MASTER

Requirements and potential of supply chain collaboration in grocery retailing

A comparative study

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Award date:
2022

EINDHOVEN UNIVERSITY OF TECHNOLOGY

Department of Industrial Engineering and Innovation Sciences
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Eindhoven May, 2022

Preface

This Master's Thesis Project is the final step in completing my Master's Degree in Operations Management and Logistics at Eindhoven University of Technology (TU/e). The project was conducted at the Forecast and Replenishment department of Jumbo. The project was supervised by dr. K.H. van Donselaar and dr. N.R. Mutlu from the TU/e and by Judith Belo from Jumbo.

First of all, I would like to express my gratitude to my mentor and first supervisor, dr. K.H. van Donselaar. From the start of my master's degree, I always enjoyed working with you. Throughout my master thesis project, your passion and enthusiasm always motivated me and boosted my positive energy. During the feedback meetings, you provided me with constrictive and critical feedback and made me view the problem from different perspectives. I have always greatly appreciated this feedback which brought the research to a higher level. Furthermore, I would like to thank my second supervisor, dr. N.R. Mutlu. Her knowledge and critical attitude towards decisions in the project enhanced the quality of the research.

Secondly, I would like to thank my company supervisor, Judith Belo, for the opportunity to perform my research within Jumbo and the guidance throughout the project. From the first introduction meeting, I felt at home at Jumbo and in the team. During the project, you always showed me the confidence and freedom to develop myself and design the project. In addition, I would like to thank the entire team for the many enjoyable moments and pleasant working atmosphere.

Finally, I would like to thank my girlfriend Minouche, my friends, 'A.V. Sodalitate' in particular, and my family for their unconditional support. Your company has made me enjoy my student life immensely, and your support and fun activities over the past months have helped me to complete this project.

Koen van Wershoven,

Eindhoven, May 2022

Abstract

The increasing pressure on the grocery supply chain is forcing retailers to continuously seek improvements in order to survive in the highly competitive market. Supply chain collaboration is widely acknowledged as an opportunity to excel under this pressure. Despite the will to establish supply chain collaboration, there is a lack of clear vision and detailed plan to achieve such collaboration. This study examines the requirements and potential of supply chain collaboration in grocery retailing. The collaboration requirements and desires of a wide variety of suppliers are examined by conducting in-depth interviews. Afterwards, the quantitative effects of multiple collaboration scenarios are examined through a discrete-event simulation in a perishable three-echelon divergent supply chain. The interviewees recognised the potential of supply chain collaboration and mainly addressed data-related improvement possibilities. Successful collaboration requires an aligned collaboration vision and goals, an extensive information sharing system, and transparency about the data quality. The simulation study reveals that order forecast sharing is preferred and enhances the relative supply chain outdating by 17.5 per cent and the freshness delivered to the consumers by 3.5 per cent. Moreover, the disruptive effects of order batching and shelf life reinforce the added value of information sharing. Therefore, it is suggested to expand the collaboration in the supply chain to improve the performance of the entire supply chain and better serve the consumers starting with products suffering more from supply chain disruptions due to order batching and outdating.

Management Summary

This master thesis project is conducted in cooperation with Jumbo Supermarkten, referred to as Jumbo. Jumbo is a Dutch chain of supermarkets of the Royal Jumbo Food Group. This management summary provides an overview of the most important research outcomes.

Introduction

Supply chain collaboration (SCC) has been widely discussed in the literature, and it is generally accepted that creating a seamless, synchronised supply chain (SC) leads to better performance. As SCC has become essential for achieving competitive advantage, top management interest in this topic has increased in recent decades, including Jumbo's (Hollmann et al., 2015; Jumbo, 2020). From the mission statement of the forecast and replenishment department, it can be deduced that Jumbo aims to maximize customer satisfaction by ensuring maximum availability, quality, and freshness at optimal costs by managing the entire SC. Despite the widely supported belief that SCC improves performance, there are several barriers to successful collaboration (Nimmy et al., 2019). Jumbo's focus on intensifying its SCC is implementing Collaborative Planning, Forecasting, and Replenishment (CPFR). CPFR is a bundling of business processes to improve overall SC performance through joint planning and decision making by sharing information, synchronised forecasts, risks, costs and benefits (VICS, 2004). However, literature and practical applications distinguish several challenges, barriers, and maturity levels, hampering the selection of the appropriate SCC model. Therefore, the goal of this research is to provide guidelines on how Jumbo could intensify its SCC, directing to the following research question:

Which supply chain collaboration model should be used to efficiently improve supply chain performance considering different supply chain conditions (e.g., perishability, demand variability, case pack sizes)?

This research mainly focuses on improving SC performance by intensifying external collaboration limited to the forecast and replenishment processes of Jumbo's SC.

Research design

This research is divided into an exploratory and explanatory research phase. The exploratory research conducts qualitative data analysis, aiming to gain insights into the needs and desires of the suppliers, and define requirements for SCC. The qualitative data for the explanatory research is gathered through in-depth interviews with a broad range of suppliers. To ensure a representative group of suppliers, emphasis is placed on the following selection criteria: brand type, shelf life, and experience with SCC. Moreover, a semi-structured interview guide is employed for guidance, developed through an interview process consulting the stakeholders and consists of five topics: current collaboration, desired collaboration, SCC expertise, benchmarking, and influential factors. The outline of the qualitative data analysis is based on the data analysis process of Creswell & Creswell (2018), consisting of six iterative steps: organizing and preparing data, reading through all data, coding the data, interrelating themes and description, interpreting the meaning of themes and descriptions, and validating information accuracy.

The explanatory research aims to acquire an in-depth understanding of the impact and applicability of different SCC models by quantitative analysis. This research considers six SCC scenarios, differing in applied replenishment strategies and shared information. The current situation is modelled as a baseline to assess the effect of each scenario. An age-based replenishment policy (EWA policy) is implemented in the first scenario to account for outdating. A consumer demand forecast is shared in the second scenario, supplemented with expected outdating in the third scenario. The fourth scenario includes order forecast sharing. Finally, an echelon based EWA replenishment policy is applied in the fifth scenario. Each scenario aims to reduce waste in the entire SC and increase freshness without compromising availability. The scenarios are evaluated in a three-echelon divergent perishable SC with lost sales and order batching using discrete event simulation. Moreover, non-stationary demand is considered due to promotions, whereby consumer demand is generated by a discrete demand distribution fitted on empirical regular and promotion sales data. Finally, fixed shelf life and unlimited supply at the retailer's supplier are assumed.

