashboard's final version after the changes mentioned in the evaluative interviews were implemented.

Presenting the dashboard: This took around 10 minutes. Every stakeholder is familiar with this dashboard. I explained the changes made to the dashboard, such as the colouring added to the stocks and explained to them the updating procedure. This last part was new for them because I was the one updating the dashboard (bi)-weekly.

The stakeholders’ questions: just two questions were asked: (1) about updating the dashboard with the Retailer Dashboard and its bookmarks and (2) How I can make sure the data within the dashboard is reliable.

The stakeholder’s discussion: During the focus groups, participants were asked a series of open-ended questions to obtain their thoughts and views about the program. The questions included:

1. Did using the tool get easier the more often it was used?
2. How has the program impacted the forecasting process?
3. Can you describe a time when you felt the program was particularly helpful?
4. Do you notice better collaboration and communication regarding the forecasting process because of the tool used?
5. Have you recommended the program to others? Why or why not?

Notes were taken during the discussion to use for the data analysis.

The findings of the focus group align with those of the evaluative interviews. However, the former is grounded in actual, in-depth experience utilizing the dashboard to anticipate and forecast the sell-in for the retailer. At the same time, the latter was more speculative and concentrated on future thoughts about the dashboard and its results. The Channel manager reported a brief, productive discussion about the forecast, indicating that the dashboard positively affected the forecasting process. In addition to participant 1 and CDP, the other stakeholders also reported regularly utilizing the tool. Besides that, the stakeholders indicated that the tool boosted forecasting collaboration, resulting in more well-thought forecasts made by the stakeholders. Even though participant 1, CDP, and Channel Manager did not offer concrete statistical proof of the accuracy of the forecasts generated using the dashboard, they still claimed to have found it to be an effective tool in their work. Some stakeholders recommended that other KAMs or TSMs with the organization adopt this tool for their clients.

It is crucial to note that the stakeholders' evaluation of the dashboard's impact on the forecasting process was primarily based on their subjective experiences and perceptions. Therefore, more research is required to evaluate the accuracy and effectiveness of the dashboard objectively. Nonetheless, the stakeholder's positive feedback provides some preliminary evidence that the dashboard has the potential to improve the forecasting process and increase collaboration among stakeholders.

As a result, the stakeholders' feedback indicates that the dashboard is an effective tool for predicting the sell-in for the retailer and contributes to more internal alignment among the stakeholders. Positive effects on forecasting and greater stakeholder engagement are promising indicators of the dashboards' efficacy. The focus group provided valuable insight into the experiences and opinions of the stakeholders about the dashboard. Group discussions allow for a rich exchange of ideas and perspectives, generating valuable insights not available through individual interviews.

6.2.6 Analysis of the results

The evaluative interviews aimed to evaluate the dashboard and its usefulness, whereafter adaptions could be made. The results of the evaluative interviews showed the visualisations of the data, the consistent format, and faster and clearer information as direct benefits of the dashboard. Indirectly, the participants state that the internal stakeholders are more aligned, which may lead to less frustration or disagreements. To improve the dashboard, some improvements were mentioned in the interviews. Three main points for improvement were mentioned: (1) the file crashes due to the large number of formulas in the sheets. This problem has been tackled by switching off autosaving. The document now only saves and calculates the formulas when the 'save' button is clicked or when the Excel file is closed. Crashes or a slow laptop due to the dashboard will no longer occur. (2) Adding colour to the sheet to make more visible what is going on. Conditional formatting is added to the stocks. After iterating with the KAM and CDP and trying to add colouring for the sell-in, sell-out, and stocks, the best option was to only add the colouring to the stocks. The formatting is added line for line to prevent an SKU with very high stock and high sell-in and sell-out is always green, and an SKU that is sold less and thus has lower stock is permanently coloured red. The idea behind the formatting is to see SKU by SKU the change in stocks whereby red indicates a (too) high stock and green a (too) low stock. When the KAM sees the stock was red last week, he has to be aware that there will not be a sell-in soon for that SKU. (3) Improving the updatability. The updatability has improved from a lengthy manual process to a short manual process and partly automized process. Unfortunately, this process is not able to fully automatically update because data is needed from another tool. The data from the third party is stored in a format in their tool. This format is saved in a bookmark making it very easy to immediately see the table needed to update the dashboard with the measures and dimensions pre-selected. This table has to be exported and pasted into the Excel document. Then refresh the formulas, and the dashboard will be updated automatically.

The goal of the focus group was to evaluate the final version of the dashboard. The participants stated that they used the tool more than before. Participant 1 use it the most. He started using it intensively two weeks before the evaluative interview. Currently, he uses it during weekly meetings with the CDP and sometimes the TSM or Channel Manager. According to participant 1, CDP and Channel Manager, the forecasting process is impacted positively. On a small scale, this dashboard can improve the unhealthy stock, which is in line with the business strategy. Lastly, the participants stated that the dashboard increases the collaboration frequency and quality of forecasting the sell-in, which is in line with what they expected and experienced when they were interviewed.

The downfalls of this dashboard are that it is built in Excel. This tool is limited in functionality and does not integrate with other systems used by the case company. The CDP, however, said that he works with Excel as well because this is standard within the case company. However, he mentioned that he would rather use other tools specifically designed to forecast demand. This is a limitation of the dashboard but unsolvable for this research because this is part of the case company' culture and ICT infrastructure.

6.2.7 Summary and conclusion

As discussed above, the dashboard has advantages, improvements, and downfalls.

The participants mentioned in the evaluative and focus group the benefits of the dashboard, such as clarity, ease to use, and alignment with the stakeholders regarding the forecasting. These are valuable improvements to the forecasting process and could even improve the KPIs and contribute to the business strategy.

The improvements, which are in the scope of this research, are made after the evaluative interviews. This includes the colour, updatability, and reliability regarding the calculations of the formulas.

Although improvements are made to the dashboard and its functionality, there still are some downfalls. The tool used (Excel) does not integrate with other tools. New infrastructure or collaboration with a tool used for forecasting can improve the forecasting process even further, according to the CDP. This, however, is out of the scope of this research.

7. Discussion and conclusion

This article highlights the importance of demand forecasting in supply chain management (SCM) to achieve lower logistical costs, optimal inventory levels, and better customer service. The paper specifically focuses on evaluating forecasting methods for the case company to predict intermittent demand of the retailer in the retail industry. The research aims to explore how alternative forecasting methods can help the use of judgmental forecasting and how this can lead to more internal alignment among the stakeholders involved in the forecasting process. The study involves measuring the performance of quantitative methods and evaluating the dashboard's effect on internal alignment through interviews. By combining historical data with external factors, demand forecasting can help reduce inventory stock and costs, providing a significant competitive advantage to businesses. The research proposes a design where a relatively simple forecasting technique can support the judgmental forecasting techniques used by most KAMs in large, established companies.

This chapter will discuss the findings of the study and draw conclusions based on the results. Firstly, the research question will be answered whereafter the theoretical implications will be discussed, and three contributions are given. Thirdly, the limitations of this study will be discussed whereafter possible research directions will be given for further research. Lastly, practical implications will be discussed, and recommendations will be given.

7.1 Answer to the research question

This chapter provides an explanation of how the sales team of the case company may use various forecasting techniques. To predict the sell-in for the following period and to what degree this can result in more internal alignment.

The study was designed around the following research question:

'How can alternative forecasting methods outperform the use of solely judgmental forecasting within the case company regarding the prediction of sell-in for various future time periods, and to what extent can this lead to more internal alignment among the stakeholders involved in the forecasting process?'

To address the research question, a two-stage action research was employed. Five SKUs were the subject of stage 1's quantitative testing of three quantitative forecasting techniques, while stage 2's qualitative testing of a forecasting dashboard featured evaluative interviews and a focus group with stakeholders. This methodology was chosen for its ability to provide practical solutions to real-world problems while generating knowledge through rigorous analysis of data and feedback from stakeholders.

In stage 1, the three forecasting techniques were tested on five SKUs for every forecasting method and measured by the RMSE value. SARIMA performed the best with an average RMSE of 22.53, followed by Holt Winters' method with an RMSE of 160.65 and lastly, Croston's method with an average RMSE of 569 which is significantly higher than the others. SKU 4 especially performed far worse on Croston's method.

In stage 2, evaluative interviews and a focus group were used to construct and test the forecasting dashboard. Five stakeholders with different backgrounds participated in the evaluative interviews to provide input on the dashboard's usability, design, functionality, and, ultimately, the ability to lead to more internal alignment. Based on this input, changes were made to the dashboard design to make it more user-friendly and reliable, such as improving the updatability of the dashboard and adding conditional formatting.

The dashboard's final iteration was subsequently discussed in a focus group with four stakeholders who had previously used it. According to the findings, the dashboard boosted internal alignment in the case company's forecasting process of the …. channel. The focus group members specifically mentioned that the dashboard leads to an increase in the collaboration frequency and quality of forecasting. This leads to an enhanced collaboration within this channel with team members of multiple departments.

It can be concluded, according to the study's findings, that SARIMA performed the best on the tested SKUs and their data. This forecasting technique best predicted the sell-out of the next period(s), which is needed to predict the sell-in better. The dashboard helped forecast the demand by adding data to the judgmental process. The involved stakeholders positively receive this hybrid form of forecasting. These results show the significance of using quantitative techniques in order to increase forecasting alignment and accuracy.

7.2 Theoretical implications

The research conducted in this thesis has profound effects on forecasting theory and practice. This study offers insights into the efficiency of integrating quantitative and qualitative techniques in forecasting by evaluating various forecasting methods and implementing the best-performing method into a forecasting dashboard.

The results of this study demonstrate the benefits of adopting various forecasting techniques over only judgmental forecasting in terms of increasing collaboration and quality of the forecast. The findings of the quantitative testing of three forecasting techniques, namely: SARIMA, Croston's method, and Holt-Winters, showed that SARIMA performed best for the five SKUs tested.

Important theoretical implications are also provided by the qualitative testing of the forecasting dashboard utilizing evaluative interviews and a focus group. The study emphasizes how crucial it is to include stakeholders in the forecasting process and give them visual tools, such as dashboards, to aid in their understanding of the data and decision-making. The study also highlights how crucial it is to continuously review and update forecasting dashboards in order to increase their usefulness and efficiency.

Previous literature has identified a significant knowledge gap regarding the integration of time series forecasting and judgmental forecasting in the implementation of the results in real-world applications (Hyndeman & Koehler, 2006; Siregar et al., 2017; Wang et al., 2022). Limited understanding of the development of dashboards that can effectively communicate the results of time series forecasting to help stakeholders make their judgmental forecasts. In this study, forecasting techniques were tested, and the best performing technique was implemented in the dashboard, whereafter, the dashboard was tested on collaboration and communication among stakeholders to better align them. This study used a two-staged approach to integrate quantitative and qualitative data and made three contributions to the existing knowledge in the field in order to improve forecasting within the supply chain context.

The *first contribution* concerns the real-world complexities of inventory sales forecasting. A study by Wang & Petropoulos (2016) found that the effectiveness of combining quantitative and judgmental forecasting depends on the level of expertise of the forecasters and the accuracy of the model used. Alvi, Nabi & greaves (2011) used a two-pronged approach to separate domain knowledge from operational knowledge where Kisi, Mani & Rojas (2014) evaluated the efficiency of labour-intensive construction operations using a two-pronged approach. These three studies, however, use a simulation-based approach to evaluate the performance. This can provide valuable insights, but they do not necessarily reflect the real-world complexities of (sales) forecasting. This study, however, uses real-world data from the case company retailers to test the performance of each forecasting method. This data covers the complexity of intermittent demand and human judgments regarding the ordering patterns of the retailer.

The *second contribution* relates to building the dashboard for the stakeholders to have a look at the historical and forecasted data. Arunraj, Arhens & Fernandes (2016) argue that the supplier has to look at more than historical data to forecast sales. They include external factors such as competition and product promotions influencing the forecast; thus, the forecasting techniques should take these into account. Human expertise is still an important aspect of the forecasting process. A study by Trapero et al. (2013) takes into account the combination of a quantitative forecast whereafter judgmental adjustments are made. This second stage, the judgmental adjustments, are made independently of the baseline forecast the quantitative method provided. The experts have no access to the historical data or the benchmark methods. In practice, the experts may have access to this information, which can affect the quality and consistency of the judgmental adjustments. This study, however, provided an artefact (the dashboard) which can allow the stakeholders to have a look at the historical data and, therefore, may improve the quality of the forecast. The development of the dashboard as an artefact contributes to the field by providing stakeholders with a more comprehensive view of the data, which leads to improved accuracy and consistency of sales forecasts.

The *third contribution* of this study pertains to examining the qualitative outcomes resulting from implementing a forecasting dashboard. The literature lacks in-depth analyses of how the use of such tools may impact stakeholders. By investigating the extent to which the deployment of a forecasting dashboard can foster increased internal alignment. Among stakeholders, this study adds to the existing body of knowledge on internal consistency in forecasting. The study's findings suggest that the involvement of stakeholders in the forecasting process, coupled with the provision of a unified forecasting tool, can assist in improving internal alignment. This contribution is significant, as it highlights the need to consider the human element in the forecasting process and emphasizes the importance of fostering collaborative relationships between stakeholders. Overall, this study's third contribution provides valuable insights into the impact of forecasting dashboards on internal alignment, thereby contributing to the advancement of knowledge in the field of sales forecasting.

Overall, this study provides important insights into the benefits of using alternative forecasting techniques and the implementation of forecasting dashboards in improving forecasting accuracy and internal alignment. These theoretical implications can be helpful for forecasting professionals as well as for academics who seek to explore the efficacy of various forecasting techniques and instruments.

7.3 Limitations

Although this study has shed important light on the usefulness of alternative forecasting techniques to support judgmental forecasting with a forecasting dashboard, certain research limitations should be considered.

The *first limitation* relates to the SKUs and participants. Just five SKUs were employed to evaluate the forecasting methodologies, making the sample size of the study rather limited. This was done to guarantee a focused and thorough investigation, although it might not be totally indicative of the forecasting difficulties experienced by the case company on a larger scale. The same holds for the participants of the evaluative interviews and the focus groups. Limited sample sizes were used to assess the forecasting dashboard's qualitative capabilities. This was done to make sure that the comments were thoroughly analysed, although they might not be totally representative of the larger stakeholder group for other channels within or outside.

The *second limitation* concerns the research data. The data used were historical sales figures and did not account for any outside variables that may have influenced consumer demand for the items under review. Despite the fact that this was done on purpose to isolate the performance of the forecasting approaches, it might not entirely reflect how difficult forecasting is in real-world circumstances. It should be emphasized that the data utilized in this study only included sales data for retailer SKUs in addition to the constraints already mentioned. As such, it is possible that the results do not accurately reflect the whole consumer market and cannot be applied to other product categories or sectors. This restriction may affect the external validity of the study's findings, even if it was also deliberately to create a focused and controlled examination. Therefore, caution should be exercised in interpreting and applying these findings beyond the specific context of the study.

The *third limitation* of this study relates to quantitatively measuring the impact of the dashboard. The present study, while exploring the efficacy of the forecasting dashboard, faced certain limitations, one of which pertains to the absence of quantitative measurement techniques to assess the impact of the dashboard. As the study relied solely on qualitative techniques, future research endeavours could incorporate quantitative methods, such as surveys, which would enable statistical analysis to provide a more comprehensive understanding of the forecasting dashboard's effectiveness. Moreover, investigating alternative evaluation techniques, such as A/B testing or randomized controlled trials, may potentially reveal additional insights regarding the efficacy of the dashboard. Hence, incorporating these methods in future research endeavours may prove to be beneficial in gaining further insights into the forecasting dashboard's performance.

Finally, it is crucial to highlight that although the study showed that using the forecasting dashboard is sometimes better to perform than judgmental forecasting only, other factors that may be at play were not considered. Considering these findings in light of the unique forecasting difficulties encountered by the case company is crucial.

Overall, even if the study offers insightful information on the efficacy of alternative forecasting techniques and the possible advantages of installing a forecasting dashboard, it is vital to recognize its limits and consider them when making a future decision.

7.4 Practical implications and recommendations

This chapter discusses the practical implications of the research findings and provides recommendations for implementing the forecasting dashboard within the case company.

7.4.1 Practical implications

The presented study offers useful recommendations for retail businesses to increase internal stakeholder alignment and demand forecasting accuracy. According to the study's findings, combining alternative forecasting methods, such as SARIMA, in conjunction with judgmental forecasting can improve demand forecasting accuracy. Stage 2 findings point to the possibility that a forecasting dashboard might increase coherence inside an organization. The evaluative interviews and focus group results showed that the dashboard helped stakeholders communicate and work together by facilitating a shared understanding of the projected sales statistics. As a result, the forecasting dashboard may improve the consistency and accuracy of the sales prediction, which will allow the sales team to make better decisions.

In order to increase demand forecasting accuracy practically, the study emphasizes the need to adopt quantitative forecasting techniques and technology-driven solutions. Organizations can better predict customer demand and reduce inventory costs by utilising these techniques. Furthermore, the study emphasizes the importance of involving stakeholders from different functional areas in the forecasting process and promoting open discussion to foster internal alignment.

The study's practical implications extend beyond the retail business, as demand forecasting accuracy is vital for many other industries, such as manufacturing, healthcare, and transportation. The employment of alternative forecasting methods and forecasting dashboards in various sectors can also lead to improved forecasting accuracy and reduced costs.

7.4.2 Recommendations

Based on the findings of this research, the following recommendations are made for implementing the forecasting dashboard within the case company.

Firstly, it is recommended to use a combination of both quantitative and judgmental forecasting methods. This approach ensures that the forecast considers both historical data and the judgement of the forecasting team, thereby enhancing the accuracy and reliability of the forecast. The quantitative forecasting method, which in this case is SARIMA, can provide valuable insights into trends, seasonality, and calendar events, while judgmental forecasting can incorporate expert knowledge and insights.

Secondly, it is advised to train the forecasting team to ensure they can utilize the dashboard efficiently. This would involve providing training on the new tools or software used in the dashboard and ensuring that the team has the necessary skills to interpret and act on the forecasting insights generated by the dashboard.

Thirdly, it is essential to review and update the forecasting dashboard regularly. It is recommended to conduct this task on a weekly basis. This regular review and update process would ensure that the forecasting dashboard remains a valuable and pertinent tool in the organization's decision-making process.

Fourthly, stakeholders from various organizational departments should be involved in the implementation process. This would ensure that the dashboard meets all stakeholders' requirements and is successfully incorporated into a different channel or business unit.

In summary, implementing a forecasting dashboard requires training of the forecasting team, regular review and update of the dashboard, and involvement of stakeholders in the implementation process. This will promote the effective use of the forecasting dashboard, enhance the accuracy and reliability of the forecasts, and lead to better decision-making and internal alignment among the stakeholders in the forecasting process.

7.4.3 Conclusion

Within The case company, the deployment of a forecasting dashboard combining quantitative and judgmental forecasting techniques can result in more precise and consistent sales projections. The suggestions made in this chapter can serve as a roadmap for implementation and support the dashboard's success.

7.5 Future research

The current study offers insightful information on applying various forecasting techniques to enhance sell-in estimates within the case company. However, several directions for further study might expand on this work.

The *first research direction* is to investigate using machine learning techniques for demand forecasting. While this work emphasises time series forecasting, which may offer stakeholders insightful information and forecasts, machine learning algorithms have shown promising results for forecasting short-term demand (Punia et al., 2020). Joiner et al. (2022) conducted such a research about short-term forecasting, this however, concerned financial forecasting instead of demand forecasting. Due to the capacity, expertise, and infrastructure limitations, machine learning methods have not been implemented inside the case company despite their potential benefits. As a result, future studies might examine whether using machine learning approaches to forecast demand is feasible and what advantages they might have. This might entail determining the resources, capabilities, and infrastructure needed to use machine learning successfully. Zohdi, Rafiee & Kayvanfar (2022) did conduct research about using ML techniques in the retail sector to forecast demand although this is a single forecasting method used to forecast the demand. Future research might be conducted to evaluate a hybrid approach, using ML techniques to forecast the demand, implement this in a dashboard, whereafter the stakeholders involved in the forecasting process can adapt this forecast by using judgmental forecasting. In the specific context of the case company, this would offer insightful information on the possible advantages and limits of machine learning approaches for demand forecasting. Such research might ultimately guide choices on the application of machine learning methods for demand forecasting and perhaps improve the precision and efficiency of demand forecasting procedures.

The *second research direction* is to investigate the benefits of collaborative forecasting. Collaborative forecasting involves sharing information and collaborating with external partners, such as suppliers and customers, to forecast demand more accurately. Collaborative forecasting has the potential to improve demand forecasting accuracy by incorporating insights and data from multiple sources. Furthermore, it can enhance communication and collaboration between stakeholders internally and externally, potentially leading to improved supply chain coordination and efficiency. Therefore, future research could investigate the potential benefits of collaborative forecasting for the case company and explore the feasibility of implementing collaborative forecasting practices with external partners. This could involve assessing the resources, skills, and infrastructure necessary to implement collaborative forecasting effectively. Further research may be conducted to determine the variables that may affect collaborative forecasting's performance as well as any obstacles that might stand in the way of its adoption. Such research might assist in implementing collaborative forecasting and perhaps improve the accuracy and efficacy of the case company's demand forecasting process.

A *third research direction* would be to extend the study's investigation to a wider variety of SKUs to understand the usefulness of different forecasting techniques. Additionally, investigating how well these strategies work in other companies might provide insight into their potential influence. To increase the generalizability and validity of findings and to pinpoint possible areas of forecasting strategy development, future research should take these elements into account.

A *fourth research* direction concerns other supply chain components. While this study concentrated on enhancing sell-in prediction accuracy, there is also an opportunity to investigate the effects of alternate forecasting techniques on other supply chain components. The effectiveness of the supply chain as a whole and inventory management, for instance, may be affected by the adoption of these techniques. In order to find areas for development, future studies should examine the potential advantages of these methods for inventory management and other supply chain components.

Finally, it may be possible for future studies to investigate how technology might enhance predicting precision and consistency. For instance, applying artificial intelligence and machine learning algorithms may lead to significant advancements in predicting precision and consistency.

Overall, this study provides a foundation for future research. Pursuing these lines of inquiry may yield further information on the efficiency of various forecasting techniques and the application of technology to enhance supply chain management.

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9. Appendices

9.1 Interviews

9.1.1 Exploratory and Evaluative interview questions

Exploratory phase:

General Questions:
1. Could you describe your current role within the organization? 2. What are your responsibilities? 3. Can you tell me something about your day-to-day work? 4. What role plays data in your daily work? 5. How does your role interact with other departments or teams within The case company?
Regarding data:
1. What are obstacles you encounter? 2. According to your opinion, are there new possibilities for data to help you doing your work? 3. How easy is it to receive the data you need? 4. Where do you use data for in your role? 5. How easy is it to get value from that data at this moment for your work? 6. What could be improved in receiving or visualizing the data?
For KAM:
1. How do you estimate the sell-in of your client(s)? 2. For what period do you forecast the demand? 3. What is the most difficult part about forecasting? 4. What parameters do you take into account when forecasting the sell-in? 5. Can you walk me through the process of planning the demand? 6. What specific problem could a sell-in, sell-out and stock dashboard solve for you?
For CDP:
1. How do you estimate the sell-in of your clients? 2. For what period do you forecast the demand? 3. How long is the delivery time of the case company products from the factory to your availability? 4. What is the most difficult part about forecasting? 5. What parameters do you take into account when forecasting the sell-in? 6. Is the forecasting different for each client? 7. What specific problem could a sell-in, sell-out and stock dashboard solve for you? 8. Can you walk me through the process of planning the demand?
For TSM:
1. What is your role regarding the products for the clients? 2. In what way can you help the KAM and/or CDP regarding supplying relevant data / visualizing the data? 3. Are you involved into forecasting the sell-in? → if yes, in what way? 4. What specific problem could a sell-in, sell-out and stock dashboard solve for you?

General Questions:
1. How have you been using the data provided on the dashboard to inform your decision making? 2. Can you share an example of a situation where the dashboard helped you identify a trend or problem and how you addressed it? 3. How does the dashboard integrate with other systems and tools that you use? 4. How does the dashboard help you with forecasting and planning the customers sell-in? 5. In your opinion, what are the most valuable features of the dashboard? 6. Are there any features or data that you feel are missing from the dashboard that would be helpful for you? 7. What are the main points of improvement of this dashboard? 8. How does the dashboard help to organize data across the different stakeholders? 9. Can you give an example of an issue that was caused by an inconsistent forecast and how the dashboard helped solve it? 10. Do you think other KAM's and CDP's within the .... channel or outside of it can benefit from a forecasting dashboard as well? 11. Can you describe if and/or how the dashboard makes it easier to share and collaborate on forecasting data across teams? 12. Can you share specific KPI('s) that have seen a significant improvement within the team using the dashboard? 13. How does the dashboard help align the forecast process with the overall business strategy? 14. How does the dashboard support standardize the forecast across the team? 15. How did the dashboard help to improve forecasting process consistency across your team? 16. How has the use of the dashboard affected the communication and collaboration with the other stakeholders involved (internally)? 17. How has the use of the dashboard affected the communication and collaboration with the other stakeholders involved (externally)? 18. Have you noticed any improvements in your performance or in the performance of your team since using the dashboard?
For KAM:
1. How has the dashboard helped you in managing and analyzing your key accounts? 2. Do you think other KAM's within the .... channel or outside of it can benefit from a forecasting dashboard as well?
For CDP:
1. How suitable is this dashboard for your monthly forecast? 2. Do you think other CDP's within the .... channel or outside of it can benefit from a forecasting dashboard as well?
For TSM:
1. How valuable is this dashboard for your role?

Evaluation phase:

9.1.2 Participant 1

Interviewer: How did you use the data on the dashboard to make a decision or inform decision-making? Did you use it to do that?

Participant 1: Yeah sure, the dashboard is obviously a combination of a number of things that are very, very closely related, so you have sell-in, you have sell-out and basically the result of that is the stocks. So those are the facts that are in there. In addition, of course, we have the periods that we have in them. So we can see very well that way what the current situation is with the client. We can see the history, but it also allows us to look ahead and that is actually what it is for. So making an estimate based on any trends we see in the development of the sell-in, of the sell-out, of the stocks. What should our forecast be? Based on the data that's in the dashboard. So that's the way we work with it.

Interviewer: And that decision, for example, and decision-making. When we talk about that, does that mainly have to do with the forecast that's planned or that you want to plan for in the future?

Participant 1: Yes, that's primarily what that's for. Yes, so that's mainly a tool to make decisions about how much product we want to have to come in from the factories in the coming months.

Interviewer: And has there ever been a situation where a dashboard has helped identify, say, a trend or a problem or a particular adjustment to a forecast? Or is it the other way around? That you go look at it and then find out that there's a possible adjustment that needs to be made to the forecast?

Participant 1: The reason for building a dashboard was a situation we had a year and a half ago and we didn't realize that the customer had ordered a lot of one product. That we had not properly documented or had it in a dashboard and therefore were hoping for new orders they were not coming. Whereas actually, we could have known if we had had the dashboard. So that's the reason for creating this Dashboard it's actually a tool that was created to prevent what happened then from happening again. So it's now more of a preventative tool than an explanatory tool.

Interviewer: And does this dashboard integrate with other systems, Excel documents or tools that you use, or is it that you see them side by side mainly?

Participant 1: They're not linked in the sense that automatic links lie, say, excel links but the input is obviously refreshed by the data from other systems and the output, say as the dashboard looks that we use or the things we see in it, we use to populate the forecast tool. That's a separate tool, but it's filled based on the things we get from the dashboard.

Interviewer: And you said the dashboard helps with forecasting. So that helps with forecasting and planning the sell-in? So the sell-out you get to see and you actually base the forecast for the sell-in on that?

Participant 1: Yes, so we particularly look at the sell-out that's what we always look at first. We generally see that the sell-out and sell-in at the retailer, that are similar on a year-over-year basis, often on a quarterly basis as well. There can be some small shifts in between. So that's why actually the sell-out is, is leading the, for the sell-in. If your sell-out goes well or gets higher, then you know you have to start raising the sell-in as well. So your forecast has to go up. Where, the stocks are actually kind of an indicator for any declining sell-out and therefore sell-in and toe. If you four there that you're going to run in the red, then you know there's something with the sell-out and had, so sell-out is leading and everything else is a derivative of that.

Interviewer: Okay, and for you, what are the most valuable features of the dashboard?

Participant 1: Yeah, I really like that there's kind of a three-time dimension in there. We can look at a week level. We can look at a monthly level, we can look at a quarterly level, and even can look at a yearly level, so I really like that. How that we, yes, how we plan. We sometimes look at what at a higher level, at a quarterly level then we zoom in on the months and within the current month we always look at: okay, what's going to be ordered this week, this month? Have they already stated? So everything is actually in there. So that's a very fine dimension. And in addition to that, I also find the comparison with last year that those are in there. We're not just looking at this year, but we're also looking. What was with that product, what did we do last year and is it explainable what is happening with this product this year? Is it more or is it less? And why is it more or is it less? So yeah, there's basically everything in there. So a piece of history is in there and the time dimension for all, for all the targets that we have, so for all the relevant KPIs that we have, is the sales for the current month, some longer-term at the quarterly level and also even at the yearly level where do we end up? Do we plan at a yearly level the volume we need, think we need?

Interviewer: And for your functions, are there any that are missing or that would still be useful in the future, for example for the new, internally? For the distant or near future?

Participant 1: No, no new features. The only thing I personally, but that's more of a technical thing, is that I occasionally find it slow or with that automatic refresh that if you don't turn off the formulas then it's slow all at once. And then it flips out sometimes. So I think that's the only drawback. But yes, well, I don't think you can do anything about that. That's just also how it is built and all the links that are in it. yes, maybe still but it's more of a question mark is not that there is not in it, but is there enough security built-in to be sure that everything is right? I don't know if there are yet, because it's so many numbers, but are all the links right? They could still build that in somewhere kind of a double-check tab where we say, okay, the additions of that sheet and that sheet match. So everything should be right.

Interviewer: To increase reliability?

Participant 1: That reliability yes. You want to avoid, of course, that you're sitting planning on and you find out at some point, that maybe a couple of lines are wrong. A wrong link, things like that, because it's still a fairly manually built system. Of course, hey, but otherwise golden, but you know that.

Interviewer: And does the dashboard help you organize the data across the different stakeholders so for example, you're often sitting with your CDP, but maybe also looking at it with TSM or maybe with a channel manager? Does this dashboard help you with consistency?

Participant 1: I, can very quickly. Can I, and I do like that can see very quickly, also through the time dimensions what's going on with certain elements, sit with the sell-in. What about the sell-out, what about the stocks? Those are kind of the three elements where you can answer questions very quickly. So it certainly helps me, especially of course with the Customer Demand Planner. But suppose I get a question like why? Why is there less ordering? I can click on the sell-out of two years and I see at once okay, the sell-out is disappointing compared to last year and that's then the explanation, that the sell-in is disappointing. Or another situation can be, the sell-in in the current month or in the last two months is disappointing and I can then explain that because I had a very large order three months ago, which didn't run off very fast in the stores. So yes, it is for multiple disciplines, Customer Demand planners, but also the sales team or even marketing. Is it explainable what is going on to explain things or reassure people if necessary

Interviewer: And do you think that other, Key Account Managers or Customer Demand Planners within or outside the channel you're currently in, would also benefit from this file for their particular retailer or customer?

Participant 1: Yeah, sure, yeah, basically everything is in here. So anyone who works this way and has to deal, especially with customers who work with an inventory. Look these are chain stores with an inventory. With an online player, it's a little different. We have two weeks of stock on hand. Yes, there, there will never be very high inventories there. But particularly so the top component is super interesting for stores, for retailers with physical stores, because there often stock can become fixed, so your whole sell-in is disappointing again.

Participant 1: Counter yes, so in a general sense it will definitely be usable there, provided you have the data that we have available from the customer. From the retailer have all the data and that's not the case with every retailer.

Interviewer: And this is more of an insight question, but do you have specific KPIs that, in your understanding have been able to see significant improvement by using this dashboard? Do you think certain KPIs have improved or gotten worse? But at least changed by using this dashboard for your client then?

KAM Drug Stores: Yeah, I think we've actually only recently become very active with it, but I think particularly that forecast accuracy. That will and certainly will increase. And not so much on a monthly level but certainly on a quarterly level, I think because you don't know exactly when the customer orders. The last week of the previous month or the first week of the next month. But at the quarterly level, I think we are much closer to the truth. And I also think new insights have emerged. By the way, I also want to mention that in terms of that I sell-out and sell-in however beautiful. How yes, no matter how nice it is, at the end of the year it always runs smoothly at a retailer, so you just see that they permanently adjust their inventories based on the stocks in the store. So if there's a lot lying around then they're going to order a little less and if things are going well, they're going to order some more. At the end of the year the figures almost all match. So that's kind of nice to see.

Interviewer: You use for this customer then specifically, no collaborative forecasting. What actually is the reason for that?

Participant 1: Yeah, I think we are too small as a supplier, so that they say, yeah, an hour of time that we put into a supplier they would probably rather put into a very large supplier than a smaller supplier. I think that's an important one, and in addition to that, I don't know if we're already at that level ourselves, that we can act at that level, the way those big suppliers handle it, at that level. With the people we have. I think there is an expectation that at a company like Unilever or Proctor&Gamble, there is a much larger and more professional team there on these kinds of issues and more experienced as well. I think that plays into it.

Interviewer: And does, in your opinion, the dashboard support standardizing the forecast within the team?

Participant 1: Within the team do you mean our channel team?

Interviewer: Yes, the channel team indeed. If everybody, if all the Key Account Managers would use this within the team. So does it help then, do you think with standardizing and then mainly, I think, for the CDP, which is overarching planning for standardizing the forecasts?

Participant 1: Yes, basically the perfect tool for everybody actually, for every Account Manager with that nuance of: yes is it a retailer with a lot of stores, or is it a retailer with only a webshop and you need that data? So if you don't have that stock data or you don't have that sell-out data at the weekly level, then it's really of no use. Then again, the big retailers generally do share their data with us. So for the big customers can certainly work well. With that you actually, if you look the retailer is obviously a big one within the channel and then also a big player. You actually have your total forecast accuracy across all customers. So if you apply to the big customers everywhere, then maybe 80 per cent of your revenue is already covered with a nice tool.

Interviewer: And what is the difference between an offline retailer like Watsons and an online retailer like Bol.com in forecasting demand?

Participant 1: They work further ahead, so we as the case company already have to order products for promotions or listings that won't happen for six months. I think that's an important one. And of course, you don't know how the inventories of say the next six months are going to develop. If there are two moments in between, which create a lot of inventory in the stores, then that affects your sell-in six months from now and that's obviously a little bit different with the online players. Then you also have to plan alone, you are less likely to run into the story that there is a lot of stock. With them there is a lot of stock, so they put on the brakes. So I think that's actually the most important one. And that risk of a stock is also much higher because if things go wrong with a certain action, whatever, then there is really a huge amount of stock at the retailer and then it takes a long time before you get another order. So that also means that you can't get an order at all for, say, two months. Whereas with a pure player, you get fewer orders but you do get something. E does get something back on order. So I think that's the biggest difference.

Interviewer: We had within the case company. A while back we had the challenge to lower unhealthy stock as a zone. Do you think a tool like this forecasting file contributes to that?

Participant 1: This should definitely start contributing to preventing unhealthy stock. So really on a local level.Eurpoese excess stock that yes. I'm just a small part of that. But as you improve your own forecast and in theory, all retailers or all Account Managers would work with a such goal along with CDPers, you should see that. It is rollout-able and recommendable.

Interviewer: Okay, and did the use of the dashboard affect the communication and collaboration with the CDPer or TSMer, for example?

Participant 1: With Trade Marketing wasn't too bad. And with the Customer Demand Planner, I've actually only been really using it for a couple of weeks, very intensively. So we both did get excited. The Customer Demand Planner and I both did get excited about the usability and yeah just opening up four screens and all. Yeah seemed like a big forecast cockpit that we were in. So yeah, it's a keeper if I can put it that way in terms of the tool.

Interviewer: Good to hear, because the TSMer is not included when there is a big promo moment, for example? That is not included in the forecasting of what that person then thinks is going to be ordered, is that your understanding?

Participant 1: Yes, TSM is involved, but to a lesser extent about the forecast itself. The TSMer indicates what that person thinks the impact will be. But I know with other customers that's the case there yes that's more kind of historical, that I'm more into the numbers than the TSMer is with me. So I'm a little deeper in the volumes. Actually, I'm sell-in responsible and the TSMer is sell-out responsible. But where sell-in does, again, is the result of a good sell-out or a good sell-out. So a bad sell-out also hits me in the sell-in. So I'm more in the sell-in numbers but again, the funny thing is that sell-out and sell-in are simultaneous. So in theory a TSMer should be able to do it as well. So in fact I should be able to adopt the sell-out an the TSMer 1-to-1.

Interviewer: That would be the best thing. You mentioned it a little bit, the collaboration with Watson, it's not very strong on forecasting if I can call it that. So has the use of this dashboard improved communication or collaboration with external stakeholders like Watsons or has it not affected that?

Participant 1: No, not yet, to the extent that of course, we keep that data a little bit to ourselves as well. We're working with it, more internally and I do think there's also really, yes, again, internally very good use. But Watsons has the same data and they have sort of an automatic ordering system so they will say, yes, just make sure you sell-out, then your sell-in will come naturally and the tool confirms that as well. So yes, analyzing numbers that actually makes a lot of sense. I don't believe we have a vendor like The case company for that, time and investment so.

Interviewer: And for example for your negotiating position I mention listings as an example you have an influence on that.

Participant 1: I don't think so because what we do there, we, we compare ourselves more with competition and competition is not in this tool and then again you have IRI for that that we look if you look at the sell-out of our existing products compared to those of the competition, which you can then get out of IRI, that's what we use that tool for. To justify that to do the expansion. I have to tell you and that's where a tool is indirectly a tool. A good forecast with few out-of-stock problems at The case company also helps you and gives you confidence with a retailer and that does make it easier to get listings. So because you have proven that you can deliver well with the products that are already on the shelf. Or just the other way around. If you would have problems with you with three existing products on your shelf and you with all three problems, then the willingness for that retailer to say, well, I'll put one more product on there, with all the risks involved, that's pretty limited. So indirectly it does help you.

Interviewer: How has the dashboard helped you manage and analyse your key account? In this case, Watsons, is that mainly in the forecasting area?