Results

From the exploration research, three requirements for supply chain collaboration are acquired. First, it is essential to align the goals of the collaboration and develop a joint strategic long-term vision. From these goals and vision, concrete objectives must be formulated and then translated into KPIs that can be pursued and influenced by all parties. All parties must agree on the measurement and evaluation method of the KPIs. Second, an unambiguous, automated, standardized, and supplier-tailored information sharing system is required. Such an information sharing system ensures effective integration of the shared information in daily processes and triggers a continuous improvement process. Third, transparency of the shared information and forecast quality is required because it directly affects the applicability of the shared information. Furthermore, suppliers classified forecast, inventory, and point of sales (POS) information as valuable information, ascending in intensity. Finally, from the interviews, four guiding principles for supplier selection are concluded: the desired flexibility in selecting suppliers, the goals of the collaboration, the ease of establishing collaboration, and the potential impact.

The explanatory research shows that implementing the EWA replenishment policy, in mainly the stores, improves the relative SC outdating without collaboration but does not impact the delivered freshness. Furthermore, the order forecast sharing and centralised EWA replenishment policy perform approximately similar. POS forecast sharing becomes attractive when consumer demand is sufficiently high to reduce the disruptive effects of order batching and outdating. Supplementing the POS forecast with the estimated outdating has barely any effect. The freshness enhances with order forecast sharing and centralised EWA replenishment but remains the same with POS forecast sharing. Besides, the differences in relative SC outdating between POS forecast sharing, order forecast sharing, and centralised EWA replenishment are minimal when consumer demand is sufficiently high to reduce the disruptive effects of order batching and outdating. Since suppliers and the retailer favour order forecast sharing, order forecast sharing is preferred. In the current situation, order forecast sharing can reduce the relative SC outdating by 17.5% and increase the freshness of the products delivered to the consumer by 3.5%. Furthermore, the disruptions of order batching and product shelf life expand the benefits of information sharing. Additionally, upstream EWA implementations have a limited effect on SC performances. Finally, the results show potential in reducing upstream safety stocks to increase performance without compromising consumer availability.

Conclusions & recommendations

In conclusion, collaboration in the supply chain positively influences the performance of the SC. Therefore, establishing supply chain collaboration is advisable. Three recommendations are formulated to achieve successful collaboration.

First, Jumbo needs a detailed understanding of what it wants to achieve with which type of supplier so that this can be communicated and can form the basis of the collaboration. The desired degree of flexibility in supplier selection, intended collaboration goal, ease of establishing collaboration, and potential impact can be used as guidelines for supplier selection. Additionally, the determined goals and vision must be aligned with the cooperating supplier and translated into KPIs that can be pursued and influenced by all parties. Finally, the retailer and supplier must comply with the KPIs measurement and evaluation method and specified norms.

Second, independent of the type of shared information, a productive collaboration requires an unambiguous, automated, standardized, and vendor-tailored information sharing system. Additionally, mutual trust and transparency about information quality and accuracy are essential. Consequently, it is suggested that Jumbo investigates how to establish such an information-sharing system.

Third, the explanatory research reveals that order forecast sharing is the preferred type of information sharing for perishable supply chains. Order forecast sharing improves the relative SC outdating and freshness of the products delivered to consumers, as each echelon can synchronize supply and demand. Since the added value of order forecast sharing increases with the disruptive effects of order batching and shelf life, it is advisable to initiate order forecast sharing with more impacted products. Finally, it is advised to implement an age-based replenishment policy (EWA policy) in the stores.

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List of Abbreviations

Abbreviation	Definition
CPFR	Collaborative planning, forecasting, and replenishment
DC	Distribution centre
EDI	Electronic Data Interchange
EWA	Estimated withdrawal & Aging
F&R	Forecast and replenishment
FCC	Fresh Case Cover
FIFO	First-In-First-Out
IS	Information sharing
ISA	In-Store Availability
KPIs	Key performance indicators
LIFO	Last-In-First-Out
MER	Multi echelon replenishment
OSA	On-Shelf Availability
POS	Point of sales data
SC	Supply chain
SCC	Supply chain collaboration
SCM	Supply chain management
SKU	Stock keeping unit
VMI	Vendor manged inventory

Chapter 1

Introduction

A supply chain (SC) could be defined as a network of organisations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the ultimate customer (Christopher, 1999). Therefore, an SC involves raw materials and suppliers of components, including all manufacturers, distributors, and retailers, until the final product has reached the end customer. Many times the retailer is considered as the final stage in the SC. However, the entire SC operates to serve the customer, making it crucial to consider the customer as an integral part of the SC. The purpose of the SC is fulfilling demand from consumers or downstream SC members with supplies delivered by upstream members (Nimmy et al., 2019). The pressure on many industries has increased due to the desire for shorter product life cycles, increased product variety, and better-informed customers. To excel under this pressure, companies must effectively design their material management and distribution channels (Sari, 2008a). It is generally accepted in the literature that supply chain collaboration (SCC) can contribute to an appropriate synchronization of demand and supply between the SC members achieving competitive advantage (Barratt & Oliveira, 2001; Ramanathan et al., 2011). SCC could be defined as a process aiming to promote inter-organisational cooperating, joint work, openness, information and knowledge sharing, inter-company decision making, and customer-supplier intimacy (Danese, 2011; Simatupang & Sridharan, 2002). In the past three decades, practical implementations of SCC are established, resulting in several benefits. The success story of SCC between Wal-Mart and upstream suppliers (e.g. Proctor & Gamble) triggered global interest in SCC (Simchi-Levi et al., 1999).

Despite all the potential benefits of SCC and success stories of practical implementations discussed in the literature, there are also some barriers and challenges which could result in failures in establishing SCC (Hollmann et al., 2015). Due to the different SCC characteristics, conditions and products, it can be challenging to determine the optimal SCC technique. Moreover, SCC techniques differ in many ways, such as the type of information shared and the extent to which planning, ordering and forecasting policies are applied by other SC members. These different SCC possibilities and SC characteristics make successful implementation or intensifying SCCs harder.

This chapter provides an introduction to the study. Firstly, the cooperating company is introduced in Section 1.1. Afterwards, the problem definition including research questions are presented in Section 1.2. Then the scope of the research is discussed in Section 1.3, followed by the methodology in Section 1.4. Lastly, Section 1.5 presents the structure of the remaining of this report.

1.1 Company description

The project is conducted in cooperation with the forecast and replenishment (F&R) department of Jumbo supermarkets B.V., hereafter referred to as Jumbo introduced in Section 1.1.1. Next, Section 1.1.2 provides a detailed description of the F&R department and processes.