Participant 1: Yes, yes, definitely. You see there's that whole ordering pattern as done from the retailer, which can be different for each product. So internal elements of the customer play a role there as well. To that extent that was clear to us last one. You have the logistics component, ordering per pallet low or not or per whole pallet so that plays into it. So you also get that insight by looking at that tool. And in addition, you also see that sometimes there are inexplicable sell-in patterns in it. And if you then. We recently had a meeting with the retailer,, then it turns out that a supply planner from v says: yes, I do understand why this happened, because that buyer thinks it's Q4, let's send in enough so I can also sell a lot and there you notice that inexplicable things happen for us. So high orders with a lower sell-out expectation, are caused by probably an internal KPI of a buyer at retail. And you see that very nicely reflected in the tool, that you don't understand inexplicable things and that there is an underlying thought behind it. That's nice, also a nice element in how do you say that? A qualitative conclusion from a quantitative tool.

Interviewer: Yes, yes, and you mainly plan on a weekly level, at least you see the data per week and also look at what promos are there per week, for example, if I say correctly, and the Customer Demand Planner per month are quantities. Do you notice that's tricky, that you look by the week and he looks by the month? Does that differ at all? Because I would imagine that weeks do stagger.

Participant 1: Yes, I'm actually also because of this tool, I've moved away a little bit from planning per week. In the past I planned all at SKU level per week, the volume if there were promotions and also per store formula, so retailer Netherlands, retailer Belgium, another retailer and I plan now, and I've also gained that confidence through the tool, by looking more at okay, on a monthly, on a quarterly basis is about what should come out. Because it saves me a lot of time to stop doing it at the weekly level and at the formula level. And because of that the planner and I are actually talking about the same thing we're also now talking about both talking about monthly dates or quarterly dates whereas in the past I talked about you have to plan that for those weeks, whereas the planner was planning at the monthly level so we were always talking about different figures that when put together then had to lead to the same thing. And now we are going to work at a higher level, both at a high level, monthly or quarterly level and no deeper than that. There is a certain risk in that because let's just say there is a bit of experience of myself in that I know: if there is a very heavy action, like black Friday then I dare to put those volumes up, without really looking at the weekly level of okay, what would that Black Friday week do? But then I put a whole month a piece up, so that's how, how I work now. Yes, but that confidence has grown through the tool I must say. I didn't dare to let go of that in the past. Then was also really planning on a weekly level and on an action level.

Interviewer: Top, those were my questions. Thank you

Participant 1: So, you're welcome.

9.1.3 Participant 2

Interviewer: Alright, yes, so it's about the dashboard I created for you guys, mainly for the Participant 1, but also for you. So you know about the file. That's the thesis file. How did you or did you use the data on the dashboard to inform decision-making for a forecast? Uberhaupt.

PARTICIPANT 2: Let's ask that first. Do I have that question, yes, I do use that, yes, now that file is actually kind of finished, that's kind of easy. And what I mainly use in there is the comparison between the sell-out and sell-in from previous months, quarters and years.

PARTICIPANT 2: To analyze that and see: okay, how does that translate into the future?

Interviewer: Because what data do you use from a PARTICIPANT 2: perspective?

PARTICIPANT 2: To do planning or?

Interviewer: Yes, yes, yes, yes.

PARTICIPANT 2: Yes, that's selling to the customer. You can always see with certain products a historical trend, certain uplift in seasonality for example. But also yes MOQ is a very common one because some customers order by box or pallet.
Interviewer: So that's more for the logistics part, after planning. The latter if I understand correctly?

Interviewer: Yes, yes

Interviewer: So how am I going to package it and how is it going to be transported to the customer?

PARTICIPANT 2: Yes also what do I forecast? For example, if you have one product? Yes, name something. A pacifier which goes to Bomedys. Well, if you see okay, they order a pallet every month or every other month. Yes, then it doesn't make sense to start planning half pallets.

PARTICIPANT 2: Snapping I understand, yes.

PARTICIPANT 2: That's, yes, that's also just data that you're using. Am I using anything else? Yeah, the info raid from the customer, like in your dashboard he the sell-in data, the sell-out data. But also if a customer indicates we're short on items or too many items, yes, all of that is taken into account.

Interviewer: Can you give an example of a situation where the dashboard helped you identify a problem or identify a trend or at least helped you forecast or plan inventory?

PARTICIPANT 2: Yes, I saw. Now some time ago I sat down with the particpant 1 for an entire afternoon and really really dove deep into the data. Practically really went SKU by SKU of okay, what has been a sell-in, what has been the sell-out. How do we see that evaluation in the future? And then you really do see that yes, what I just mentioned. that some items are just ordered by pallet or by pallet layer. That's just useful information to take into the future. And if you see that, for example, for a toothbrush, they had one order, three months nothing, another order, three months nothing and another order, yes, then you can almost count on your hands that you then have to start forecasting every three months, where it is not, that they are not following that trend now and just start ordering a pallet of the same item two months in a row so Yes. You know, in that respect, there remains a bit of a crystal ball.

Interviewer: yes, I can imagine. And you may have partially answered this, just hear. But how does the dashboard thesis file integrate with the other systems and tools that you use? Do you look at your own systems first and then have a standard schedule? Do you then look in the dashboard of do any particulars occur, or is it or is it the other way around?

PARTICIPANT 2: Yes, no, this is t is already often I work from my own plan file. And if, yes, I see strange things in there, or deviations or just want some deeper info, extra information about, for example, the take-up of a product, well, then the tool is really just very handy, because it just provides immediate insight into what the take-up has been and how that might translate into the future.

Interviewer: Yes, and is it often that particpant 1 comes to you with or look at this? Does he also look at that dashboard separately? Or is it that you guys always look at the dashboard together?

PARTICIPANT 2: No, I look. I know he also looks at it separately.

Interviewer: And does he ever come up well did you think about this or would we do this way or how?

PARTICIPANT 2: Yes, that has been at times that he said: Gee, hey, look at this SKU or hey, how did you schedule this product? Because I see this and this. So that, yeah, that interaction is definitely there.

Interviewer: And for you, what are the most valuable features of the dashboard?

PARTICIPANT 2: And yes.

PARTICIPANT 2: I think a combination of both. Both the overview and that I can look at each SKU well. On the one hand, the overview you have. What I use it very much for is really sell-in, sell-out and data from the customer itself. But in addition to that, a deeper deep dive into the SKUs themselves.

Interviewer: Okay, and are there things that would like to see improved in the file? Areas of improvement or what would you like the next one to do internally, with the file?

PARTICIPANT 2: The ideal picture would be of course that if there if you can make a combination between your forecast file and my plan file. For example, if I plan for the next few months on a certain SKU number that it automatically calculates through okay, then the customer is going to order and this means your planning for inventory at the customer.

Interviewer: Yes.

PARTICIPANT 2: Well, of course, that would be totally ideal if you, if you can combine the two.

Interviewer: So the integration actually. The integration of the file into the existing systems? Am I summarizing it correctly then?

PARTICIPANT 2: Exactly yes, that's how you summarize it well only I personally think that there is better software for that than myself.

Interviewer: Yes, yes, yes, because you already use that. Or is it mainly still Excel?

PARTICIPANT 2: No, it's mainly Excel still. The plan file itself where I work is Excel based. We do upload that of course into a software tool. but yeah, it's not like that's really all put together.

Interviewer: Intertwined is?

Interviewer: Woven is yes!

Interviewer: And how does that file help organize data across stakeholders? So for example that the consistency is between the data that you see, the KAM sees and for example, the channel manager or TSMer sees that's sitting there. Does it help with that or not?

PARTICIPANT 2: That's a good one...

PARTICIPANT 2: I think it's well no-yes. we look at the same data just with a different perspective. I seem to really look from a planning perspective. Okay, what is required? And I think that an Account Manager is looking more at how is something developing. What trend do I see with a particular product, for example?

Interviewer: Yes, yes, okay thanks.

PARTICIPANT 2: : Yes, well, yes, I think so.

Interviewer: Yes, no, I can well imagine, certainly. Can you give an example of a problem that was caused by an inconsistent forecast? So for example if you made a forecast that might not be quite right and you found out through the file or is, has there been? So that something was forecast and you found out when you looked at the file there of maybe we need to adjust this.

PARTICIPANT 2: Yes, yes, we found that out right there when we were previewing the dashboard at the time. That was two weeks ago sitting with the particpant 1. Then we did find out that some items then over a quarter were too high in the forecast and some were a little too low.

PARTICIPANT 2: Yes, some items then over a quarter were too high in the forecast and others a little too low. So yeah, and that's where it does help there. Sure, okay, okay, but it's not yet that I'm really looking into the data and really was really looking at the data and thinking, hey, that's weird, this I'm planning very differently for example. That that, that's another step that, yeah, that I still have to take.

Interviewer: Is also hard to see, I think, if you have to go look for all those SKUs separately and you can't keep it all.

PARTICIPANT 2: Yes that's right. You just said, they mean mise something in the file. Yeah, maybe a is a, call that a one, a listing with the top SKUs is an idea to add to it. Well that, you know from okay, these are really just high selling. Those you can easily keep an eye on, that you're going to kind of yes your Pareto analysis okay, what sells what? Good? Why do I have to give extra to? and which ones can I say okay? Well, yeah, sometimes that makes so little difference based on sales and it's not really necessary. To really start analyzing those properly.

Interviewer: Do I understand and do you think other Key Account Managers or Customer Demand Planners, within the ….. channel or beyond could benefit from this file? Or is it especially applicable to Watsons in this case?

PARTICIPANT 2: That just depends on what data you have from the customer. I mean, wi. In the case of the retailer,, so we have so we had, Arjan is now creating the annual deal. But so do we have cell-in, sell-out data. Yeah, if you don't have those, then yeah, then actually a very big part falls away.

Interviewer: Yes, so it's important. The so the data is, is the bottleneck in this, say so if the data is there, then there would be...

PARTICIPANT 2: The data availability of data is the bottleneck indeed.

PARTICIPANT 2: And if that were different you could very well scale it and deploy a wider. Yes.

Interviewer: Let's see, that's a pretty specific question. Could be that you don't have an answer to this, you know, but there are specific KPIs there that have been improved, in your opinion, by using this file.

PARTICIPANT 2: That's pretty specific. Which I don't 1,2,3 not no, don't have a direct answer to.

Interviewer: Okay, and how do the thesis file and the forecasting that is done help with aligning with the overall business strategy, does that align with each other? So what is mandated by the channel managers, about scheduling for example or from your team?

PARTICIPANT 2: Does that align with each other?

Interviewer: Or is it an aid to strategy?

PARTICIPANT 2: I just find it very easy to have a to make a deeper analysis of the data and it helps very much with that. But is, yes, is it in line with the business strategy, yes, I think that's another broad, broad question and hard to answer.

Interviewer: Yes, but it it. It helps you forecast and therefore you can forecast more accurately, and better which is maybe the goal, say from your team. Could I argue that?

PARTICIPANT 2: Yes, yes, because yes, well, forecast accuracy is one of our KPIs and it does help with that. All yes forecast accuracy is influenced by numerous factors.

Interviewer: Yes.

PARTICIPANT 2: The willingness of the customer is one of them. But it does help to gain insight into a particular offtake pattern or a particular ordering pattern. Or to get insight. Okay, how much inventory do they actually keep at a certain point in the year of a product.

Interviewer: Okay, the thesis file, should that be used and should data be available for all KAMs in the …… channel, so for ..., ..., a .... for all those customers, that would help, for you as a PARTICIPANT 2: to create consistency in the data that you're looking at.

PARTICIPANT 2: Yes, I think it would. If you have the data correctly, from the different customers, then that definitely helps yes.

Interviewer: And do you think that would improve the forecast for any customer within the channel?

PARTICIPANT 2: Ultimately yes, I think so, just depends on how heavily you use it. I would imagine with certain customers or product groups, you can use it more specifically than in other cases.

Interviewer: And what is the effect of that? For example, Watson is a customer that's pretty much on promotions, if I say correctly, so correct me if I'm wrong. But would this file also have as big an impact on helping your schedule if less. So if for example a client is less on Promo, or is it much easier to schedule then anyway, you don't need this.

PARTICIPANT 2: Well not needing it I think is too big a word, but the impact on schedule is a little less with customers that are more baseline driven because then they do have a more yes steady offtake compared to with Watsons for example which really peaks a little bit and works up and down on certain category of products.

Interviewer: yes, has the use of the file, the communication and collaboration with the stitch holders involved so in this case that's mainly, I think Participant 1, but maybe also the Channel Manager, and the TSMer influenced do you think?

Interviewer: Yes, I think so, yes I think so.

Interviewer: In a positive sense?

PARTICIPANT 2: At both and in a positive sense Indeed, because we both, just have insightful data on what a product does. Yes, then previously it was okay, yes can call out a number, but yes, if the other person doesn't see that it's actually on the screen, for example, yes, then it's a little harder to convince than just having the hard data.

Interviewer: Yes, understandable, and are there external stakeholders so for example? Do you talk about the forecast with Watson or is that really separate the case company from Watson? So Watson just orders what they want. And we as the case company or within this team, or you and Participant 1 I can actually better say forecast on that your inventory?

PARTICIPANT 2: Yes, yes, we don't have a collaborative forecast with Watsons yet unfortunately, they didn't want that yet. But you do notice that with customers, with where there is a collaborative forecast, yes, that you do A much faster switching with the individuals themselves and also, yes, that the output of your work is actually much better.

Interviewer: Yes. do you know the reason why you what she doesn't want that?

PARTICIPANT 2: No, you would have to ask v. I think A: their system wasn't that far along yet and the output they were getting from their system, that they themselves didn't think was reliable enough.

Interviewer: No.

PARTICIPANT 2: Yes, you would have to ask the KAM Drug Stores about that further. For me, that was one of the reasons they weren't doing that yet.

Interviewer: Okay, and you plan at the monthly level?

PARTICIPANT 2: Yes.

Interviewer: And that's different from the KAM Drug Stores. I think, which looks more on a weekly level of when are there promos is that correct?

PARTICIPANT 2: Yes.

Interviewer: And how does that go together? Does the dashboard help with that so that Participant 1 can look at the dashboard at this is it per week and how that translates to per month?

PARTICIPANT 2: That's still a tricky thing sometimes. With building, you noticed it yourself. The case company calendar and the annual calendar sometimes don't match. That you sometimes have shifted between one month and another. It's just how the week falls. But anyway, that's something to take into account.

Interviewer: And do you think other CDPers, so outside the ....channel could benefit from that thesis file?

PARTICIPANT 2: Yes, if you have the data then yes! That's the most important thing.

9.1.4 Participant 3

Interviewer: Hi …, Thank you for letting me interview you. I interview you regarding my master's project about data visualisation and forecasting within The case company . How have you been using the data provided on the dashboard to inform your decision-making?

TSM: I use the dashboard not that much, to be honest. I do use it when there is a promo to check how we performed in sell-in and sell-outs that week(s) and the weeks after. But it depends on the KAM and how much I use it. Some KAMs are more into the data than others. But I can assist in a good way when there is a promo. This is because I am working between the sales and the marketing team. This combination gives me knowledge about the upcoming event as well as knowledge about the data. I compare a lot of data from The case company with the data of competitors like Proctor & Gamble. For example the market share. This is a very important KPI for us. The dashboard does not take into account the competition and thus it is less helpful for me than for the KAM, but it is a simple tool to see clearly and easily the sell-in and sell-out over the weeks, months or quarter for a specific product as well as for a whole category or Article Group.

Interviewer: Can you share an example of a situation where the dashboard helped you identify a trend or problem and how you addressed it?

TSM: A time ago, I was looking at the dashboard to see how we perform on the base line of our toothbrushes, here I saw that the HX…. was performing way better than the HX…. Then I looked back into the data in the dashboard and saw that that the HX…. indeed was performing better in the past than the HX…., but that they now switched positions. We did some more research and concluded that there was a trend in the market for cheaper toothbrushes. By luck, I got this information due to the information from the dashboard.

Interviewer: I did not know this happened haha. How does the dashboard integrate with other systems and tools that you use?

TSM: For me, it does not integrate with other systems, but it works well next to each other. We get GFK data as well and within The case company, we have a dashboard on how we perform in the market against our competition. This dashboard gives me more specific the case company data as well as an overview of all the products and the trend in time. These two combined can give me a good view of how we perform and what is going on with the case company products in the market. The dashboard is made in Excel which makes t difficult to implement in any other system, but I have to be honest to say that within the case company we use a lot of systems parallel to each other. It should be a good idea for the case company to integrate them all in just a hand full of tools to use haha. But that it big dreaming I think.

Interviewer: yes, I think so too haha. And how does the dashboard help you with forecasting and planning the customer's sell-in?

TSM: I do not really use it to forecast, the forecast is made by the KAM and CDP most of the time. Sometimes I am involved in this process. For example when there is a new product or there is a special event. For new products, we don't have data except for predecessors. Then we use this dashboard and data from the predecessor to predict the sales. But within this channel, we work with 'invading' as we call that in Dutch. They do buy a lot from us before the product is launched. When the product is launched, the retailers have for example 10 items of that SKU in every shop. This is discussed and based on the predicted sell-out. We can use this dashboard for that purpose.

Interviewer: Oké, so the forecasting is mainly done by KAM and CDP and for special events, you are involved use the dashboard as well as other sources of data to help them estimate the sell-out?
TSM: Exactly. we do this for years and now we have an additional tool which can provide us sometimes with relevant data we use for the estimation. I am 'responsible' for the sales of the retailer, so I work closely with the marketing department to promote the right SKUs that need it. At the beginning of the year, there is always a strategy for which categories to push and what the goals are from a marketing perspective. Thus I know better than the KAM the promos which are coming, but the KAM has more knowledge about the client itself. For example, what a normal stock is for a particular client, the KAM knows it, but I know it is just on the category level and not that precise.

Interviewer: In your opinion, what are the most valuable features of the dashboard?
TSM: For me, this is the ability to see in one view the base line sales and spikes when there is an event in sell-in and sell-out. We can have a look at past events what the sell-in and sell-out were there and we can see how the sell-out was spread out over the weeks after the event occurred. This can be valuable information for next year. Most of the marketing events or promos we do, we did already. Thus we can look back at the data on what that promo was doing with the sell-in and sell-out and adapt the forecast on that and can take a look into the future of what is working and what is not. If we see a promo that does not show a significant sell-out after, then we can think about what was going on, why it did not work and if we want the same promo next year for that SKU. Some marketing formulas work better than others. We can see that in the data as well. And I think for the CDP and KAM the most valuable data is the overview of stock, sell-in and sell-out with ordering patterns of Watsons. Especially for this client, these order patterns are important.

Interviewer: Are there any features or data that you feel are missing from the dashboard that would be helpful for you?
TSM: I think It can be a good idea to add a graph for every Article group or SKU so that instead of seeing the trend in numbers it can be seen in a line. A line is easier to interpret if you ask me and this can thus give an easier understanding of the trend or what is going on. Working with colours can visualise the trends better and lines are easier to interpret than just the data in a data table. Maybe that is me from the marketing department, haha, but for me, visualisations with lines or with bars work better to see directly what is going on. And what can be improved, but that is not on a systematic or data basis but is what we know about the data. I do not have the time to have a look at this dashboard every week and take out the knowledge of what is going on. So the translation from the data we have into insights can be valuable. Although I think this takes a lot of time, so maybe it is not doable. We have to take into account the time spent on this and the trade-off with the value we get from it. But you can try or ask Participant 1 if this can be handy or not.

Interviewer: Oké thank you. What are for you the main points of improvement for this dashboard?
TSM: I think what I just mentioned, is that there will be a line added to the dashboard to see the trend. And from that, it should be made easier to update the dashboard. I know we use difficult sources of data to get the information from but we want to use this dashboard as well when you are gone and for us, it thus is important that the next intern can update this dashboard as well in an easy and simple way. And for the interpretability with notes you can add you have to ask the KAM and CDP. For me, it is not that valuable because I do not have a look that regularly, but maybe it can help them a lot!

Interviewer: I can imagine indeed. How does the dashboard help to organize data across different stakeholders?

TSM: This is one of the main 'sources of data' that issued by the CDP and KAM, and sometimes with me to forecast or look at how we are performing on a retailer level and specified per SKU. This is the strength of the dashboard. The stakeholders involved within the team are more aligned with each other and the data is publicly available to them in a very easy matter. They do not have to go into Cliksense, check which parameters and measurements to select etcetera. This overview gives a good summary by just opening the document.

Interviewer: Can you give an example of an issue that was caused by an inconsistent forecast and how the dashboard helped solve it?

TSM: I do not think that I had this experience, to be honest. You can ask the CDP or KAM for this question.

Interviewer: Oké, Do you think other KAMs and CDPs within or outside the ....channel can benefit from a forecasting dashboard as well?

TSM: I do think, however, every channel is very different from the other. I think it can be implemented well in the chains channel, but there the sell-in is more constant so the dashboard is less applicable. It can be used by CDPs and KAMs in the online team as well I think, but within the online team the clients are ordering on a daily basis, 5 days a week. This is different from the weekly ordering we face. Thus the dashboard can be applied, but have to be adapted a bit I think.

Interviewer: Can you describe if and how the dashboard makes it easier to share and collaborate on forecasting data across teams?

TSM: Across teams you said?

Interviewer: Yes indeed!

TSM: Well, across teams we do not forecast a lot. The Benelux stock, and thus sell-in and sell-out indirectly is forecasted high over. We do not forecast for a specific retailer on the EU level. So the stock we have within the Benelux zone is determined by the average stock needed to supply our clients within the Benelux team, and when there is a shortage of a product, we get the same percentage as normal but then decreased the number of products. So every zone gets their percentage but then less than needed. But the stock on that level is not forecasted for every client.

The idea is that the stock will be spread out for all clients within a zone. Thus one event of a client will not increase the overall stock needed just by one client. And within the Benelux marketing team, we make sure there is not one period with a promo for every client. Except for Black Friday, Christmas deals et cetera, those events are always every year and thus the stock is adapted to it. Every team has different clients, thus it is very difficult to use it across channels I think.

Interviewer: I mean more across teams as in the TSM, marketing, sales and customer demand team instead of specific channels.

TSM: Ah. The process of forecasting is already multi-disciplinary so yes, of course, I think this dashboard is used by multiple teams. This dashboard displays the data in an easy manner and is constant for everyone. This is the strength I think.

Interviewer: Can you share specific KPI('s) that have seen a significant improvement within the team using the dashboard?

TSM: I think the most important one is in stock. Thus unhealthy and healthy stock. We had a challenge within the Western Europe market about an unhealthy stock. Therefore it was very important to plan the stock in the right way. Not too much stock in our warehouse, but also in the client's warehouse. If there is a lot of stock in the warehouse of our client, they will not buy products from us in the next weeks and thus our warehouse gets more packed.

Interviewer: You mentioned already the alignment of the teams the dashboard helps with, but how does the dashboard help to align the forecast process with the overall business strategy?

TSM: Actually this I the same answer as the question you just asked. The business strategy of the past periods is to better forecast and assign stock. This dashboard helps with that by visualizing the current stock and sales of products.

Interviewer: How does the dashboard support standardising the forecast across the team?

TSM: It gives us the data in an easy-to-interpret way. All employees involved or team members are looking into the same data. This improves the time used to forecast. It makes it possible to have a short look at what is going on and thus can be tracked more often. This can lead to fewer 'surprises' about forecasts which are incorrect. It can lead eventually maybe to less frustration or disagreements. The KAM, CDP and sometimes I can have a look at the dashboard for example every month and plan all the SKUs or categories together with each other. Everyone can give his or her input from their perspective and background and thus this ensures that no one can say: why have you planned it like this, now I do not have stock, for example. We are all responsible when you plan together using the same file. Of course, the file has to be up-to-date and the data should be reliable, otherwise, we are planning correctly according to the data but the data is incorrect and thus we are planning not well.

Interviewer: How did the dashboard help to improve forecasting process consistency across your team?

TSM: In this ....team we see the same data, as mentioned earlier. This leads to more consistency because we no longer have to look at different platforms for our data or have to decide which measurements or parameters to select. It is preselected now and well thought about with you, the KAM, CDP and me. No need to change these parameters or measurements, They are good as they are and give us the possibility to compare in an easy manner.

Interviewer: How has the use of the dashboard affected the communication and collaboration with the other stakeholders involved?

TSM: This dashboard is used on a weekly basis, which is way more frequent than the forecast discussed before. The regularity of sitting together is improved by this dashboard because it makes it easy to sit together for an hour or so and directly see what is going on.

Interviewer: And what is the impact on the communication then you think?

TSM: The frequency of communicating with each other about the forecast and status of sales and stock is increased and the dashboard makes it easier to talk about this topic because all stakeholders use this dashboard regularly and thus know how it works.

Interviewer: How has the use of the dashboard affected the communication and collaboration with the other stakeholders involved externally?

TSM: We do not have a lot of external stakeholders involved in the forecasting process. Especially Watsons, they do not want to collaborate on forecasting making it a more internal process. But when you consider the marketing team and the channel manager as external, then I think the dashboard also for them leads to more consistency. One source of truth or one source of data makes it way easier to interpret.

Interviewer: Have you noticed any improvements in your performance or in the performance of your team since using the dashboard?

TSM: I think so yes. The overall unhealthy stock decreased as was seen in the coffee corner. We perform well compared to other markets. And in the team as well, I think we can plan better the forecast than before. I however do not know if the data is supporting this, but that can be the case due to the fluctuations of sell-in. overall I think we perform better and this will be even better when using it more and for a longer period. Making using this dashboard a standard procedure to check with forecasting improve the forecast if you ask me.

Interviewer: How valuable is this dashboard for your role?

TSM: It is valuable, but less than it is for the KAM and CDP I think. For me, it is valuable in the sense that it gives me a very fast insight into the trend and baseline of products. When I need to deep dive into one SKU I first look in the dashboard whereafter I look into GFK data or other tools to compare to the market and competition to decide how we perform. This gives an internal as well as external and thus a more complete overview of what is going on.

Interviewer: Oké, that is it. This was the interview. Thank you a lot for your time and support!

TSM: No problem. Good luck with it.

9.1.5 Participant 4

Interviewer: Can you describe your role in the forecasting process and how you use the dashboard to support it?

Channel Manager: As a channel manager I am responsible for the sales of the …. channel. We have targeted every quarter for sales. These are targets for the overall sales channels but we as a management team split this target into the different channels at the beginning of the quarter to make it easier measurable within the channels. I do not forecast a lot, but the Key Account Manager and Customer Demand planner do so. I speak regularly to the KAMs within my team and I use the information from the forecast to estimate how many products we will sell in the next week or month. This can be crucial, especially at the end of the quarter to reach our targets. When we have this information, we can ask a KAM to bring the sales to this quarter instead of the next one to make sure we reach our targets.

Interviewer: So you are telling me that you do not forecast. Do you use the dashboard and if so, how often do you access the dashboard, and what triggers you to do so?

Channel Manager: Yes, I do use the dashboard. But not that much and always with the responsible Key Account Manager and sometimes the *Customer Demand Planner* to discuss a particular topic. There has to be a reason to have a look at the dashboard with the KAM for me. When there is no reason to have a look I do not look at it.

Interviewer: Oké, and what can trigger you to have a look at the dashboard?

Channel Manager: This can be the case when I see a KPI that is performing not well. For example, the sell-in for a particular client is going down. Then we can look at what is going on here. Maybe the sell-out of that client is not good, then it is logical that the sell-in is not performing well either. But there could be more reasons the sell-in is not what we expected. Another reason for me to have a look at the dashboard is when a KAM asks me to do so. The KAM can ask me to have a look at the dashboard to discuss the sell-in or sell-out for the forecast. This can be the case for special events such as Black Friday. This is an extraordinary weekend comparing it to other weekends. The sell-in is very high the weeks before and the sell-out in the weekend and the week after. To estimate this properly, we need to make a good forecast. Last year we underestimated the sell-out of Bol.com leading to a lot of missing sales. All the sales of our out-of-stock products went to Amazon instead of Bol.com. We need to prevent ourselves from that but at the same time do not want to overestimate the sell-out because this can lead to very low or no sell-in the weeks after the event.

Interviewer: Are there any aspects of the dashboard that toy find particularly useful or that you would like to see improved?

Channel Manager: I think the strength of the dashboard is the ease to see what is going on at the SKU level. The dashboard is there and is updated weekly or bi-weekly, so we have the most current data and are always in the same format. This makes it easy to interpret the data. The improvement of the dashboard is mostly visualisation I think. Now it is a table with data, which is good, but it can be a good idea to make more visible what is going on exactly. Working with colours can mark good or bad results or values. This triggers me, the KAM or the CDP immediately when opening the document.

Interviewer: Thank you for your critical look at the dashboard. Have you encountered any problems when using the dashboard, and if so, how did you go about resolving them?

Channel Manager: I do not have a lot of issues, but an issue I faces was when I have this dashboard open and I have another Excel file open and I close that. The autosave is saving that document. But at the same time, the formulas are calculated in this sheet. This takes a couple of minutes to get finished or can crash my laptop. This of course is not what we want. The second problem I had was that the dashboard was not updated once. This is not that big of a problem because I immediately saw it because the column of that week was empty, but then we have older data and we therefore can perform our analysis less accurately.

Interviewer: How does the dashboard fit into your overall workflow and decision-making process and forecasting?

Channel Manager: As said I do not use it on a daily or weekly basis, but when there is a specific reason to have a look at the dashboard. This dashboard is useful to have a look at what is going on with our sales for a specific client at the SKU level. This can give us valuable insights and we can act properly and based on data.

Interviewer: And does the dashboard influence your decision-making?

Channel Manager: Normally it does not, but it can be the case that we need to move a sell-in from another retailer to this quarter to reach our targets. And strategically, for example at the jaargesprekken or when there is a new listing we can use this data for specific products to negotiate with the client.

Interviewer: How does the dashboard integrate with other systems and tools that you use?

Channel Manager: It does not integrate with systems or tools. It is used separately by me but it can give me additional insights into what is going on.

Interviewer: What are the most valuable features of the dashboard for you?

Channel Manager: The overall ability to have a quick look at what is going on. The format and availability and visualisation of the data are the most valuable for me. This dashboard saves me or the KAM time because we do not have to 'build' our custom report in Qliksense for every deep dive.

Interviewer: Are there any features or data that you feel are missing from the dashboard that would be helpful for you?

Channel Manager: As said the colouring of exceptionally high or low stock, sell-in or a sell-out, but apart from that no.

Interviewer: And what are the main points of improvement for this dashboard according to you?

Channel Manager: That is the visualization of the data I think, to make it easier for us to see what is going on, even when we do not have a specific reason to have a look at the dashboard.

Interviewer: What do you mean by that? That the dashboard tells you what is going on?

Channel Manager: I mean, when we open the dashboard when we do not have a specific reason to have a look at a particular SKU for the sell-out for example, that we can see in the dashboard when there is something performing worse. This can avoid us from overlooking or forgetting an SKU performing not well.

Interviewer: How does the dashboard help to organize data across the different stakeholders?

Channel Manager: This dashboard is a good tool to make sure every stakeholder sees the same data in the same format. This enables us to compare and discuss the data easier and faster. As said earlier, this dashboard' uses its data from Qliksense. We can receive the same data from there, but these dashboards visualize the data better. Besides that, this dashboard uses the most important data, which is the sell-in, sell-out and stock below each other in a line. Therefore it is very easy to see what is going on. The consistency of the format is crucial.

Interviewer: How does the dashboard support your collaboration with other members of your team, such as the KAM and CDP?

Channel Manager: The KAM and CDP use this dashboard the most. They use this on a daily or weekly basis. I do not use this dashboard that often. When someone wants to have a closer look at what is going on he or she can have a look at the document and figure it out. Sometimes we have to discuss what to do with the insights we receive from the dashboard. Then we plan a meeting and I am invited as well. The collaboration is therefore in my opinion on an optimal level. I am not involved in all the weekly forecasts. I can not help them with that because they have the insights from a marketing, client and logistical perspective. When they need me I will be invited to look at them what is going on or what will be our strategy.

Interviewer: Do you think other KAMs and CDPs within the ....channel or outside of it can benefit from a forecasting dashboard as well?

Channel Manager: It really depends on the client I think. I do think some KAMs and clients can work, but every client is different and we have different agreements with them. For the KAM 2 I think this dashboard can be valuable. Another retailer is similar to the retailer in its ordering patterns. The difference between them is how large they are, but this has nothing to do with the possibilities for the dashboard. In the chains channel, we have other agreements and collaborative forecasting is done more frequently. We are trying to do that without clients in this channel as well, but that is very difficult we discovered. In the Online channel t is dashboard however can be valuable I think. The only drawback is that our online clients can order every day instead of weekly. This makes it more difficult to use this dashboard I think. They have more accurate and faster data availability as well because they receive it from the client and in this channel, we receive it from a third party.

Interviewer: Can you describe if and/or how the dashboard makes it easier to share and collaborate on forecasting data across teams?

Channel Manager: I do not think forecasting is done across teams. Every KAM has its own clients and forecasts for or client. The CDP and TSM are involved in this process and those employees do support more than one KAM. They cannot use the data from one client for another other I think. They manage the European stock, so they do have a better overview. But when they can forecast without a supply constraint it is not necessary to have a look at other clients. When we do have constraints some clients of The case company have priority over others. This is written down in a confident document but we use this priority rarely luckily enough.

Interviewer: Can you share specific KPIs that have a significant improvement within the team using the dashboard?

Channel Manager: The unhealthy stock has decreased. We measure that KPI. There was a push from the European team to reduce the unhealthy stock. Due to the shift from two warehouses in the Western European region to one central DC, every zone had to decrease the stock in the warehouse. Otherwise, the new healthy stock was not able to come inside the DC. This was a very important KPI for us within the Benelux although we were performing relatively well. This KPI has improved partly due to this dashboard I think. This gives us clarity and insight into what is going on. In the past, we did not look that often into the data. Participant 1 did, however, use the data more than other KAMs, but in my opinion, this increased the use of data in our forecasting and other processes.

Interviewer: How has the use of the dashboard affected the communication and collaboration with the other stakeholders involved internally and externally?

Channel Manager: What do you mean by internal and external stakeholders?

Interviewer: With internal stakeholders, I mean the stakeholders directly involved in the forecasting process. Thus, the KAM, CDP and partly the TSM. By external stakeholders I mean you, the other KAMs, the Sales Lead, the client etcetera.

Channel Manager: Internally, this dashboard leads to more visibility and consistency in looking at the data. Externally I do not think the communication has improved with our clients. They do not want to forecast collaboratively and thus we are building our own forecast. This collaboration is not closer now than in the past with our clients, unfortunately. The communication between me, the Sales Lead and the employees making the forecast is improved, I think. Transparency and the fact given by the data can help us to support why decisions are made and help us make better decisions about our stock.

Interviewer: How do you think the dashboard helps to align the forecast process with the overall business strategy?

Channel Manager: It fits well, the strategy is to lower the stock in our warehouse. This is a great tool for us to make that happen.

Interviewer: Have you noticed any improvements in your performance or in the performance of your team using the dashboard?

Channel Manager: Not based on the data because we do not have the specific data for that and the period is too short. I do however see the improvement in the retailers forecasts and, sell-in, sell-out and stock. Watsons is performing very well this year even though this was one of the only shops open last year and thus performed well last year. We are outperforming last year with sales and stock allocation as well. We have less out of stock and our stock in the European warehouse has declined over the past period. It takes time to better measure the effectiveness of the dashboard and it always stays a measure with a korrel of zout.

Interviewer: Is there anything else that you would like to add about the dashboard and its impact on the forecasting process?

Channel Manager: I want to thank you for building this dashboard. We are very happy with this result from your internship and I can say that for Arjan as well. He is very happy with this. He is a data-oriented employee but did not have the time to implement a dashboard like this.

9.1.6 Participant 5

Interviewer: Can you tell me about your current forecasting process?

Participant 5: yes, I forecast one month in advance but this is adaptable weekly or daily. My client has ordered us every day coming us. When there is a product low in stock, they can order this and they will receive it a week later on the same day most of the time. That is the idea, but I have to be honest, the delivery times can vary a lot, unfortunately. The ordering of my client is mostly automated on the baseline of the most sold products. These products thus are the easiest products to forecast. I know their sell-out of the past period and can make a fairly good prediction of their sell-in as well. The client orders regularly, and this makes it even easier because we, therefore, do not have high stocks before the order of my client comes in. The exceptions are the most difficult to forecast. These are products that are not sold on a continued basis and products with promos. I need to adapt the forecast for these SKUs. When I know from the marketing team that there will be a promo 6 weeks in advance, I know I have to increase the forecasted number of products. My client knows that the promoted products will lead to an increase in sell-outs and thus they order more in advance to make sure they have enough stock. I have regular meetings with my counterpart the client to discuss these promos. Doing this will help to forecast. Unfortunately, my counterpart has left a couple of weeks ago, thus this is more difficult these days.

Interviewer: Oké, so you collaborate with the client about the forecast?

Participant 5: Yes, we try to. We are both very busy, but we try to discuss this topic in the meeting. It is high over but gives me and him an idea of the impact of the marketing event.

Interviewer: What tools and methods do you use to forecast demand for your products or services?

Participant 5: I have a look at the retailer dashboard to see the sell-out. This gives me an idea about the sell-out and thus how much my client is selling every week. My client orders regularly, which makes it easier to adapt to increasing sales. I do also discuss upcoming marketing events with the TSMer and look at the Market marketing plans for upcoming events. This Market Marketing plan is a blueprint for the upcoming year's activities in terms of marketing. For example, the Team Gullit event we had last week was an event whereby I forecast the Oneblades handles and blades higher than I normally do because I think they will be sold more than on a normal week. So, all these data combined will lead to the forecast I make. I discuss this with the CDP and adapt the forecast to the new forecast. I make the latest view with what I think will be sold in the upcoming weeks. The CDP plans according to this latest view but wants to have a high forecast accuracy. We thus have different KPIs. Sometimes it can be difficult to align our KPIs.

Interviewer: Yes, I understand that can be difficult sometimes. What does your forecasting process differ from forecasting Watsons demand do you think?

Participant 5: Well, Participant 1 have a very difficult account. This is a very big client for us, has low margins and their ordering pattern and distribution are different. My client is a webshop. Thus, the products will go to the distribution centre of the client, from there on the client will distribute the products to the consumers who buy the products. For Watsons, the product will flow from our warehouse to the warehouse of Watsons, whereafter this product will be distributed to the stores. And they have a lot of stores! Finally, the products will be bought in the shops by the consumers. Watsons have a very irregular sell-in which makes it very difficult for the KAM to forecast. The combination of high volume with irregular demand makes forecasting very difficult. For my forecast, I can plan two weeks ahead, because we can deliver every day and the ordering systems are automized and easy to track due to one distribution centre they have and no physical shops. I can plan for two weeks ahead and Arjan has to plan on a weekly level, but he does have to plan at least a month in advance.

Interviewer: Ah yes, so the difference is mostly the volume and irregular demand?