1.1.1 Company introduction

Jumbo is a Dutch supermarket chain founded in 1921. Jumbo is the second-largest grocery retailer in the Netherlands, with a market share of 21.8% at the end of 2021. Besides, Jumbo is a family-owned service-oriented supermarket using an omnichannel strategy to be where the customers would like to be served. First, Jumbo has approximately 705 stores in the Netherlands and Belgium. Second, they offer a food market concept in which the idea of regular supermarkets is extended with freshly prepared food by professional chefs. Third, they operate in urban areas with compact Jumbo city stores. Finally, Jumbo offers products online and deliver via home delivery or pick up points. In recent years, Jumbo has experienced strong growth mainly through acquisitions of other supermarkets and the construction of new stores. As for now, Jumbo employs approximately 100.000 people, realizing a turnover of 9.91 billion in 2021 (Jumbo, 2021).

The goal of Jumbo is to continuously exceed customers' expectations. Therefore, they aim to surprise their customers every day, with the unique combination of a large assortment, the best service, and low prices. Besides, Jumbo formulates their goal into the following seven certainties: (1) Euros cheaper, (2) Service with a smile, (2) For all your groceries, (4) Fresh is also really fresh, (5) Smooth shopping, (6) Not satisfied? Money back!, (7) Your wishes are most important. Jumbo implemented these certainties through their entire SC. Based on these seven certainties, it can be stated that the goal of Jumbo is to offer a large variety of products with high quality and freshness for the lowest possible price while simultaneously focusing on customer satisfaction. Finally, Jumbo operates according to an Every Day Low Pricing principle. They seem to be gradually moving away from this principle by launching various promotions recently.

1.1.2 Forecast and replenishment

The F&R department of Jumbo is part of the supply chain business unit. This unit is split into four product groups determined by the team division based on the replenishment responsibility for different products. Two of the product groups concern non-perishable products, and two groups concern perishable products. Each product group is divided into sub-product categories. For example, one perishable product group consists of the subgroups AGF (potatoes, vegetables, fruit), bread, ready-made meals, fresh juices, and frozen goods. The product's shelf life differs strongly among these subgroups. The product's shelf life differs strongly among these subgroups. Additionally, the F&R department formulated a mission in line with the seven certainties of Jumbo. This mission statement reads:

"Forecasting & Replenishment contributes to customer satisfaction by ensuring maximum availability, quality and freshness at optimal costs by managing the entire supply chain from supplier to fridge and cabinet, for bricks and clicks."

From this mission, a few smaller goals can be derived. The F&R department aims to maximize customer satisfaction by ensuring maximum availability, quality, and freshness. Therefore, availability, quality, and freshness could be classified as the key performance indicators of the F&R department. Jumbo aims to satisfy these goals at optimal cost by managing the entire SC from supplier to customer for both online and offline shopping. As a result, Jumbo is convinced

SC management and collaboration are effective means to achieve their goals. To realize this F&R mission, Jumbo set up a distribution network containing six distribution centres (DC). There are two types of DCs, regional DCs and national DCs. The national DCs distribute products to all the Jumbo stores. However, regional DCs only distribute products to stores in their region. Therefore, approximately the same products are stored on the regional DCs.

There are two product flows in the DCs of Jumbo, stocked, and non-stocked. The non-stocked product flow is labelled as cross-docking, meaning that products delivered at the DC are directly distributed to the stores. Moreover, the replenishment process of the DCs is be divided into three processes, manual replenishment, multi-echelon replenishment (MER), and vendor managed inventory (VMI). In addition, the replenishment policy of Jumbo in the DCs and stores is a standard (R,s,nQ) inventory model. This classic inventory model means that every review period (R) is checked if the inventory position is below the reorder level (s). If this is true, an order of size (n) times the order quantity (Q) units is placed, with n the minimum integer needed to bring the inventory position after ordering back to or above the reorder level (Donselaar van & Broekmeulen, 2014). Finally, stores place orders in two ways, hands-off and hands-on. Hands-off means that stores cannot modify automatically generated orders. With hands-on, however, stores can adjust the recommended orders.

The manual replenishment process uses DC outflow (orders from stores to DCs), DC inventory, and goods in transit for replenishment decisions. The replenisher manually estimates the required DC inventory based on historical DC outflow data, considering DC inventory, goods in transit, order batching, lead times, and review periods. Therefore, the manual replenishment process is not based on any forecast but only on historical DC outflow data. A consumer demand forecast is shared ahead of special periods like promotions. Moreover, Jumbo introduced multi-echelon replenishment (MER) to establish internal collaboration. MER employ the consumer demand forecast, store and DC inventory, and goods in transit to create an order proposal for the stores and DCs. Forecasters influence this forecast by adjusting some parameters like weather information, promotions, and holidays. MER generates order advice for the Jumbo stores and the DCs, based on the consumer demand forecast, DC and stores inventory, goods in transit, and safety stock norms. The expected aggregated store demand at each DC is derived from the proposed store orders, used to generate the order advice for the DC to the supplier. Almost all frozen and non-perishable products are forecasted and replenished by MER. However, less than 5% of the perishable products are replenished by MER. Since MER is considered a more accurate and less labour-intensive replenishment system, Jumbo aims to increase this percentage. This lagging percentage on perishable products is due to insufficient aggregated forecast accuracy, caused by the ability of stores to adjust orders and not accounting for waste. Finally, Jumbo introduced a VMI collaboration with a limited amount of suppliers. These suppliers manage the inventory of Jumbo by using DC inventory and store demand information. Data sharing with VMI suppliers occurs via Electronic Data Interchange (EDI).

When it comes to the current collaboration and information sharing between Jumbo and its suppliers, Jumbo distinguishes three categories: commodity, tactic, and strategic. The commodity level contains suppliers with the least intensive collaboration, mainly based on short-term contracts of about 12 to 18 months. During this period, suppliers receive weekly updates regarding the performance on primarily delivery KPI's like delivery completeness and punctuality, for which they are held accountable. The tactic level contains suppliers with a medium-intensive collaboration. These collaborations are based on multiple-year contracts of approximately 24 to 36 months. In cooperation with suppliers, replenishers focus on operational excellence by keeping track of performance deviations in predefined KPIs. Performance improvements are initiated and assessed from the perspective of collaboration and mutual dependence. Furthermore, agreements regarding seasonal trends and maintenance are monitored and prepared. The strategic level contains suppliers with extensive collaborations, based on contracts of at least 36 months. With these suppliers, collaboration projects are initiated on availability, responsiveness, quality, and SC costs. Besides, joint forecasting is performed with suppliers with tactic and strategic collaborations. Joint forecasting is mainly Excel based complicating the coordination and implementation of the forecasts. Finally, a substantial part of the information sharing and communication between Jumbo and its suppliers is manual by exchanging data stored in Excel via Email or telephone.