Participant 5: I think the irregular demand especially. I have a high demand as well, but this is ordered regularly. And I am not that much dependent on promos. Watsons is purely driven by promotions for its products. The consumers coming into those shops look for sales and all products are relatively cheap. That6 is also the reason I have different SKUs from Watsons. Watsons have the more low-end products from the case company and I have the mid and high-end products.

Interviewer: Oke, does the product type, so the high-end versus the low-end products have an impact on the forecasting?

Participant 5: uh, I do not think this has an impact on the forecasting. But yes, when forecasting too high with high-end products, the value of the products in their warehouse is very high. This leads to a low-value sell-in in the next weeks because they have enough products for the next weeks. For Participant 1 when he plans too much, then the number of products is very large in the warehouse of Watsons. They are not happy with that, because they have a lot of different products in those shops. So, both have their difficulties, but we try to plan as well as we can and when I plan wrong, the value will be high compared to the number of products for v it is the other way around most of the time.

Interviewer: Have you seen the forecasting dashboard used by the other team?

Participant 5: Yes, you told me about it and showed it to me a time ago. It looks good. The layout gives a good overview! You and I are now working on a comparable dashboard for me. I am very excited about that because it can help me and the other KAM of the online team a lot with getting insights into the items with a too-high stock and the items with a too-low stock or coverage by our clients. We can better track the coverage of individual products.

Interviewer: What is your initial impression of the dashboard, the dashboard I built for Arjan, and how could it be useful for your work?

Participant 5: My first impression was that it gives me a good overview of what is going on week by week. It is very handy for me to have a dashboard for me as well, thus we are building one together. With a little different layout and goal. But the basis of this dashboard is very nice because this saves me time looking the data up in the Retailer dashboard. The data is not new to me, but the way it is visualised is pleasant. I do however have to mention that the impact for me on my forecast will be less than for Participant 1 I think Because forecasting is less important for me and I spend less time forecasting than KAM because it is simply easier for me to forecast than for him.

Interviewer: What are the key features you think would be necessary to make the dashboard effective for your work or your team?

Participant 5: I think the dashboard can be applied better in the other channels because our clients work with more modernised systems for ordering their stock. This does not mean that dashboard is not helpful for us. It gives a good overview of the stocks and which SKUs will be ordered soon and which one has a high stock thus the sell-in will take a while. But for me the coverage is important. Thus this is the average stock in weeks. Looking at a previous couple of weeks. When I see this is 2 or below I need to send products to them, and when it is higher than, let's say 5 weeks I have to make sure no orders are coming in for those products, otherwise they have too many products.

Interviewer: What kind of data and inputs do you think would be necessary to make the dashboard effective for your work or your team?

Participant 5: The data that we receive from our client on a weekly basis is important I think to implement. This leads to a more up-to-date dashboard because the data we receive from the client is more recent than the data of the Retailer dashboard. And a second input should be the order data. My client does not have a specific day in the week the order comes in but can order any day in the week. Thus it can be important to use this information so that an order that is ordered this week but will be delivered two weeks after will be marked. It is then likely that we do not have enough stock for that SKU. When that is marked in the dashboard I can have a conversation with the client and with our logistical department to try to bring the delivery date to the front.

Interviewer: What kind of training or support would you need to implement the dashboard within your team?

Participant 5: uh, yes, firstly, it is important that everyone in the team knows about the dashboard and its functionality. Then the employees involved know how and when to use the dashboard. After that, it is important how to keep the dashboard up-to-date. This is crucial to the success of the dashboard.

Interviewer: oke, oke, and what are the potential benefits and drawbacks of using the forecasting dashboard for your work or within the team?

Participant 5: Uhh, the changing delivery dates as mentioned earlier can be a potential problem. But the overview with this dashboard and the consistency between team members to have a look at the same data or sheet can save a lot of time I think. I think for our channel it is important what the coverage is for an SKU. I mean with that the weeks of stock we have when taking into account the average sales. Using that can make it even more visible what the current status is. This, however, will not work for v I think because he is heavily dependent on promotions and thus the sales will fluctuate a lot, which makes it very difficult to get a good average sell-out and thus a good coverage. But this will work for our team I think.

Interviewer: Are there any concerns you have about implementing the dashboard within your team?

Participant 5: No, I think it is not difficult to implement. You need to get their attention and explain what the dashboard is able to do and how to update it, but apart from that it is not difficult to implement in our team taking into account the changes in the dashboard about the coverage. Doing this will help the usability of the dashboard for the employees in the online team.

Interviewer: How would the dashboard fit into your existing workflows and processes?

Participant 5: uhh, yes, I think this dashboard or the adapted one will help me with forecasting and keeping the stock on a good level. This document will not be integrated into any software or so. We work mostly in Excel. Those documents are not integrated into the software we use. We use the software from Qliksense to get the data from third parties, such as sell-in, sell-out, stock, IGM etcetera, so yes.

Interviewer: Oké, and within your existing workflow processes?

Participant 5: It can fit within my workflow processes because this is part of the alignment of stock with the sell-out. This is an important KPI for the KAMs within the case company and when doing this incorrectly can give a less accurate latest view. The sell-in is one of the most important KPIs within the sales team. When I have set my latest view too high, for example when there is a lot of stock in my client's warehouse and not that much sell-out and I did not know this, then I do not reach the sales I put into the latest view. The total sales of our channel and thus of the case company Benelux will decrease and this is not what we want. We want to have a realistic latest view so that we can work towards our goal at the end of the quarter. We are a listed company and especially in the times we are in now with the case company it is very important to give a realistic image and a good result at the end regarding the sales.

Interviewer: Yes, understandable. And can you tell me what the impact can be when implementing this dashboard into your team and what the impact will be on the performance?

Participant 5: I think the forecasting accuracy will increase. This dashboard has a direct influence on that I think. All the KAMs can see the data for their account and can act according to what is needed when looking at these data. And uhh, I think this dashboard will save time as well. When we want this data to have, we have to go to the Retailer dashboard, click on a lot of measures and dimensions, have to transform the table etcetera and then we have the data. We do not have a layout or a conditional format for the dashboard. Thus the dashboard gives more clarity I think. Faster and more clear information regarding the sell-in, sell-out and stock is the most important thing I think.

Interviewer: Oké, so can I understand from your question that the productivity will go up as well?

Participant 5: yes, I think so, yes because of the time it saves and the insights we have with this dashboard. We know the data is there and easy to access. When we have that in the back of our heads, we will use it more I think. And thus we will better forecast just because we use data more than we do know. I think forecasting on the basis of data gives more structure and less wet fingerwork.

Interviewer: haha, and do you think that your team would embrace the new dashboard and be willing to adopt it in their work?

Participant 5: Yes, I do think so, it does not ask us an effort to get this dashboard and it is easy to handle and view. These are important things for a KAM because we are almost always very busy with our work. I have to be honest that when something very difficult is built or when we have to give a lot of input on how and what we want, this will not work for a KAM. Just because we do not have the time for it to help. This dashboard is now already built and can be adapted to every client I think. This is an advantage and helps a lot. So it is very easy to implement I think. Just explain the KAM involved and how it works in a short meeting and that is it.

Interviewer: How do you think, does the dashboard help to organize data across the different stakeholders?

Participant 5: Uhh difficult question. The good thing about this dashboard of course is that everyone sees the same data. By with same data I mean the same layout of the data, we can see the same trends in the data and we measure the same. It can be the case that in the past I was looking at the SKU level and the TSM was looking at the MAG level, then it can be possible to see different trends. This dashboard enables everyone to have easy access to the data and makes sure everyone sees the same.

Interviewer: Can you describe if and/or how the dashboard makes it easier to share and collaborate on forecasting data across teams?

Participant 5: Well that is similar to what I just said, the data can be shared very easily. Just put the document in the Teams environment and every employee who needs it can access the document. The documents are all the same for every KAM and client except for the data input and thus everyone can have a look. For example, the MT as well, to have a look at what is going on. This is the advantage of this dashboard. So for collaboration with the CDP, we can have a look at the SKUs individually and when I see that one SKU had a high sell-in and not that high sell-out last week, we can decline the forecast because it is very likely the client will order less in the upcoming periods. The

CDPer sees the same data thus he/she will have the same conclusion. Looking at different data is a bottleneck in the forecasting process we now have. I do not understand the data, software or document he uses and vice versa haha.

Interviewer: Oke, thank you a lot for your time and answers to these questions!

9.1.7 Coding scheme evaluative interviews

Category	Level	Dimension	Empirical indicators
Usability	Dashboard usability (external from channel)	Usability dashboard for clients or channels	• Depends on the client • For similar clients it is useful • In the online channel it can be valuable • Everything is in here, so anyone can work with this • When the retailers' data is available it can be applied for every client
	Dashboard usability	Usability of the dashboard	• Has to be a reason to have a look at the dashboard • Weekly using it • KAM and CDP use it the most • Can fit within my workflow processes
		Usefulness of the dashboard	• Strength is ease to see what is going on at SKU level • Easy to interpret data and helps in visualizing it • Transparency • Contributes to prevent unhealthy stock • Gives more structure on the forecasting process
Advantages	Intention	Reason to use the dashboard	• When a KPI is not performing well • When the KAM asks me to do • To have extra information or deep-dive into a SKU • To check how a promo performed
	Dashboard insights	Most valuable features	• Overall ability to have a quick look on what is going on (the overview) • The visibility and availability of the data • The consistency of the format • Three dimensions (Weekly, Monthly and Quarterly data) • The comparison with last year • Faster and more clear data
		Insights from the dashboard	• Insight in logistical data (whole pallet or pallet layer) • Understanding ordering patterns • Identify trends
		Example where the dashboard can help with	• Prevention of out of stocks • Getting insights in the ordering of the client • Explanation with insights how SKU sales perform • Data based supporting decisions • Logistical insights (ordering per pallet or per pallet layer) • Insights in how a promo performed
Stakeholders	Involvement	Involvement different stakeholders	• TSM and Channel manager are involved when asked or when there is a need • Every stakeholders looks at the data from a different perspective • KAM and CDP are involved weekly
	Information sharing among stakeholders	Organize data across stakeholders	• Seeing the same data across all stakeholders • Helps forecasting • Getting insights in why patterns occur • The main source of data used by CDP and KAM
Implementation	Dashboard implementation (technical)	Integration of the dashboard	• Does not integrate with systems or tools • Not linked automatically • Within The case companywe work with a lot of systems in parallel
	Dashboard implementation (external channel)	Implementation online team	• Can be adopted • Very easy to implement

	Dashboard implementation (strategy)	Alignment with the business strategy	• Is in line • Most important alignment is decreasing the stock • Unhealthy stock challenge aligned perfectly • Is an important KPI
Improvements	Improvements to be made	Improving the dashboard even further	• Visualisation • Colouring • Refreshing speed improvement • Reliability • Translation of the data into insights • Updatability when owner is gone
	User improvements	Improvements using the dashboard	• Unhealthy stock has decreased • Forecasting accuracy increased • Keeping the stock at a good level • Save time
		Forecast improvements due to the dashboard	• Not based on the data, but the Channel Manager sees improvement • Outperforming last year with sales accuracy and stock allocation • Less out of stocks and European stock declined • Take time to better measure the effect
Challenges	Dashboard input	Inputs needed for dashboard online channel	• Weekly (more recent data) • Order data should be added
	Dashboard challenges	Different time-stamp forecasting	• Moved away from weekly planning the sell-in due to confidence in the dashboard
		Issues with the dashboard	• The autosave takes time • Dashboard was not updated • Changing delivery dates may be a problem
	Training	Training or support	• The stakeholders who use it know how to use it • It is important that everyone in the team knows about the dashboard and its functionality
Way of working	Forecasting	Forecasting sales	• Use information to estimate we will sell next week
		Forecasting across teams	• It is already multi-disciplinary, so yes it could be used by multiple teams
		Forecasting	• One month in advance • CDP plans according to the latest view based on the dashboard • TSM does not forecast
	Difference in channels	Difference online channel vs ..../NB	• Online channel works further ahead • Ordering pattern and distribution is different • Irregular demand for the ....channel
	Targets	Sales targets	• Every quarter new targets • Crucial to achieve/reach the targets
Communication & Collaboration	Collaborative forecasting	Collaborative forecasting with clients	• The case companyis too small as a supplier • The case companyis not at that level yet • Try to discuss during the meetings with the client • Unfortunately do not collaborative forecast with clients • No supporting systems
	Communication and Collaboration (external channel)	Dashboard affecting communication and collaboration with other external stakeholders	• Leads to more visibility and consistency • Internally it does, not externally • Leads to more alignment • One source of truth of data
	Communication and Collaboration (internal)	Dashboard affecting communication and collaboration with internal stakeholders	• Everyone has access and sees the same data • Collaboration frequency and quality increased between KAM and CDP • Supports discussing the sell-in between stakeholders • Frequency of communicating increased
	Support Decision making	Dashboard influencing decision-making	• Sometimes it does • Strategically (annual review with the client) • Logistical decisions
	Discussing forecast	Conversation using the dashboard	• Always with the responsible KAM • Sometimes with the CDP

9.1.8 Focus group notes

Focus Group
The dashboard is presented and changes made after the evaluative interviews are highlighted and explained. Question answered regarding the updatability of the dashboard with the Retailer Dashboard (data from a third party) and about the reliability of the dashboard. The stakeholders understand the answers and the fact that we are depend on Qliksense data and its reliability. They indicated that they use the tool more than before. Especially the past weeks the dashboard is used a lot. Not only by the KAM and CDP, but also the other stakeholders indicate that they use it on a regular basis. The collaboration frequency and quality of forecasting the sell-in is increased according to the stakeholders. Participant 1 indicated that he is very happy about this tool and uses it a lot. <u>Discussion</u>: *Did using the tool get easier the more often it was used* They do think so. In the beginning, they needed to get used to this format, but after working with it two times it worked perfectly and it is really clear. *How has the program impacted the forecasting process?* Participant 1, CDP and Channel Manager indicate that the forecasting process is positively impacted due to the dashboard. They do indicate that this is based on gut feeling regarding the outcome (accuracy) but they find it a good tool to work with and support them in their work. *Can you describe a time when you felt like this program was particularly helpful?* v is referring to the interview and adds that in general, this tool is very helpful for them. The others agree. The ability to forecast with the support of data and the fact that it is visible to every stakeholder in the process are the biggest positives. *Do you notice better collaboration and communication regarding the forecasting process because of the tool used?* The Channel Manager indicated that he likes the more frequent collaboration and short positive discussions about the forecasts. Some assumptions about products were negated by the dashboard data which was insightful for us. *Have you recommended the program to others? Why or why not?* They did discuss with some KAMs from other channels and the abilities of their customer / channel and Participant 1 did indicate he recommended some KAMs and TSMs to use it when this dashboard is expanded.

9.2 Rstudio ARIMA programming code (generalized for SKU)

```
Class(> library(readxl)
> SKU <- read_excel("SKU.xlsx")
> View(SKU)
> library(forecast)
> view(SKU)
> class(SKU)
> SKUtimes = ts(SKU$`Sell Out Qty CY`, start = min(SKU$Period), max(SKU$Period), frequency = 52)
> class(SKUtimes)
> acf(SKUtimes)
> pacf(SKUtimes)
> adf.test(SKUtimes)
> SKUmodel = auto.arima(SKUtimes, ic = "aic", trace = TRUE)
> SKUmodel
> acf(ts(SKUmodel$residuals))
> pacf(ts(SKUmodel$residuals))
> mySKUforecast = forecast(SKUmodel, level = c(95), h=52)
> plot(mySKUforecast)
> Box.test(mySKUforecast$resid, lag = 5, type = 'Ljung-Box')
> Box.test(mySKUforecast$resid, lag = 10, type = 'Ljung-Box')
> Box.test(mySKUforecast$resid, lag = 15, type = 'Ljung-Box')
> Box.test(mySKUforecast$resid, lag = 20, type = 'Ljung-Box')
> Box.test(mySKUforecast$resid, lag = 50, type = 'Ljung-Box')
> Box.test(mySKUforecast$resid, lag = 100, type = 'Ljung-Box')
```

9.3 Dashboard & Data

9.3.1 Dashboard most imortant formula's

What to code	**Code**
Sell in LY (for weeks)	=IFERROR(INDEX('15. Import THE RETAILER 2021 Weeks'!$H:$H;MATCH(1;('15. Import THE RETAILER 2021 Weeks'!$G:$G=$G9)*('15. Import THE RETAILER 2021 Weeks'!$B:$B=BH$2);0));"")
Sell out LY (for weeks)	=IFERROR(INDEX('15. Import THE RETAILER 2021 Weeks'!$J:$J;MATCH(1;('15. Import THE RETAILER 2021 Weeks'!$G:$G=$G9)*('15. Import THE RETAILER 2021 Weeks'!$B:$B=BH$2);0));"")
Sell in CY (for weeks)	=IFERROR(INDEX('13. Import THE RETAILER 2022 Weeks'!$H:$H;MATCH(1;('13. Import THE RETAILER 2022 Weeks'!$G:$G=$G9)*('13. Import THE RETAILER 2022 Weeks'!$B:$B=BH$2);0));"")
Sell out CY (for weeks)	=IFERROR(INDEX('13. Import THE RETAILER 2022 Weeks'!$J:$J;MATCH(1;('13. Import THE RETAILER 2022 Weeks'!$G:$G=$G9)*('13. Import THE RETAILER 2022 Weeks'!$B:$B=BH$2);0));"")

Stock LY (for weeks)	=IFERROR(INDEX('15. Import THE RETAILER 2021 Weeks'!$L:$L;MATCH(1;('15. Import THE RETAILER 2021 Weeks'!$G:$G=$G9)*('15. Import THE RETAILER 2021 Weeks'!$B:$B=BH$2);0));"")
Stock CY (for weeks)	=IF(IFERROR(INDEX('13. Import THE RETAILER 2022 Weeks'!$L:$L;MATCH(1;('13. Import THE RETAILER 2022 Weeks'!$G:$G=$G9)*('13. Import THE RETAILER 2022 Weeks'!$B:$B=BH$2);0));"")=0;"";IFERROR(INDEX('13. Import THE RETAILER 2022 Weeks'!$L:$L;MATCH(1;('13. Import THE RETAILER 2022 Weeks'!$G:$G=$G9)*('13. Import THE RETAILER 2022 Weeks'!$B:$B=BH$2);0));""))
Sell In LY (for Months)	=IFERROR(INDEX('14. Import THE RETAILER 2021 Months'!$H:$H;MATCH(1;('14. Import THE RETAILER 2021 Months'!$G:$G=$G9)*('14. Import THE RETAILER 2021 Months'!$B:$B=BL$2);0));"")

9.3.2 Most sold products Watsons

Banner	BG	Category	MAG	AG	Product_ID	Sell Out NNN CY
[redacted]						

[redacted]

[redacted]

[redacted]

[redacted]

9.4 Rstudio SARIMA results (per SKU)

9.4.1 Rstudio SARIMA code explanation

```
> library(readxl)
```

```
> SKU 2 <- read_excel("C:/Users/320177728/OneDrive - The case company/scriptie/Programming data/Pd SKU 1.xlsx")
```

```
> View(SKU 2)
```

```
> library(forecast)
```

```
> view(SKU 2)
```

```
> class(SKU 2)
```

The 'class()' function is a built-in function of Rstudio that returns a character vector representing the class of the object passed as an argument (R Core Team, 2021). The class function returns a 'data frame' when the Excel file is imported. To execute the SARIMA performance test and forecast this data frame should be changed to a time-series class.

```
> SKU 2times = ts(SKU 2$`Sell Out Qty CY`, start = min(SKU 2$Period), max(SKU 2$Period), frequency = 52)
```