1.2 Problem definition

This section presents a detailed definition of the problem Jumbo faces. Section 1.2.1, provides the problem statement, followed by the corresponding research questions in Section 1.2.2.

1.2.1 Problem statement

The F&R roadmap of 2020 states that Jumbo aims to intensify the collaboration in the SC by integrating its suppliers. Moreover, Jumbo aims to further improve their internal collaboration in their SC by, among others, including perishable items in the MER system and realizing hand-off store orders for all products to increase the forecast accuracy. These objectives stem from positive effects on the performance of products that have already achieved a higher level of internal collaboration. In addition, in the F&R mission, it is stated that SC management and collaboration could result in enhanced, availability, quality, freshness, and costs (Jumbo, 2020).

The current form of collaboration in Jumbo's SC leaves a lot of potential untapped to enhance SC performance. Nowadays, there is a limited large-scale collaboration in Jumbo's SC on a tactical and strategic level like structural and continuous information sharing and concrete process redesigns. Additionally, Jumbo has established intensive collaboration with a select number of suppliers. This limited collaboration level results in some contemporary problems. Firstly, suppliers have no insight into future orders, so suppliers make individual demand forecasts. Second, suppliers keep high inventory levels to achieve decent service levels at the expense of freshness and quality for perishables. Third, suppliers produce inefficiently and cannot deliver everything on time due to unexpectedly high orders. According to the roadmap, Jumbo believes that SCC could reduce safety stocks, lead times, and costs in the SC by reducing demand uncertainties and matching supply and demand (Jumbo, 2020). The reviewed literature, in Chapter 2, confirms these potential benefits of SCC.

In addition to information sharing, synchronisation of demand and supply processes between the retailer and manufacturer is another SCC approach. SC synchronisation can be achieved by coordinating the timing and quantity of orders by sharing the production schedules so products can be shipped immediately after production and making agreements about the order quantity (Haijema, 2013; Haijema & Minner, 2016; Vlist van der, 2007). Since Gosselink (2019) recently conducted a study on the applicability and benefits of VMI and SC synchronisation and Jumbo would like to move towards CPFR, this study mainly focuses on information sharing.

Despite the potential benefits of intensifying SCC, some challenges could attenuate these potential benefits. Jumbo already experienced some challenges during their VMI projects. The main challenge was the inability of suppliers to realize a sufficient forecast accuracy, resulting in lower service levels resulting in some failures of the VMI project. The performed literature research, provided in Chapter 2, confirms this challenge. Besides, the literature addresses additional challenges and barriers to acquiring intensive SCC. Since Jumbo already has experience with VMI, implementing Collaborative Planning, Forecasting, and Replenishment (CPFR) could be a logical next step. CPFR is a bundling of a business process to improve overall SC performance through joint planning and decision making by sharing information, synchronised forecasts, risks, costs and benefits (VICS, 2004). However, the literature distinguishes different CPFR maturity levels, each more or less effective depending on SC and product characteristics. These challenges and barriers, together with the different SCC techniques, can make it difficult to determine the most appropriate SCC form. This problem description could be summarized in the following problem statement:

Jumbo lacks a clear vision to initialize a detailed plan to establish more intensive collaboration within their supply chain.

Based on the description of the current F&R process of Jumbo as described in Section 1.1.2, more directly applicable potential process improvements can be identified. Examples of such improvements could be the inclusion of the perishable products in MER, the incorporation of waste into demand forecasting, and improving the daily forecast accuracy. Therefore, the focus of this project on intensifying the external collaboration in the SC may sound a bit too progressive. However, there are already several ongoing projects to tackle these problems and realise their potential. Accordingly, this research focuses on creating a vision for how the external SCC could be intensified.

1.2.2 Research questions

Based on the defined problem stated, the research questions can be formulated. The goal of this research is to provide guidelines on how Jumbo could intensify the SCC. These guidelines could help Jumbo create a vision on which collaboration model is advisable with which type of product(s) and supplier(s). When creating these guidelines, it is crucial to consider that Jumbo has numerous suppliers and that both Jumbo and these suppliers should acknowledge the potential of the collaboration. This research goal directs to the following research question (RQ):

Which supply chain collaboration model should be used to efficiently improve supply chain performance considering different supply chain conditions (e.g., perishability, demand variability, case pack sizes)?

To answer the main research question, five sub research questions are formulated. First, different SCC models have to be identified. In addition, the difference in potential benefits on the SC performance and the effect of SC conditions on these potential benefits must be determined. Therefore, the first research question (RQ1) is stated as follows:

RQ1: *Which supply chain collaboration models exist, and what are supply chain conditions influencing the potential of these supply chain collaboration models?*

Second, the requirements needed to successfully establish each SCC model with different types of SC members should be identified. This identification should provide insight into the requirements needed to realize various SCC models and the desires regarding SCC. Thereby, the corresponding second research question (RQ2) looks as follows:

RQ2: *What are the collaboration requirements and desires of different supply chain members considering different supply chain collaboration models?*

Third, a scientific model of a collaborative SC has to be created. It is decided to model an SC with limited collaboration to ensure an iterative decision-making process for complex modelling decisions. This model has to be in line with the system characteristics stated in Chapter 1.2. The model uses different SCC models and SC conditions as input. Moreover, research questions three to five may be limited to a subset of SC conditions and SCC models. Afterwards, the model analyses the effect of these different SCC models under the predefined SC conditions on the SC performance. The third research question (RQ3) is formulated as follows:

RQ3: *How to model a collaborative supply chain considering different SCC models?*

Fourth, the effect of the SCC models on the SC performance under various predefined SC conditions can be analysed by extending the model created in RQ3. This analysis will provide insights into the performance difference between SCC models on various SC performance indicators under different SC conditions. This leads to the fourth research question (RQ4):

RQ4: *What is the optimal supply chain collaboration model under different supply chain conditions?*

Finally, the insights gathered in the previous research questions can be combined to examine the impact of the different SCC models under different SC conditions. Based on these insights, conclusions can be drawn regarding the optimal SCC model considering various SC conditions. Altogether, the fifth and final research question (RQ5) is formulated as follows:

RQ5: *What is the impact of implementing supply chain collaboration on the supply chain performance under different supply chain conditions?*

1.3 Research scope

The focus of this research is to help Jumbo create a vision of intensifying the external collaboration in the processes of their SC. Moreover, this scope is limited to the F&R processes of Jumbo's SC. This focus means that other SC processes like transportation and product development are outside the problem scope. Accordingly, the main focus of this project is on intensifying the collaboration between Jumbo and its suppliers. In addition, the focus is limited to the impact of intensifying the collaboration in Jumbo's SC. Other solution directions to reduce SC disruptions than SCC are outside the problem scope. Finally, the distribution of potential benefits generated by SCC across the SC is beyond the scope of this study.

As will be discussed in the research structure in Section 1.4, this research consists of two phases. As both phases serve different purposes, they have different scopes. The first phase consists of a qualitative analysis aiming to gain insights into F&R related aspects of the suppliers. Since this research intends to assist Jumbo to create a vision of intensifying external collaboration, a representative mix of supplier characteristics should be selected. Therefore, the scope of the first phase is relatively broad. The second phase aims to gain quantitative insights into to potential impact of SC conditions identified in the first phase on the performance of different SCC models. However, since SC consists of various elements, processes and exceptions, the scope will be limited to a subset of SC conditions (e.g., perishability, lead times, case pack sizes, production changeover times, demand variability.). The aim is to select these conditions and SCC models based on the gained insights in the first phase.

1.4 Research methodology

The research questions can be divided into two types of research, namely exploratory and explanatory research. The exploratory research conducts qualitative data analysis and the explanatory research quantitative data analysis. The methodology that combines qualitative and quantitative research is called mixed-method research. Mixed-methods research is an approach to an inquiry involving collecting both quantitative and qualitative data, integrating these two data forms, and using distinct designs that may concern philosophical assumptions and theoretical frameworks. The core assumption of this form of inquiry is that the integration of qualitative and quantitative data yields additional insight beyond the information provided by either the quantitative or qualitative data alone (Creswell & Creswell, 2018). Since qualitative and quantitative data provide different types of information, the combination could result in a broader understanding. Creswell & Creswell (2018) defines three core mixed methods designs, convergent, explanatory sequential, and exploratory sequential. The exploratory sequential design is applied in this research. A schematic overview of this method is shown in Figure 1.1, consisting of three phases. This model is used as a guideline to ensure that all steps for proper research are conducted. The first two phases of this design are combined into one phase, the exploratory phase. Moreover, the third phase of this design is labelled as explanatory research.

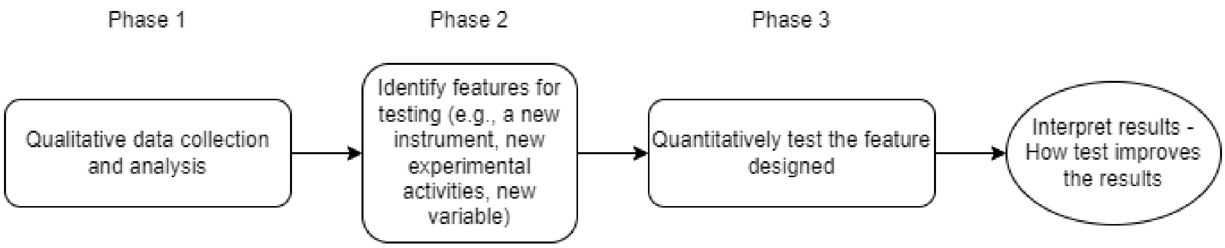

Figure 1.1: Exploratory sequential design by Creswell & Creswell (2018)

The exploratory research phase is performed to answer the first two research questions. Exploratory research is a methodological approach that investigates research questions aiming to explore something new or get an in-depth understanding. Moreover, exploratory research is often qualitative, because qualitative research is appropriate to explore new topics and identify needs and new concepts (Hennink et al., 2020). Since the first two research questions aim to explore different SCC models, influential factors, and suppliers' needs and desires, an exploratory research design with a qualitative methodology is used to answer these questions. The explanatory research phase is performed to answer research questions three to five. In this research, the explanatory research aims to acquire an in-depth understanding of the impact of different SCC models through quantitative analysis. Quantitative analysis is appropriate to reveal underlying patterns and relations based on data analysis, corresponding with the purpose of the explanatory research. The methodologies of both studies are explained in detail in the chapters of each study.

1.5 Report outline

The remainder of this report is structured as follows. Relevant literature is reviewed in Chapter 2. Chapter 3 discuss the exploratory research. Findings of the literature review and exploratory research serve as input for the explanatory research discussed in Chapter 4. Finally, the paper ends with conclusions and recommendations presented in Chapter 5.

Chapter 2

Literature review

This chapter reviews relevant literature aiming to answer the first two research questions. First, the most relevant SCC techniques are discussed in Section 2.1. Thereafter, Section 2.2 explains the development of SSC implementation frameworks. Finally, different maturity models for collaborative planning, forecasting, and replenishment from literature and reported practical implementations are reviewed in Section 2.3.

2.1 Supply chain collaboration techniques

The desire for shorter product life cycles, increased product variety, and better-informed customers has increased the pressure SCs. To excel under this increasing pressure, companies should effectively manage their SC (Sari, 2008a). Supply chain management (SCM) aims to vertically coordinate SC activities to serve end customers at a profit (Larson & Rogers, 1998). Therefore, SCM aims to responsively fulfil customer demand at the right time and place in the correct quantity. In addition, it is generally accepted that collaboration between SC members could improve SC performance by synchronizing supply and demand. Supply chain collaboration (SCC) refers to the collaboration of multiple companies to achieve a competitive advantage and higher profits than when they operate alone. Accordingly, SCC aims to generate a competitive advantage through short- or long-term partnerships between SC members (Ramanathan et al., 2011). In the past decades, several SCC techniques have been developed. However, the literature places most emphasis on the information sharing (IS), vendor managed inventory (VMI), and collaborative planning, forecasting, and replenishment (CPFR) collaboration techniques (Nimmy et al., 2019). Therefore, this research will mainly focus on these three techniques as well.

Information sharing refers to what extent information from other SC members is available for other SC members. Moreover, IS is considered as the most basic SCC technique essential to realize more intensive SCC techniques (Nimmy et al., 2019). The implementation of IS could result in a reduced bullwhip effect, reduced SC costs, and improved fill rates (Chen et al., 1994; Gavirneni, 2002; Kampen van et al., 2010; Moyaux et al., 2006). Additionally, SC could result in the delivery of fresher products in a perishable product SC (Ferguson & Ketzenberg, 2006; Ketzenberg et al., 2005). These positive effects on the SC can be enhanced for products with shorter lead times, larger batch sizes, and greater demand uncertainty (Aviv, 2001; Ketzenberg et al., 2005). Furthermore, Nimmy et al. (2019) concluded, based on a literature review, that cost associated with technology and lack of trust between SC members are the major hindrances in establishing successful IS.