Here new data is made with the name 'SKU 2times'. The data of 'SKU 2' is used and transformed to a time-series with the data from the beginning of the period till the end of the period and with a frequency of 52 due to weekly data that is used.

```
> class(SKU 2times)
```

The class now returns 'ts'. Thus a time-serie is made out of the Excel file data.

```
> acf(SKU 2times)
```

According to Box, Jenkins, and Reinsel (2015) the autocorrelation function (ACF) measures the correlation between the values of a time series at different times. The formula used to calculate this is:

ACF(k) = Cov(X_t, X_{t-k})/VARX_t)

Where X_t is the time series at time t

K is the lag

Cov is the covariance

Var is the variance

ACF can be used to identify patterns in the time series, such as seasonality and can helps to forecast values of the series (Shumway & Stoffer, 2017).

```
> pacf(SKU 2times)
```

The Partial autocorrelation function (PACF) measures as well the correlation between the values of time series, but now at different lags, after adjusting for the correlation at all lower lags. This is used to identify the number of lags to include in the autoregressive (AR) model. The formula to calculate the PACF is:

PACF(k) = Cov(X_t, X_{t-k})/Var(X_t) - \sum_{i=1}^{k-1} \ frac{Cov(X_t, X_{t-i})}{Var(X_t)}\cdot\frac{Cov(X_{t-k}, X_{t-i})}{Var(X_{t-k})}

PACF can be used to identify the lag structure for an AR model and is computed using the ACF and the inverse of the lag-k autocovariance (Box, Jenkins & Reinsel (2015).

```
> adf.test(SKU 2times)
```

The Augmented Dickey-Fuller Test (ADF) is a statistical test used to determine whether a time series is stationary or nonstationary (Bai & Perron, 2003). It tests the null hypothesis that the time series is autoregressive (AR) of order p, with a unit root (The case company& Perron, 1988).

```
> kpss.test(SKU 2times)
```

```
> SKU 2model = auto.arima(SKU 2times, ic = "aic", trace = TRUE)
```

In Rstudio, the ‚ic' argument specifies the criterion that should be used to compare different models. We use the 'aic' for this which stands for Akaike's Information Criterion. AIC is a measure of the relative quality of s statistical model. AIC tries to balance the goodness of fit of the model with the complexity of the model. The lower the AIC is, the better the fit (Burnham & Anderson, 2002).

```
> SKU 2model
```

```
> acf(ts(SKU 2model$residuals))
```

The ACF argument is used here to diagnose the presence of autocorrelation in the residuals of this statistical model.

```
> pacf(ts(SKU 2model$residuals))
```

```
> mySKU 2forecast = forecast(SKU 2model, level = c(95), h=52)
```

A new dataset is made to plot the forecast in the next step. The confidence interval is 95% and the h argument specifies the number of forecasted periods for which predictions should be generated.

```
> plot(mySKU 2forecast)
```

The forecast will be plotted here.

```
> Box.test(mySKU 2forecast$resid, lag = 5, type = 'Ljung-Box')
```

To determine whether there is autocorrelation in a time series the Ljung-Box test is used. If the statistic is larger than the critical value, then the null hypothesis of independence is rejected and the time series is considered to be autocorrelated. The Ljung-Box test can be sensitive to lag length, therefore it is recommended to use a range of different lag lengths to ensure that the results are not sensitive to any particular lag length (Montgomery & Peck, 1992). That is the reason of the test below with different values of the lengths.

```
> Box.test(mySKU 2forecast$resid, lag = 10, type = 'Ljung-Box')

> Box.test(mySKU 2forecast$resid, lag = 15, type = 'Ljung-Box')

> Box.test(mySKU 2forecast$resid, lag = 20, type = 'Ljung-Box')

> Box.test(mySKU 2forecast$resid, lag = 50, type = 'Ljung-Box')

> Box.test(mySKU 2forecast$resid, lag = 100, type = 'Ljung-Box')
```

9.4.2 SKU 3

```
> library(readxl)
> Pd_SKU 4 <- read_excel("C:/Users/320177728/OneDrive - The case company/scriptie/Programming data/Pd SKU 4.xlsx")
> View(Pd_SKU 4)
> library(forecast)
> class(Pd_SKU 4)
[1] "tbl_df"     "tbl"        "data.frame"

> Pd_SKU 4times = ts(Pd_SKU 4$`Sell Out Qty CY`, start = min(Pd_SKU 4$Period), max(Pd_SKU 4$Period), frequency = 52)
> class(Pd_SKU 4times)
[1] "ts"

> acf(Pd_SKU 4times)
> pacf(Pd_SKU 4times)
> adf.test(Pd_SKU 4times)

        Augmented Dickey-Fuller Test

data:  Pd_SKU 4times
Dickey-Fuller = -27.655, Lag order = 20, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Pd_SKU 4times) : p-value smaller than printed p-value

> Pd_SKU 4model = auto.arima(Pd_SKU 4times, ic = "aic", trace = TRUE)

 Fitting models using approximations to speed things up...

 ARIMA(2,0,2)(1,0,1)[52] with non-zero mean : 123165.6
 ARIMA(0,0,0)           with non-zero mean : 124604
 ARIMA(1,0,0)(1,0,0)[52] with non-zero mean : 123590.2
```

```
 ARIMA(0,0,1)(0,0,1)[52] with non-zero mean : 123335.7
 ARIMA(0,0,0)           with zero mean     : 134591.2
 ARIMA(2,0,2)(0,0,1)[52] with non-zero mean : 123176.1
 ARIMA(2,0,2)(1,0,0)[52] with non-zero mean : 123181.4
 ARIMA(2,0,2)(2,0,1)[52] with non-zero mean : 123155.4
 ARIMA(2,0,2)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(2,0,2)(2,0,2)[52] with non-zero mean : Inf
 ARIMA(2,0,2)(1,0,2)[52] with non-zero mean : 123157.4
 ARIMA(1,0,2)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(2,0,1)(2,0,1)[52] with non-zero mean : 123286.8
 ARIMA(3,0,2)(2,0,1)[52] with non-zero mean : 123135.4
 ARIMA(3,0,2)(1,0,1)[52] with non-zero mean : 123149.5
 ARIMA(3,0,2)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(3,0,2)(2,0,2)[52] with non-zero mean : Inf
 ARIMA(3,0,2)(1,0,0)[52] with non-zero mean : 123164.6
 ARIMA(3,0,2)(1,0,2)[52] with non-zero mean : 123140.6
 ARIMA(3,0,1)(2,0,1)[52] with non-zero mean : 123269.8
 ARIMA(4,0,2)(2,0,1)[52] with non-zero mean : 123136.3
 ARIMA(3,0,3)(2,0,1)[52] with non-zero mean : 123130.2
 ARIMA(3,0,3)(1,0,1)[52] with non-zero mean : 123152
 ARIMA(3,0,3)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(3,0,3)(2,0,2)[52] with non-zero mean : Inf
 ARIMA(3,0,3)(1,0,0)[52] with non-zero mean : 123166.7
 ARIMA(3,0,3)(1,0,2)[52] with non-zero mean : Inf
 ARIMA(2,0,3)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(4,0,3)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(3,0,4)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(2,0,4)(2,0,1)[52] with non-zero mean : 123141.1
 ARIMA(4,0,4)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(3,0,3)(2,0,1)[52] with zero mean     : Inf

 Now re-fitting the best model(s) without approximations...

 ARIMA(3,0,3)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(3,0,2)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(4,0,2)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(3,0,2)(1,0,2)[52] with non-zero mean : 123148.1

 Best model: ARIMA(3,0,2)(1,0,2)[52] with non-zero mean

> Pd_SKU 4model
Series: Pd_SKU 4times
ARIMA(3,0,2)(1,0,2)[52] with non-zero mean

Coefficients:
         ar1      ar2     ar3     ma1     ma2   sar1    sma1     sma2      mean
     -0.8147  -0.4042  0.0832  1.2113  0.6980  0.059  0.0778  -0.0459  910.0812
s.e.  0.0404   0.0235  0.0188  0.0376  0.0342  0.137  0.1370   0.0214    8.7991

sigma^2 = 278390:  log likelihood = -61564.06
AIC=123148.1   AICc=123148.1   BIC=123218

> acf(ts(Pd_SKU 4model$residuals))
```

```
> pacf(ts(Pd_SKU 4model$residuals))
> myPd_SKU 4forecast = forecast(Pd_SKU 4model, level = c(95), h=52)
> plot(myPd_SKU 4forecast)
> Box.test(myPd_SKU 4forecast$resid, lag = 5, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 2.0873, df = 5, p-value = 0.8369

> Box.test(myPd_SKU 4forecast$resid, lag = 10, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 45.018, df = 10, p-value = 2.158e-06

> Box.test(myPd_SKU 4forecast$resid, lag = 15, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 112.94, df = 15, p-value < 2.2e-16

> Box.test(myPd_SKU 4forecast$resid, lag = 20, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 316.06, df = 20, p-value < 2.2e-16
```

9.4.3 SKU 3

```
> library(readxl)
> Pd_SKU 3 <- read_excel("C:/Users/320177728/OneDrive - The case company/scriptie/Programming data/Pd SKU 3.xlsx")
> View(Pd_SKU 3)
> library(forecast)
> class(Pd_SKU 3)
[1] "tbl_df"     "tbl"        "data.frame"

> Pd_SKU 3times = ts(Pd_SKU 3$`Sell Out Qty CY`, start = min(Pd_SKU 3$Period), max(Pd_SKU 3$Period), frequency = 52)
> class(Pd_SKU 3times)
[1] "ts"

> acf(Pd_SKU 3times)
> pacf(Pd_SKU 3times)
> adf.test(Pd_SKU 3times)

	Augmented Dickey-Fuller Test

data:  Pd_SKU 3times
```

```
Dickey-Fuller = -22.482, Lag order = 19, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Pd_SKU 3times) : p-value smaller than printed p-value

> Pd_SKU 3model = auto.arima(Pd_SKU 3times, ic = "aic", trace = TRUE)

 Fitting models using approximations to speed things up...

 ARIMA(2,0,2)(1,0,1)[52] with non-zero mean : 108382.4
 ARIMA(0,0,0)            with non-zero mean : 110350.3
 ARIMA(1,0,0)(1,0,0)[52] with non-zero mean : 108545.7
 ARIMA(0,0,1)(0,0,1)[52] with non-zero mean : 108792.6
 ARIMA(0,0,0)            with zero mean     : 117790.4
 ARIMA(2,0,2)(0,0,1)[52] with non-zero mean : 108488.6
 ARIMA(2,0,2)(1,0,0)[52] with non-zero mean : 108431.3
 ARIMA(2,0,2)(2,0,1)[52] with non-zero mean : 108351.6
 ARIMA(2,0,2)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(2,0,2)(2,0,2)[52] with non-zero mean : Inf
 ARIMA(2,0,2)(1,0,2)[52] with non-zero mean : Inf
 ARIMA(1,0,2)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(2,0,1)(2,0,1)[52] with non-zero mean : 108463.4
 ARIMA(3,0,2)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(2,0,3)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(1,0,1)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(1,0,3)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(3,0,1)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(3,0,3)(2,0,1)[52] with non-zero mean : 108096.3
 ARIMA(3,0,3)(1,0,1)[52] with non-zero mean : 108114.8
 ARIMA(3,0,3)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(3,0,3)(2,0,2)[52] with non-zero mean : 108098
 ARIMA(3,0,3)(1,0,0)[52] with non-zero mean : 108183.1
 ARIMA(3,0,3)(1,0,2)[52] with non-zero mean : 108093.1
 ARIMA(3,0,3)(0,0,2)[52] with non-zero mean : Inf
 ARIMA(3,0,3)(0,0,1)[52] with non-zero mean : 108247.2
 ARIMA(2,0,3)(1,0,2)[52] with non-zero mean : Inf
 ARIMA(3,0,2)(1,0,2)[52] with non-zero mean : Inf
 ARIMA(4,0,3)(1,0,2)[52] with non-zero mean : 108067.1
 ARIMA(4,0,3)(0,0,2)[52] with non-zero mean : Inf
 ARIMA(4,0,3)(1,0,1)[52] with non-zero mean : 108086.9
 ARIMA(4,0,3)(2,0,2)[52] with non-zero mean : Inf
 ARIMA(4,0,3)(0,0,1)[52] with non-zero mean : 108216
 ARIMA(4,0,3)(2,0,1)[52] with non-zero mean : 108063.1
 ARIMA(4,0,3)(2,0,0)[52] with non-zero mean : 108062.9
 ARIMA(4,0,3)(1,0,0)[52] with non-zero mean : 108148.8
 ARIMA(4,0,2)(2,0,0)[52] with non-zero mean : 108080.3
 ARIMA(5,0,3)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(4,0,4)(2,0,0)[52] with non-zero mean : 107959.7
 ARIMA(4,0,4)(1,0,0)[52] with non-zero mean : 108026.9
 ARIMA(4,0,4)(2,0,1)[52] with non-zero mean : 107960.9
 ARIMA(4,0,4)(1,0,1)[52] with non-zero mean : 107977.7
 ARIMA(3,0,4)(2,0,0)[52] with non-zero mean : 108047.3
```

```
 ARIMA(5,0,4)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(4,0,5)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(3,0,5)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(5,0,5)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(4,0,4)(2,0,0)[52] with zero mean     : Inf

 Now re-fitting the best model(s) without approximations...

 ARIMA(4,0,4)(2,0,0)[52] with non-zero mean : 107984.6

 Best model: ARIMA(4,0,4)(2,0,0)[52] with non-zero mean

> Pd_SKU 3model
Series: Pd_SKU 3times
ARIMA(4,0,4)(2,0,0)[52] with non-zero mean

Coefficients:
        ar1     ar2     ar3      ar4      ma1      ma2      ma3      ma4   sar1    sar2      mean
     0.7538  0.0057  0.1317  -0.3907  -0.3757  -0.1828  -0.1313  0.549  0.1591  0.0917  325.1174
s.e.  0.1007  0.0449  0.0716   0.0350   0.1002   0.0551   0.0451  0.042  0.0119  0.0117    5.7535

sigma^2 = 50030:  log likelihood = -53980.31
AIC=107984.6   AICc=107984.7   BIC=108068.3

> acf(ts(Pd_SKU 3model$residuals))
> pacf(ts(Pd_SKU 3model$residuals))
> myPd_SKU 3forecast = forecast(Pd_SKU 3model, level = c(95), h=52)
> plot(myPd_SKU 3forecast)
> Box.test(myPd_SKU 3forecast$resid, lag = 5, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 3forecast$resid
X-squared = 7.5305, df = 5, p-value = 0.1841

> Box.test(myPd_SKU 3forecast$resid, lag = 10, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 3forecast$resid
X-squared = 47.276, df = 10, p-value = 8.41e-07

> Box.test(myPd_SKU 3forecast$resid, lag = 15, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 3forecast$resid
X-squared = 218.85, df = 15, p-value < 2.2e-16

> Box.test(myPd_SKU 3forecast$resid, lag = 20, type = 'Ljung-Box')

	Box-Ljung test
```

data: myPd_SKU 3forecast$resid
X-squared = 303.2, df = 20, p-value < 2.2e-16

9.4.4 SKU 2

```
> library(readxl)
> Pd_SKU 2 <- read_excel("C:/Users/320177728/OneDrive - The case company/scriptie/Programming data/Pd SKU 2.xlsx")
> View(Pd_SKU 2)
> Pd_SKU 2times = ts(Pd_SKU 2$`Sell Out Qty CY`, start = min(Pd_SKU 2$Period), max(Pd_SKU 2$Period), frequency = 52)
> class(Pd_SKU 2times)
[1] "ts"
> acf(Pd_SKU 2times)
> pacf(Pd_SKU 2times)
> adf.test(Pd_SKU 2times)

	Augmented Dickey-Fuller Test

data:  Pd_SKU 2times
Dickey-Fuller = -12.941, Lag order = 19, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Pd_SKU 2times) : p-value smaller than printed p-value

> Pd_SKU 2model = auto.arima(Pd_SKU 2times, ic = "aic", trace = TRUE)

 Fitting models using approximations to speed things up...

 ARIMA(2,0,2)(1,0,1)[52] with non-zero mean : 107669.9
 ARIMA(0,0,0)            with non-zero mean : 111184.9
 ARIMA(1,0,0)(1,0,0)[52] with non-zero mean : 109082.7
 ARIMA(0,0,1)(0,0,1)[52] with non-zero mean : 109433.8
 ARIMA(0,0,0)            with zero mean     : 121811.2
 ARIMA(2,0,2)(0,0,1)[52] with non-zero mean : 107745.2
 ARIMA(2,0,2)(1,0,0)[52] with non-zero mean : 107667.8
 ARIMA(2,0,2)            with non-zero mean : 107743.2
 ARIMA(2,0,2)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(2,0,2)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(1,0,2)(1,0,0)[52] with non-zero mean : 108040.5
 ARIMA(2,0,1)(1,0,0)[52] with non-zero mean : 108070
 ARIMA(3,0,2)(1,0,0)[52] with non-zero mean : 107661.7
 ARIMA(3,0,2)            with non-zero mean : 107738.5
 ARIMA(3,0,2)(2,0,0)[52] with non-zero mean : 107657.1
 ARIMA(3,0,2)(2,0,1)[52] with non-zero mean : 107659
 ARIMA(3,0,2)(1,0,1)[52] with non-zero mean : 107663.1
 ARIMA(3,0,1)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(4,0,2)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(3,0,3)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(2,0,1)(2,0,0)[52] with non-zero mean : 108072.9
 ARIMA(2,0,3)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(4,0,1)(2,0,0)[52] with non-zero mean : 107605.8
```

```
 ARIMA(4,0,1)(1,0,0)[52] with non-zero mean : 107606.7
 ARIMA(4,0,1)(2,0,1)[52] with non-zero mean : 107607.6
 ARIMA(4,0,1)(1,0,1)[52] with non-zero mean : 107608.1
 ARIMA(4,0,0)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(5,0,1)(2,0,0)[52] with non-zero mean : 107602.4
 ARIMA(5,0,1)(1,0,0)[52] with non-zero mean : 107605.5
 ARIMA(5,0,1)(2,0,1)[52] with non-zero mean : 107604.4
 ARIMA(5,0,1)(1,0,1)[52] with non-zero mean : 107606.3
 ARIMA(5,0,0)(2,0,0)[52] with non-zero mean : 107695.8
 ARIMA(5,0,2)(2,0,0)[52] with non-zero mean : 107487.1
 ARIMA(5,0,2)(1,0,0)[52] with non-zero mean : 107494.9
 ARIMA(5,0,2)(2,0,1)[52] with non-zero mean : 107488.8
 ARIMA(5,0,2)(1,0,1)[52] with non-zero mean : 107496.4
 ARIMA(5,0,3)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(4,0,3)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(5,0,2)(2,0,0)[52] with zero mean     : Inf

 Now re-fitting the best model(s) without approximations...

 ARIMA(5,0,2)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(5,0,2)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(5,0,2)(1,0,0)[52] with non-zero mean : 107569.5

 Best model: ARIMA(5,0,2)(1,0,0)[52] with non-zero mean

> Pd_SKU 2model
Series: Pd_SKU 2times
ARIMA(5,0,2)(1,0,0)[52] with non-zero mean

Coefficients:
         ar1     ar2     ar3     ar4      ar5     ma1      ma2     sar1      mean
      0.1776  0.7443  0.1041  0.0627  -0.1586  0.1445  -0.7602  -0.0094  461.2650
s.e.  0.0222  0.0177  0.0149  0.0147   0.0147  0.0185   0.0176   0.0115   13.3099

sigma^2 = 47495:  log likelihood = -53774.76
AIC=107569.5   AICc=107569.6   BIC=107639.3

> acf(ts(Pd_SKU 2model$residuals))
> pacf(ts(Pd_SKU 2model$residuals))
> myPd_SKU 2forecast = forecast(Pd_SKU 2model, level = c(95), h=52)
> plot(myPd_SKU 2forecast)
> Box.test(myPd_SKU 2forecast$resid, lag = 5, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 2forecast$resid
X-squared = 26.271, df = 5, p-value = 7.907e-05

> Box.test(myPd_SKU 2forecast$resid, lag = 10, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 2forecast$resid
```