Vendor managed inventory implies that the vendor manages the inventory levels of the retailer, and thereby, transparency is created by sharing real-time customer demand at the retailer with the vendor (Waller et al., 1999). The most emphasized benefits of VMI in the literature are a reduced demand uncertainty and fluctuations resulting in a reduced bullwhip effect, and reduced SC costs (Ramanathan et al., 2011; Waller et al., 1999). Moreover, VMI could improve the transport and production planning, enhance the service levels, and improve the product availability (Hidayat et al., 2011). In perishable product SCs, VMI implementations could reduce spoilage costs (Ketzenberg & Ferguson, 2008). Furthermore, the SC conditions influencing the VMI performance are similar to those mentioned for IS. Finally, trust and a proper information sharing system are the most addressed challenges in the literature (Borade et al., 2013).

As the name implies, CPFR includes collaborative planning, forecasting, and replenishment in a single framework. The idea behind CPFR is that a cohesive bundle of a business process aiming to improve overall SC performance through joint planning and decision making by sharing information, synchronized forecasts, risks, costs, and benefits (Thomé et al., 2014; VICS, 2004). The most emphasized benefits of CPFR are: improved service level; reduced inventory and SC costs; greater integration, visibility, and cooperation; and a holistic SC management approach (Hollmann et al., 2015). In the perishable product SC, CPFR could realize additional benefits, improved service levels, less waste, and lower inventory levels (Du et al., 2009; Shen et al., 2009, 2011). Furthermore, the benefits of CPFR could increase when inventory holding costs, demand variability, backorder penalty costs, and delivery lead times increase (Kamalapur & Lyth, 2014). However, since CPFR is less specific and requires a higher collaboration level, a greater variety of challenges and obstacles have been identified in the literature (Hollmann et al., 2015; Niemann et al., 2018). The main difference between VMI and CPFR is that the retailer and producer are jointly responsible for the planning, forecasting, and replenishment processes of CPFR, whereas with VMI the responsibility of the replenishment process lies with the supplier, and the production operations and demand synchronization occur internally at the supplier.

Altogether, IS is the most basic SCC technique required to implement a more intensive SSC technique, like VMI and CPFR. Therefore, it is impossible to implement VMI or CPFR without implementing IS. Besides, CPFR requires a more intensive collaboration level between SC members than VMI. Moreover, it could be expected that VMI results in better SC performance than IS and that CPFR, in turn, outperforms VMI under ideal conditions (Sari, 2008b). Nonetheless, it is more interesting how the gained performance from each SCC is influenced by specific SC conditions. Based on the literature review of the individual SCC techniques and the comparison of these techniques, it could be concluded that SCC initiatives with a higher level of collaboration seem to have a higher potential in improving SC performance indicators. The performance gap between these different SCC initiatives seems reduced by specific conditions (short lead times, low demand variability, tight capacities, and inaccurate information) (Audy et al., 2012; Kamalapur et al., 2013; Ketzenberg & Ferguson, 2008). Additionally, a more comprehensive and intensive SCC technique could be associated with greater implementation barriers and challenges. Concluding, a cost-benefit analysis should be performed to select the most applicable SCC technique.

2.2 Supply chain collaboration implementation frameworks

In addition to the definition and effects of the SCC techniques, the literature also focuses on the implementation of these techniques. Based on the literature review, there seems to be a lack of concrete frameworks and guidelines on how to implement IS and VMI. Contradictory, quite some literature focuses on defining an efficient framework for CPFR implementation. This difference may be explained by the difference in complexity of implementing IS or VMI compared to CPFR.

Concerning the general implementations frameworks, like IS and VMI, two frameworks are developed in the literature. The first model developed by Min et al. (2005) covers the progression of an SCC in three phases named antecedents, collaboration, and consequences. Criticism on this model is that this model does not include any iterate step (Ho et al., 2019). Iterative steps should be included in the implementation process to achieve a never-ending process with continuous improvements which are critical to the success of SCC (Ho et al., 2019). The model developed by Fawcett et al. (2008) contains three phases to guide organizations through the SCC implementation process by mainly focusing on the transformation phase. However, this model only provides guidelines on the transformation instead of the complete implementation process (Ho et al., 2019). Concluding, there seems to be no generally accepted SCC implementation framework in the literature.

In contrast to the general implementation frameworks, a relatively large variety of CPFR implementation models are developed. A significant proportion of these models are based on the framework developed by VICS (1998). This framework consists of a linear model with nine activities: (1) develop front end agreement, (2) create a joint business plan, (3) create a sales forecast, (4) identify exceptions to sales forecast, (5) resolve exceptions to sales forecast, (6) create order to forecast, (7) identify exceptions to order forecast, (8) resolve exceptions to order forecast, (9) generate orders. Several studies made small adjustments to this original CPFR implementation framework. However, Fliedner (2003) was the first to introduce an iterative framework containing 5 steps. In 2004 adopted this iterative idea and transformed the original framework from 1998 to a cycle model with four activities and eight tasks as displayed in Figure 2.1. However, this iterative model is not accepted in the literature because a relatively large number of different types of frameworks is developed afterwards. Finally, Niemann et al. (2018) concluded that practical CPFR implementations are hardly based on the implementation models developed in the literature indicating the difficulty in developing useful implementation frameworks.

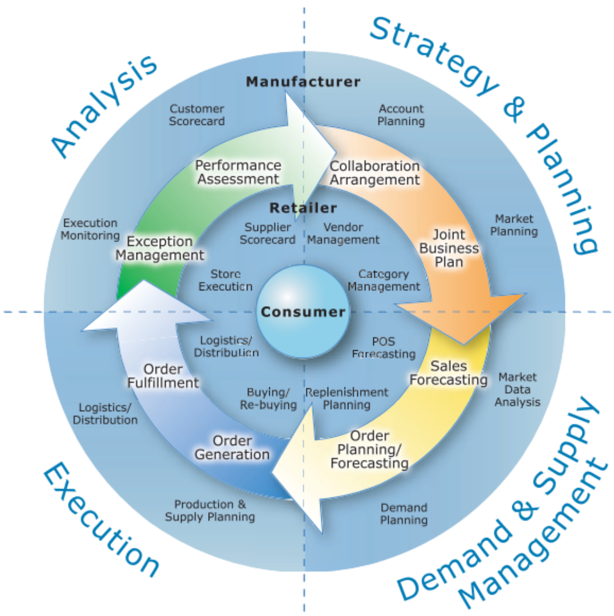

Figure 2.1: Manufacturer and retailer tasks CPFR by VICS (2004)

2.3 CPFR maturity models

In addition to the focus on implementation frameworks, the literature also emphasizes the development of CPFR maturity models. This emphasis seems to have arisen from the practical desire for a more concrete interpretation of CPFR. In contradiction to IS and VMI, CPFR is a more comprehensive SCC technique. This comprehensiveness means that CPFR can generate high potential benefits but is less concrete than IS and VMI.