X-squared = 137.1, df = 10, p-value < 2.2e-16

```
> Box.test(myPd_SKU 2forecast$resid, lag = 15, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 2forecast$resid
X-squared = 607.66, df = 15, p-value < 2.2e-16
```

9.4.5 SKU 1

```
> library(readxl)
> Pd_SKU 4 <- read_excel("C:/Users/320177728/OneDrive - The case company/scriptie/Programming data/Pd SKU 4.xlsx")
> View(Pd_SKU 4)
> library(forecast)
> class(Pd_SKU 4)
[1] "tbl_df"     "tbl"        "data.frame"

> Pd_SKU 4times = ts(Pd_SKU 4$`Sell Out Qty CY`, start = min(Pd_SKU 4$Period), max(Pd_SKU 4$Period), frequency = 52)
> class(Pd_SKU 4times)
[1] "ts"

> acf(Pd_SKU 4times)
> pacf(Pd_SKU 4times)
> adf.test(Pd_SKU 4times)

	Augmented Dickey-Fuller Test

data:  Pd_SKU 4times
Dickey-Fuller = -18.976, Lag order = 19, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Pd_SKU 4times) : p-value smaller than printed p-value

> Pd_SKU 4model = auto.arima(Pd_SKU 4times, ic = "aic", trace = TRUE)

 Fitting models using approximations to speed things up...

 ARIMA(2,0,2)(1,0,1)[52] with non-zero mean : 103701.7
 ARIMA(0,0,0)            with non-zero mean : 107343.9
 ARIMA(1,0,0)(1,0,0)[52] with non-zero mean : 104005.8
 ARIMA(0,0,1)(0,0,1)[52] with non-zero mean : 104620.8
 ARIMA(0,0,0)            with zero mean     : 120672.5
 ARIMA(2,0,2)(0,0,1)[52] with non-zero mean : 103708.6
 ARIMA(2,0,2)(1,0,0)[52] with non-zero mean : 103699.9
 ARIMA(2,0,2)            with non-zero mean : 103709.9
 ARIMA(2,0,2)(2,0,0)[52] with non-zero mean : 103697.4
 ARIMA(2,0,2)(2,0,1)[52] with non-zero mean : Inf
 ARIMA(1,0,2)(2,0,0)[52] with non-zero mean : 103700.3
 ARIMA(2,0,1)(2,0,0)[52] with non-zero mean : Inf
```

```
 ARIMA(3,0,2)(2,0,0)[52] with non-zero mean : 103138.4
 ARIMA(3,0,2)(1,0,0)[52] with non-zero mean : 103606.1
 ARIMA(3,0,2)(2,0,1)[52] with non-zero mean : 103131.2
 ARIMA(3,0,2)(1,0,1)[52] with non-zero mean : 103171
 ARIMA(3,0,2)(2,0,2)[52] with non-zero mean : 103132.8
 ARIMA(3,0,2)(1,0,2)[52] with non-zero mean : 103123.9
 ARIMA(3,0,2)(0,0,2)[52] with non-zero mean : 103122.7
 ARIMA(3,0,2)(0,0,1)[52] with non-zero mean : 103604.8
 ARIMA(2,0,2)(0,0,2)[52] with non-zero mean : Inf
 ARIMA(3,0,1)(0,0,2)[52] with non-zero mean : Inf
 ARIMA(4,0,2)(0,0,2)[52] with non-zero mean : Inf
 ARIMA(3,0,3)(0,0,2)[52] with non-zero mean : Inf
 ARIMA(2,0,1)(0,0,2)[52] with non-zero mean : 103979.8
 ARIMA(2,0,3)(0,0,2)[52] with non-zero mean : Inf
 ARIMA(4,0,1)(0,0,2)[52] with non-zero mean : 103403.3
 ARIMA(4,0,3)(0,0,2)[52] with non-zero mean : Inf
 ARIMA(3,0,2)(0,0,2)[52] with zero mean     : Inf

 Now re-fitting the best model(s) without approximations...

 ARIMA(3,0,2)(0,0,2)[52] with non-zero mean : 103119.9

 Best model: ARIMA(3,0,2)(0,0,2)[52] with non-zero mean

> Pd_SKU 4model
Series: Pd_SKU 4times
ARIMA(3,0,2)(0,0,2)[52] with non-zero mean

Coefficients:
         ar1      ar2     ar3      ma1     ma2     sma1    sma2      mean
      1.7555  -1.6113  0.6247  -1.2271  0.9430  -0.0265  0.0843  450.9820
s.e.  0.0107   0.0147  0.0091   0.0072  0.0098   0.0115  0.0121    6.0512

sigma^2 = 27049:  log likelihood = -51550.96
AIC=103119.9   AICc=103119.9   BIC=103182.7

> acf(ts(Pd_SKU 4model$residuals))
> pacf(ts(Pd_SKU 4model$residuals))
> myPd_SKU 4forecast = forecast(Pd_SKU 4model, level = c(95), h=52)
> plot(myPd_SKU 4forecast)
> Box.test(myPd_SKU 4forecast$resid, lag = 5, type = 'Ljung-Box')

        Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 271.77, df = 5, p-value < 2.2e-16

> Box.test(myPd_SKU 4forecast$resid, lag = 10, type = 'Ljung-Box')

        Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 455.29, df = 10, p-value < 2.2e-16
```

```
> Box.test(myPd_SKU 4forecast$resid, lag = 15, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 1043, df = 15, p-value < 2.2e-16

> Box.test(myPd_SKU 4forecast$resid, lag = 3, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 42.121, df = 3, p-value = 3.783e-09

> Box.test(myPd_SKU 4forecast$resid, lag = 1, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 4forecast$resid
X-squared = 2.3548, df = 1, p-value = 0.1249
```

9.4.6 SKU 5

```
> library(readxl)
> Pd_SKU 5 <- read_excel("C:/Users/320177728/OneDrive - The case company/scriptie/Programming data/Pd
SKU 5.xlsx")
> View(Pd_SKU 5)
> library(forecast)
> class(Pd_SKU 5)
[1] "tbl_df"     "tbl"        "data.frame"

> Pd_SKU 5times = ts(Pd_SKU 5$`Sell Out Qty CY`, start = min(Pd_SKU 5$Period), max(Pd_SKU 5$Period),
frequency = 52)
> class(Pd_SKU 5times)
[1] "ts"

> acf(Pd_SKU 5times)
> pacf(Pd_SKU 5times)
> adf.test(Pd_SKU 5times)

	Augmented Dickey-Fuller Test

data:  Pd_SKU 5times
Dickey-Fuller = -13.424, Lag order = 19, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(Pd_SKU 5times) : p-value smaller than printed p-value

> Pd_SKU 5model = auto.arima(Pd_SKU 5times, ic = "aic", trace = TRUE)

 Fitting models using approximations to speed things up...
```

```
ARIMA(2,0,2)(1,0,1)[52] with non-zero mean : 109867
ARIMA(0,0,0)            with non-zero mean : 130968.3
ARIMA(1,0,0)(1,0,0)[52] with non-zero mean : 109906.6
ARIMA(0,0,1)(0,0,1)[52] with non-zero mean : 122464.5
ARIMA(0,0,0)            with zero mean     : 142882.3
ARIMA(2,0,2)(0,0,1)[52] with non-zero mean : 109897.7
ARIMA(2,0,2)(1,0,0)[52] with non-zero mean : 109866.4
ARIMA(2,0,2)            with non-zero mean : 109903.1
ARIMA(2,0,2)(2,0,0)[52] with non-zero mean : 109861.9
ARIMA(2,0,2)(2,0,1)[52] with non-zero mean : 109863.7
ARIMA(1,0,2)(2,0,0)[52] with non-zero mean : 109826.9
ARIMA(1,0,2)(1,0,0)[52] with non-zero mean : 109832.9
ARIMA(1,0,2)(2,0,1)[52] with non-zero mean : Inf
ARIMA(1,0,2)(1,0,1)[52] with non-zero mean : 109833.9
ARIMA(0,0,2)(2,0,0)[52] with non-zero mean : Inf
ARIMA(1,0,1)(2,0,0)[52] with non-zero mean : Inf
ARIMA(1,0,3)(2,0,0)[52] with non-zero mean : 109827.5
ARIMA(0,0,1)(2,0,0)[52] with non-zero mean : 121959.7
ARIMA(0,0,3)(2,0,0)[52] with non-zero mean : 115188.5
ARIMA(2,0,1)(2,0,0)[52] with non-zero mean : 109860.6
ARIMA(2,0,3)(2,0,0)[52] with non-zero mean : 109738.3
ARIMA(2,0,3)(1,0,0)[52] with non-zero mean : 109747.4
ARIMA(2,0,3)(2,0,1)[52] with non-zero mean : Inf
ARIMA(2,0,3)(1,0,1)[52] with non-zero mean : 109748
ARIMA(3,0,3)(2,0,0)[52] with non-zero mean : 109295.4
ARIMA(3,0,3)(1,0,0)[52] with non-zero mean : 109315.7
ARIMA(3,0,3)(2,0,1)[52] with non-zero mean : Inf
ARIMA(3,0,3)(1,0,1)[52] with non-zero mean : 109298.6
ARIMA(3,0,2)(2,0,0)[52] with non-zero mean : Inf
ARIMA(4,0,3)(2,0,0)[52] with non-zero mean : 109281
ARIMA(4,0,3)(1,0,0)[52] with non-zero mean : 109299.6
ARIMA(4,0,3)(2,0,1)[52] with non-zero mean : Inf
ARIMA(4,0,3)(1,0,1)[52] with non-zero mean : 109282.3
ARIMA(4,0,2)(2,0,0)[52] with non-zero mean : 109297.8
ARIMA(5,0,3)(2,0,0)[52] with non-zero mean : Inf
ARIMA(4,0,4)(2,0,0)[52] with non-zero mean : Inf
ARIMA(3,0,4)(2,0,0)[52] with non-zero mean : 109256.9
ARIMA(3,0,4)(1,0,0)[52] with non-zero mean : 109289.5
ARIMA(3,0,4)(2,0,1)[52] with non-zero mean : Inf
ARIMA(3,0,4)(1,0,1)[52] with non-zero mean : 109267.5
ARIMA(2,0,4)(2,0,0)[52] with non-zero mean : Inf
ARIMA(3,0,5)(2,0,0)[52] with non-zero mean : Inf
ARIMA(2,0,5)(2,0,0)[52] with non-zero mean : 109228.9
ARIMA(2,0,5)(1,0,0)[52] with non-zero mean : 109512
ARIMA(2,0,5)(2,0,1)[52] with non-zero mean : Inf
ARIMA(2,0,5)(1,0,1)[52] with non-zero mean : 109512
ARIMA(1,0,5)(2,0,0)[52] with non-zero mean : 109538.7
ARIMA(1,0,4)(2,0,0)[52] with non-zero mean : 109557.4
ARIMA(2,0,5)(2,0,0)[52] with zero mean     : Inf

Now re-fitting the best model(s) without approximations...
```

```
 ARIMA(2,0,5)(2,0,0)[52] with non-zero mean : Inf
 ARIMA(3,0,4)(2,0,0)[52] with non-zero mean : 109270.8

 Best model: ARIMA(3,0,4)(2,0,0)[52] with non-zero mean

> Pd_SKU 5model
Series: Pd_SKU 5times
ARIMA(3,0,4)(2,0,0)[52] with non-zero mean

Coefficients:
         ar1     ar2     ar3     ma1     ma2     ma3      ma4    sar1    sar2       mean
      0.0140  0.1438  0.7649  0.9058  0.8309  0.0434  -0.0886  0.1239  0.0799  1796.4653
s.e.  0.0178  0.0145  0.0164  0.0212  0.0240  0.0188   0.0149  0.0126  0.0121   118.3404

sigma^2 = 58862:  log likelihood = -54624.42
AIC=109270.8   AICc=109270.9   BIC=109347.6

> acf(ts(Pd_SKU 5model$residuals))
> pacf(ts(Pd_SKU 5model$residuals))
> myPd_SKU 5forecast = forecast(Pd_SKU 5model, level = c(95), h=52)
> plot(myPd_SKU 5forecast)
> Box.test(myPd_SKU 5forecast$resid, lag = 5, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 5forecast$resid
X-squared = 29.966, df = 5, p-value = 1.498e-05

> Box.test(myPd_SKU 5forecast$resid, lag = 10, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 5forecast$resid
X-squared = 779.4, df = 10, p-value < 2.2e-16

> Box.test(myPd_SKU 5forecast$resid, lag = 15, type = 'Ljung-Box')

	Box-Ljung test

data:  myPd_SKU 5forecast$resid
X-squared = 848.68, df = 15, p-value < 2.2e-16
```

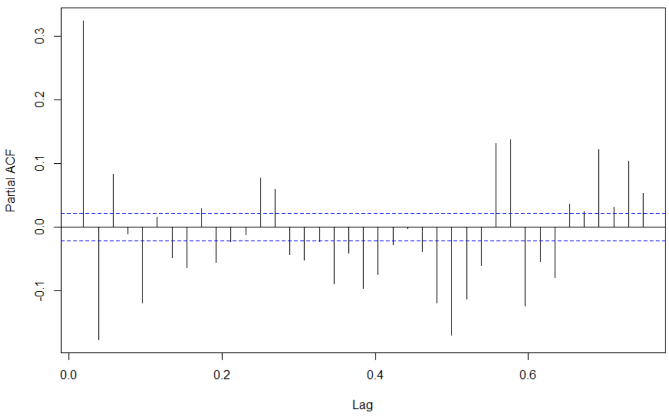
9.4.7 SARIMA performance output

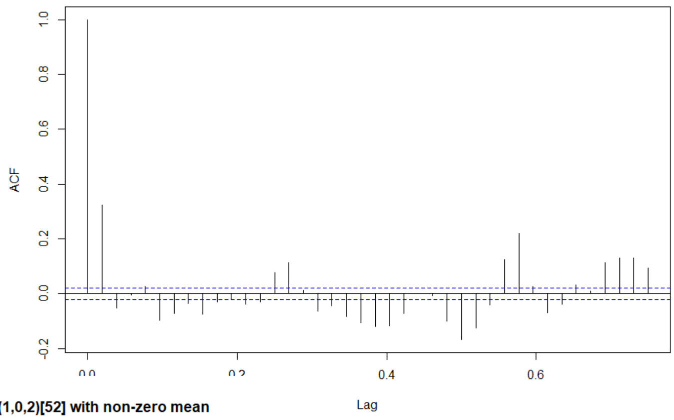
		SKU 2	SKU 1	SKU 3	SKU 4	SKU 5
ADF test	Dickey-Fuller	-12.941	-18.976	-22.482	-26.827	-20.527
	lag order	19	19	19	19	18
	p-value	<0,01	<0,01	<0,01	<0,01	<0,01
	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary
KPSS	level	0,0064274	0,0037268	0,0041708	0,0014436	0,0018055

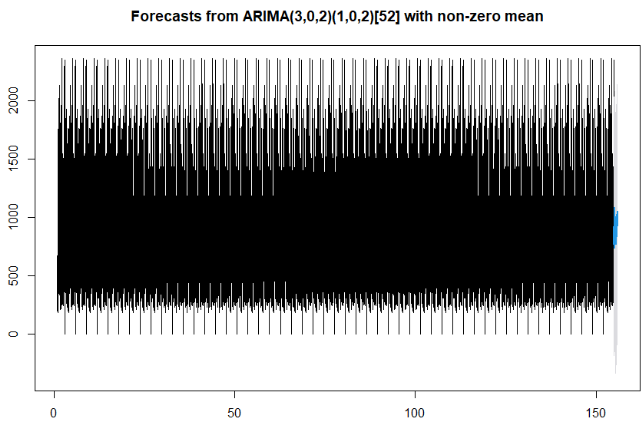
	Truncation lag parameter	11	11	11	11	11
	P-value	>0,1	>0,1	>0,1	>0,1	>0,1
	ARIMA	(5,0,2)(1,0,0)	(3,0,2)(0,0,2)	(4,0,4)(2,0,0)	(3,0,2)(1,0,1)	(5,0,2)(1,0,0)
	Sigma^2	47495	27049	50030	279813	47495
Model	log likelyhood	-53774,76	-51550,96	-53980,31	-60784.7	-53774.76
	AIC	107569,5	103119,9	107984,6	121587.4	107569.5
	AICc	107569,6	103119,9	107984,7	121587.4	107569.6
	BIC	107639,3	103182,7	108068,3	121650.2	107639.3
	Periods	153	134	153	153	119
Performance	MSE	310,42	201.86	327	1828.84	399.12
	RMSE	17,62	14,21	18,08	42,76	19,98

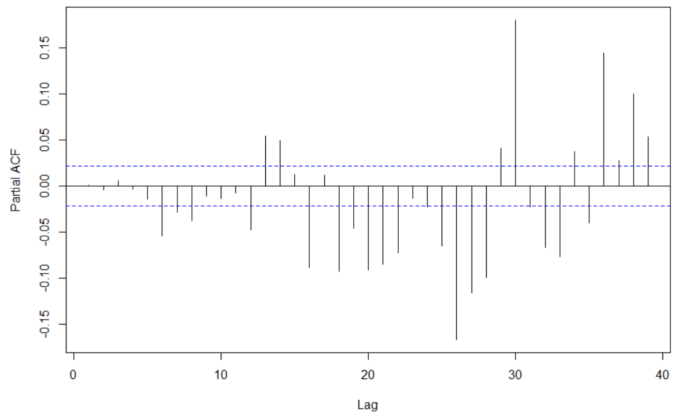
9.5 Rstudio SARIMA plots (per SKU)

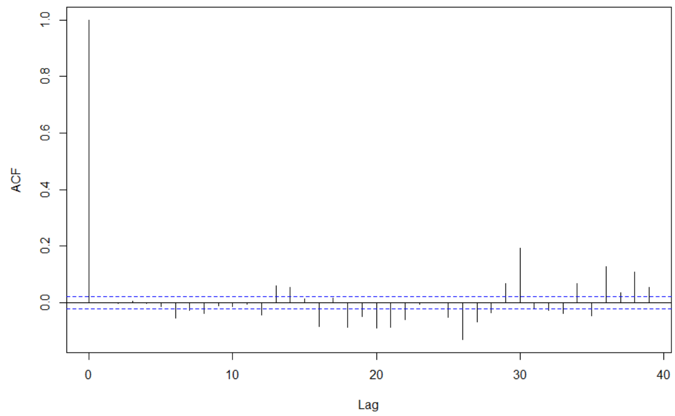
9.5.1 SKU 4



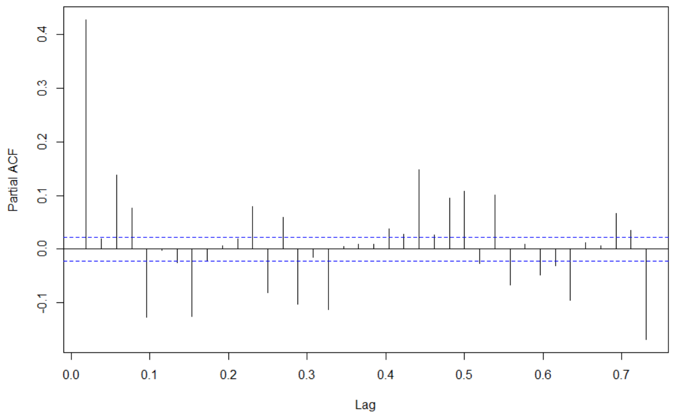


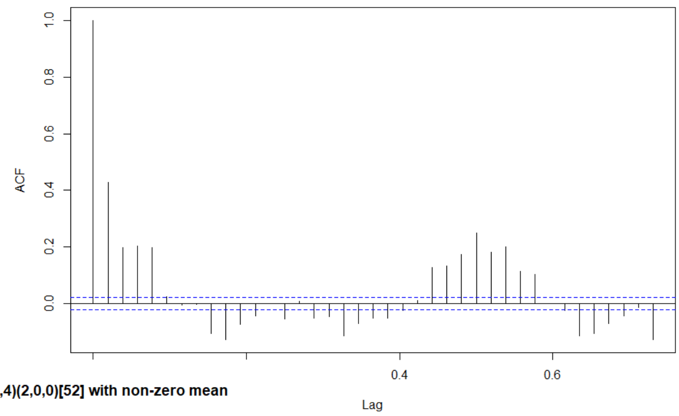


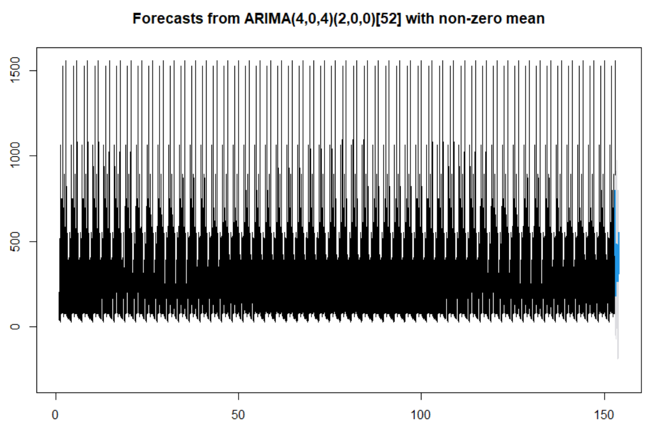

Partial ACF
Lag

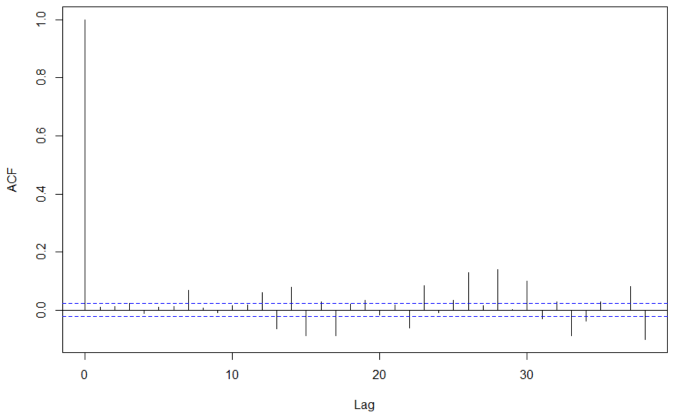

ACF
Lag

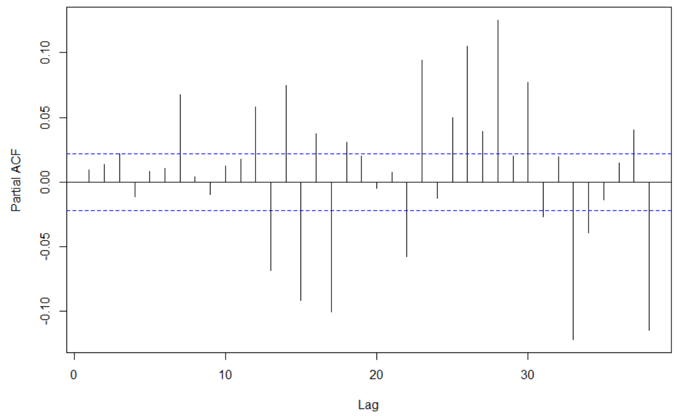
9.5.2 SKU 3


Partial ACF
Lag

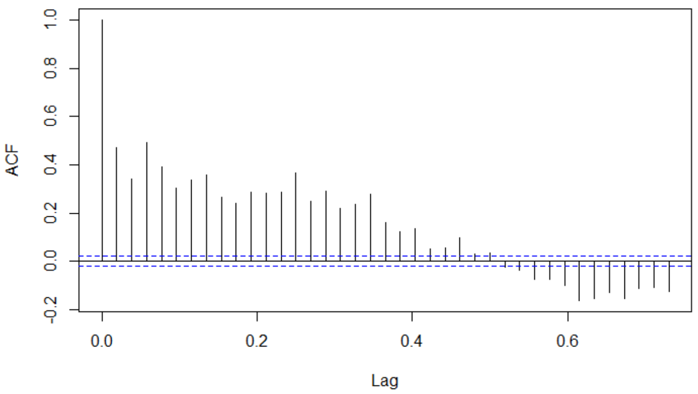

ACF
Lag

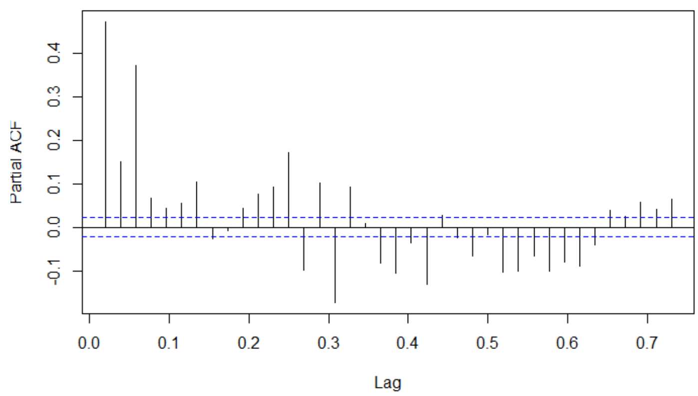

Forecasts from ARIMA(4,0,4)(2,0,0)[52] with non-zero mean

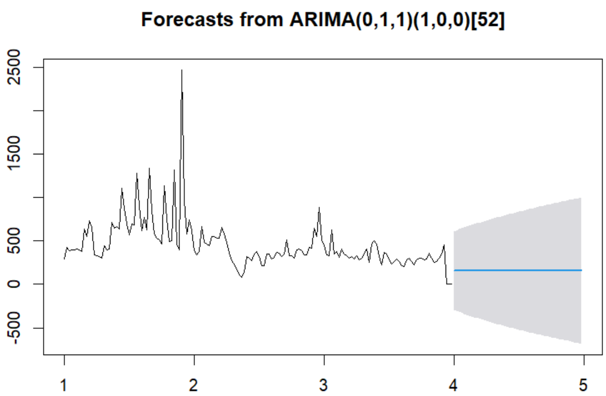

ACF
Lag
0
10
20
30
0.0
0.2
0.4
0.6
0.8
1.0

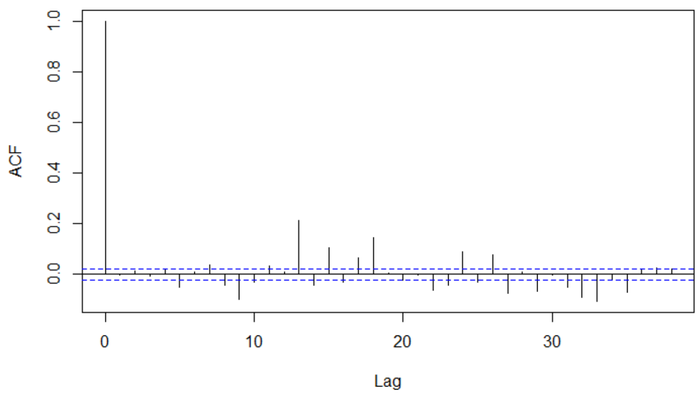

Partial ACF
Lag
0
10
20
30
-0.10
-0.05
0.00
0.05
0.10

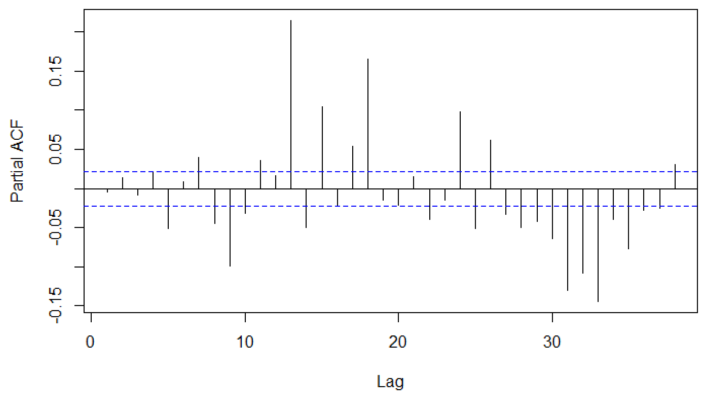
9.5.3 SKU 2


ACF
Lag
0.0
0.2
0.4
0.6
-0.2
0.0
0.2
0.4
0.6
0.8
1.0

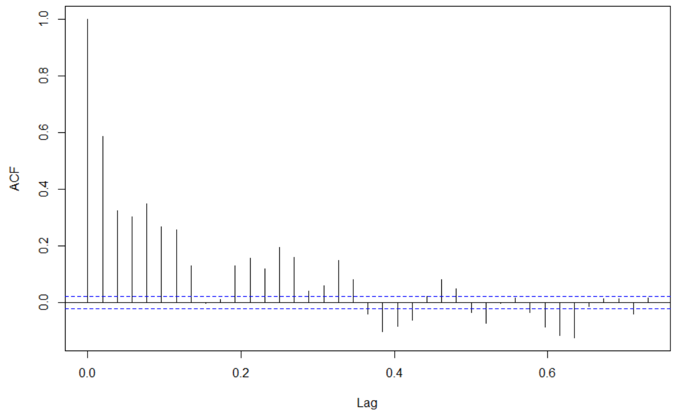

Partial ACF
Lag
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
-0.1
0.0
0.1
0.2
0.3
0.4

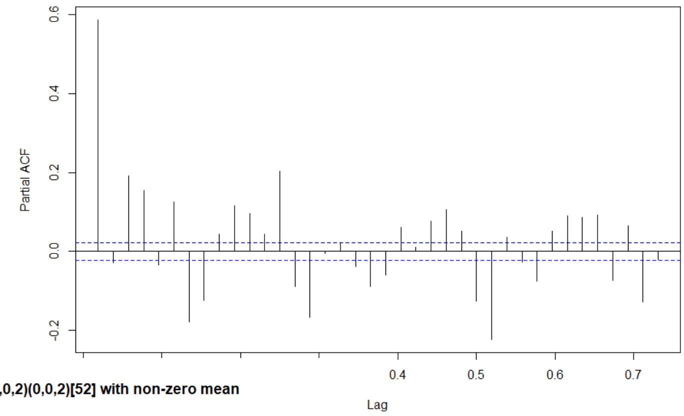

Forecasts from ARIMA(0,1,1)(1,0,0)[52]
-500
0
500
1500
2500
1
2
3
4
5

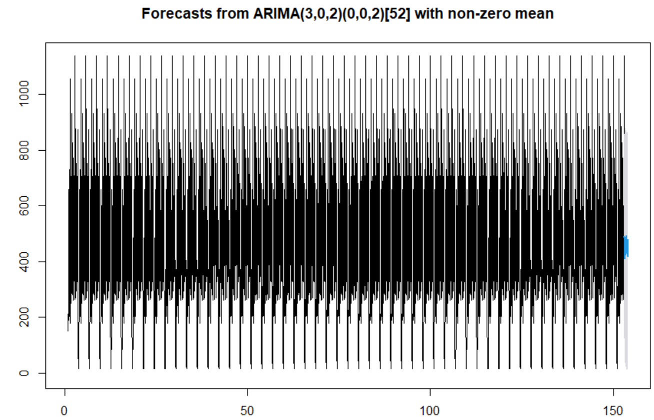

ACF
Lag

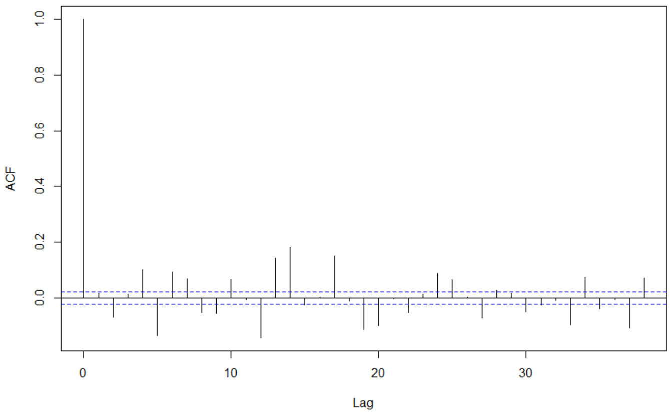

Partial ACF
Lag

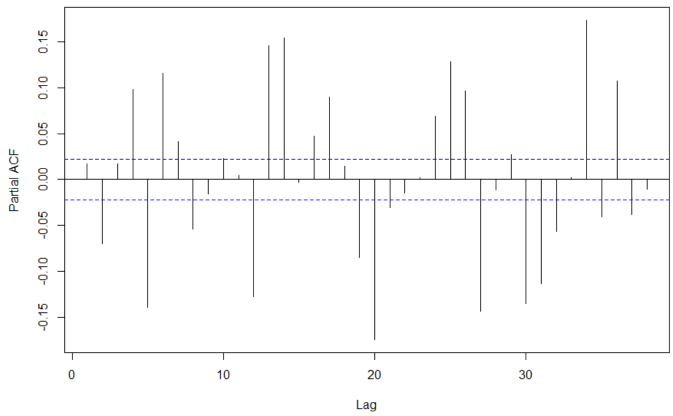
9.5.4 SKU 1


ACF
Lag

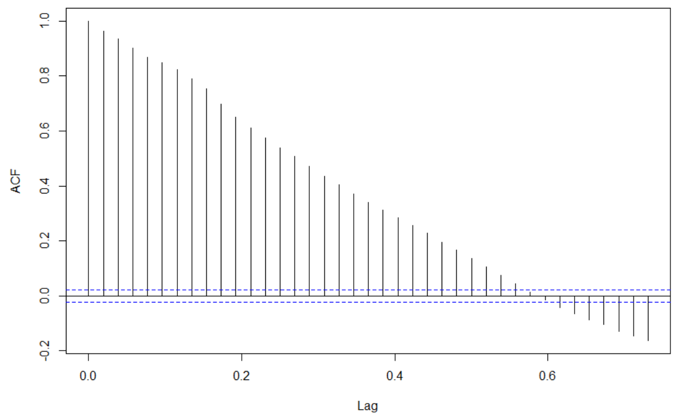

Partial ACF
Lag

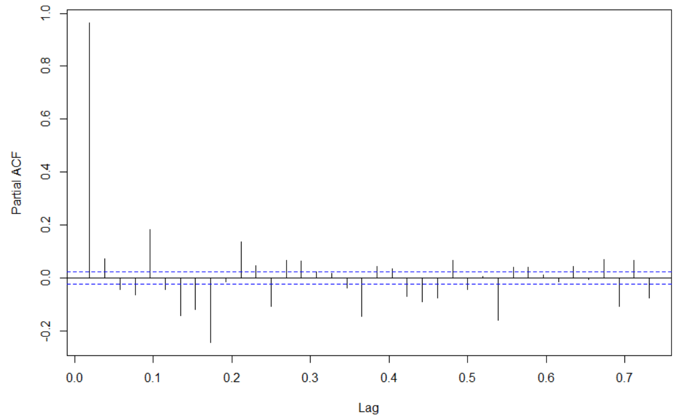

Forecasts from ARIMA(3,0,2)(0,0,2)[52] with non-zero mean

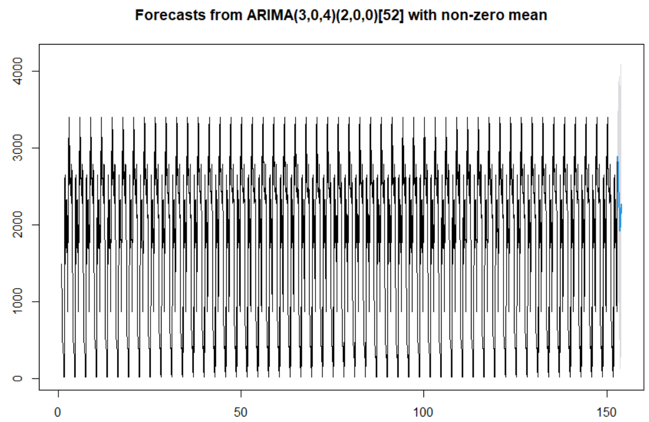

ACF
Lag

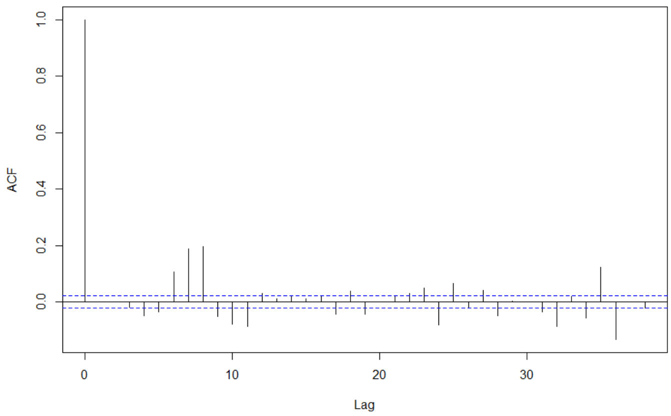

Partial ACF
Lag

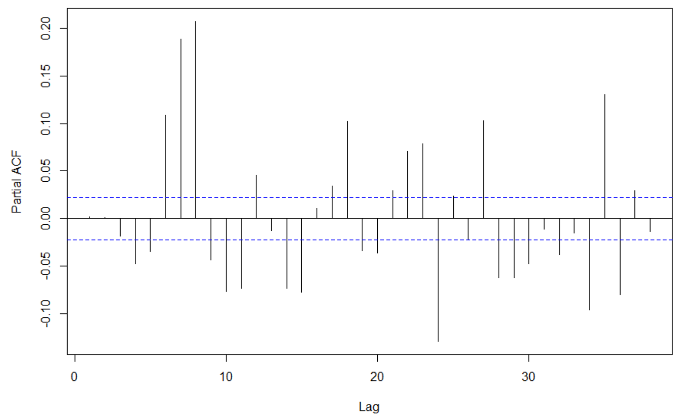
9.5.5 SKU 5


ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0.0
0.2
0.4
0.6


Partial ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7


Forecasts from ARIMA(3,0,4)(2,0,0)[52] with non-zero mean
4000
3000
2000
1000
0
0
50
100
150


ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
0
10
20
30


Partial ACF
Lag
0.20
0.15
0.10
0.05
0.00
-0.05
-0.10
0
10
20
30