Over the years, various maturity models for SCC are defined in the literature. These models differ in terms of the number of maturity levels and the level of detail. For example, the CPFR maturity model of Larsen et al. (2003) consist of three levels, basic, developed, and advanced. In this model companies access basic CPFR-like agreements due to its low transactional costs, move to a network perspective under developed CPFR and into a mutually beneficial long-term resource-based view exchange under advanced CPFR (Larsen et al., 2003). Parsa et al. (2020) recently developed a more detailed CPFR maturity model. They proposed a four-tier CPFR maturity model based on multi-object decision analysis. In this mode, tier 1 is the most advanced collaboration level and tier 4 is the most basic maturity level. Table 2.1 categorizes and describes the characteristics of these four maturity tiers. When critically evaluating these maturity levels, it could be questioned to what extent the lowest tiers are actually of a CPFR collaboration level.

Table 2.1: CPFR maturity tiers by Parsa et al. (2020)

Tiers	Collaboration Level	Collaboration areas	Planning Horizon	Information sharing level	Performance measurement level	IT proficiency
Tier 4	Nothing to minimum internal Collaboration	Sales and order generation	Short (less than a month)	Minimal forecast sharing. Reactive to demand order generation	Activity or operational level only	No collaboration technology framework
Tier 3	Mostly Inter-organizational Collaboration between departments	Key activities to support sales and operations	Medium (few weeks to 2 months)	Point of sales, demand forecasts	Some organizational level but mostly operational	Inter-departmental links to support internal operations
Tier 2	Between business partners	Forecasts, order plans, future initiatives	Internally medium -long (2-12 months). Externally a few months	Routine forecasts and order plans, promotional plans	More sophisticated based on forecast accuracy and revenue plans	Begins to link business partners through sharing spreadsheets
Tier 1	Strategic partnership with integrated business plans and common goals	Daily forecasts, order plans, and future initiatives	18-24 months	Beyond information, personnel and physical resources are shared	Key indicators such as market share and profitability. Continuous improvement initiative	Enterprise level technology solutions

In addition to the CPFR maturity levels defined in the literature, CPFR maturity levels could be extracted from practical reported CPFR implementations. Based on these practical CPFR implementations it could be concluded that the project scope of practical implementations differs from the scope suggested in the literature. First, the main focus of these practical projects is on improving forecast accuracy, service levels, stock-outs, inventory management, and production planning. Second, the project mainly focuses on the middle of the supply chain and barely use point of sales data. Third, the project seems to emphasize more on special products like promotion and new products than on standard products. Therefore, the distance between upstream SC members and the end customer is relatively large. Finally, the major challenge in this project is to integrate the improved forecast in their daily operations which attenuate the benefits of CPFR (Accenture, 2001, 2002; Seifert, 2003).

Chapter 3

Exploratory research

The previous chapter describes the current academic knowledge in the literature related to the problem, recognising the potential and complexity of SCC. This chapter considers the exploratory research phase of this study, the purpose of which is twofold. The first objective is to gain insights into the needs and desires of the retailer's suppliers. Since all cooperating parties must recognise the added value of the collaboration to be successful, it is crucial to identify their needs and desires. In addition, desires of different supplier types and factors that may influence SCC benefits can be identified. These insights can be used to differentiate the preferred SCC models based on supplier characteristics. The second objective of the exploratory phase serves as the basis for modelling SCC in the explanatory phase. In the next section, Section 3.1, the method of the exploratory research phase is defined. Then, Section 3.2 presents the results from the conducted interviews. Afterwards, these results are consolidated into an SCC model in Section 3.3. Finally, Section 3.4 concludes the exploratory research.

3.1 Method

Given the exploratory nature of the objectives described above, a qualitative research approach is selected. Qualitative research is appropriate to explore new topics and identify needs and new concepts. Therefore, qualitative research is best suited for answering "why" questions to explain and understand problems or "how" questions that describe processes or behaviours (Hennink et al., 2020). These characteristics make a qualitative research approach suitable for achieving the objectives of the exploratory research phase.

Data for the exploratory research is collected through in-depth interviews with a selection of the retailer's suppliers. An in-depth interview is a one-to-one data collection method involving an interviewer and one or multiple interviewees discussing specific topics in-depth (Hennink et al., 2020). In addition, a semi-structured interview guide is used to guide and structure the interview. An interview guide is a list of topics to be covered during the interview, with questions for each topic. Moreover, a semi-structured interview is an interview type where the interviewer asks a few predetermined questions while the remaining questions are not planned. Therefore, the interviewee gets the opportunity to elaborate and explain particular issues through the use of open-ended questions (Alsaawi, 2014). The unstructured part of the semi-structured interviews provides the necessary flexibility to gain new insights during the interview. Although, the structured part of semi-structured interviews ensures that the qualitative data is reliable and comparable (Creswell & Creswell, 2018; Hennink et al., 2020).

The interview guide is developed through an iterative process. Since there is only one opportunity to conduct each interview and the interview guide significantly affects the quality of the qualitative data, the interview guide is discussed with the project's stakeholders. Besides, insights from the literature review are considered during the development process of the interview guide. The final interview guide contains six topics: (1) introduction, (2) current collaboration, (3) desired collaboration, (4) SCC expertise and benchmarking, (5) influential factors, and (6) conclusion. The final interview guide is depicted in Appendix A. Hennink et al. (2020) recommends pilot-testing the interview guide to assess if questions are understood correctly. Due to the limited available time of suppliers, pilot testing is not performed as a separate step but is performed when discussing the interview guide with the stakeholders.

To obtain valuable information and ultimately draw valid conclusions, a representative set of suppliers must be selected. The emphasized criteria are brand type (private label or branded), shelf life (short, medium, or long), and experience in SCC. Based on the stakeholder discussions and literature review, it was expected that diversification in the SCC model could primarily take place based on shelf life and brand type. The SCC experience criteria are considered for benchmarking and learning. Suppliers are categorised as short perishable products suppliers when a majority of the product's shelf life is less than eight days, as medium when the shelf life is more than eight days but less than one month, and as long when the shelf life is more than one month. A branded product is a prominent or established product, while a private label product is a product exclusively produced for sales through a particular provider.

The supplier selection procedure was as follows. First, a supplier selection was provided by each supply chain manager based on the discussed interview goals and guide. Then, a selection was made in such a way that all criteria were adequately represented, and discussed with the retail stakeholders as final verification, after which they made initial contact with the suppliers. Through this procedure, thirteen suppliers were selected in total. Due to confidentiality, no names or unique characteristics are stated. An overview of the interviewed supplier characteristics is provided in Table 3.1. This table shows that all suppliers of short perishable items supply private label products because many ultra-fresh products do not contain a brand. In addition, the ratio of premium brand and private label suppliers is roughly equal among suppliers of non-perishable products. Finally, three suppliers supply both premium and private label products, and one supplier provides both medium and long shelf life products.

Before the interviews, concrete information regarding the scope of the study and topics to be discussed during the interviews was shared with all participating suppliers. By sharing this information in advance, the participating suppliers were given the opportunity to prepare and possibly invite colleagues to achieve the desired depth during the interviews. All interviews are recorded to allow the interviewer to concentrate on the interview rather than writing notes and to make a retrospective evaluation (Creswell & Creswell, 2018). Finally, all interviews were conducted on an online platform.

After the research design and data collection method are defined, the analysis method is discussed. The outline of the qualitative data analysis is defined based on the data analysis process in qualitative research by Creswell & Creswell (2018), consisting of 5 iterative steps. In the first step, the data is organized and prepared for analysis by extensively summarizing the interviews based on the interview guide. Therefore, the answer to each question in the guide is extensively summarized based on the recordings and notes taken. The extensive summary was shared with the interviewees to verify the findings and to revise incorrectly interpreted answers. A general feeling and first impression of the data is created in the second step by carefully reading all the data and re-listening to the recordings. In the third step, all data is coded. Coding is the

Table 3.1: Overview interviewed supplier characteristics

	Shelf life			Brand	
Supplier	**Short**	**Medium**	**Long**	**Private label**	**Premium**
A	X			X	
B	X			X	
C	X			X	
D	X			X	
E	X			X	
F		X		X	X
G		X		X	X
H			X		X
I			X		X
J			X		X
K		X	X	X	
L			X	X	
M			X	X	X

process of organising and labelling the qualitative data by putting brackets on chunks and writing a word representing a category in the margins (Rossman & Rallis, 2012). Based on the codes, themes and descriptions can be identified in the fourth step. Descriptions involve a detailed information rendering which could be used for designing detailed descriptions. However, themes are more overarching categorisations displaying multiple perspectives supported by quotations and specific evidence (Hennink et al., 2020). Finally, the descriptions and themes are represented in the fifth step to identify underlying relationships. In this research, the fifth step is performed by conveying information about each supplier in a table based on the identified themes and descriptions. In this way, it is possible to identify certain underlying relationships and identify differences between the interviewed suppliers.

3.2 Results

This section presents the results of the qualitative research obtained by the method as discussed in section 3.1. The presentation of the results will be organised in a similar sequence as the topics in the interview guide. First, the results will be presented regarding the current collaboration, followed by the desired collaboration. Then, the benchmarking results will be presented. Finally, the findings regarding factors influencing collaboration performance will be discussed. Additionally, all participants expressed their appreciation for the retailer's initiative of investigating SCC. Finally, all interviews were generally experienced as open and constructive. The interview results per interviewee are shown in Appendix B, and the interviews took approximately 43 minutes on average.

3.2.1 Current collaboration

The interview results regarding current collaborations can be divided into general collaboration (e.g., communication, personal contact) and information sharing aspects.

3.2.1.1 General collaboration aspects

All interviewees indicated satisfaction with the current collaboration and recognised the added value of SCC. However, it can be deduced from all interviews that there is potential for improvement, which could enhance the performance of the entire SC. In general, the current collaboration is described as intensive due to frequent contact with different organisation levels. Much information sharing takes place through this intensive contact. Moreover, a major part of the interviewees stated that this intensive collaboration enhanced the SC performance and maintains performance during uncertain periods like promotions or public holidays. Furthermore, most interviewees acknowledge the added value of intensive collaboration for regular products because good performances can change quickly (e.g., during COVID lockdowns), and regular product SCs can be improved. In addition, some interviewed suppliers established an extensive strategic collaboration involving common strategic objectives, intensive IS, joint forecasting, common identifying and discussing possible improvements, and proactive problem-solving. In these collaborations, the supplier thinks along proactively and provides input on optimising customer satisfaction and acts following similar objectives. This type of collaboration is the most intensive collaboration form mentioned during the interviews. Furthermore, there are no significant differences between suppliers of different brands and shelf lives.

3.2.1.2 Information sharing aspects

In terms of information sharing, a difference can be observed between suppliers of products with different shelf lives. An order forecast in advance of promotions or special periods is generally shared with all types of suppliers. The objective of this forecast sharing is to achieve good performances during these uncertain but important periods. Additionally, a consumer demand forecast is shared with some suppliers of mainly medium or long shelf life products. However, suppliers stated that this forecast is not always helpful due to the difficulty of predicting the retailer's ordering behaviour. Therefore, it is difficult for the suppliers to estimate the retailer's orders based on the consumer demand forecast. Some suppliers of mainly perishable products receive an order forecast, which is a conversion of the consumer demand forecast. Finally, any additional information (e.g. inflow or outflow of products) is shared through intensive contact between the retailer and suppliers.

The shared forecast is mainly compared to the supplier's forecast, after which significant differences are communicated with the retailer. Afterwards, the shared forecast mainly serves as input for the supplier's order forecast. As indicated above, the usefulness of the shared forecast is limited. Furthermore, several suppliers stated that the sharing frequency and forecast horizon are not coordinated. This shortcoming makes it difficult for suppliers to organise other processes, such as the production process, based on the shared forecast. The applicability of consumer demand forecast sharing depends on the extent the consumer demand is disrupted by, for example, order batching and waste. Hence, the current form of forecast sharing is mainly helpful to identify potential delivering problems by comparing the consumer demand forecast and production volumes. In addition, there is quite some discussion about the interpretation, correctness, and accuracy of the shared information, which is at the expense of applicability and impact. Moreover, some providers noted that the usefulness of the shared forecast depends on its accuracy, which leads to difficulties in correctly interpreting and using the shared information. Finally, the current IS process could be classified as labour-intensive because the information is mostly shared through personal contact and mail.

3.2.2 Desired collaboration

The results regarding the desired collaborations can be divided into general collaboration, information sharing, and collaboration objective aspects.

3.2.2.1 General collaboration aspects

The vast majority of the interviewees stated to be satisfied with the current way of collaborating. However, some interviewees mentioned that this contact intensive collaboration should yield results in the upcoming period while reducing the labour intensity. The suppliers with less intensive current collaboration expressed the need for periodic strategic meetings to align long-term objectives and focus points. The results of the common objectives will be discussed later. As discussed in Section 3.2.1, there is currently quite some discussion about the interpretation of shared information, to the detriment of the applicability and impact of this information. When standardized IS is realized, both can consider the shared information objective and factual. At this point, it is no longer necessary to discuss the completeness and correctness of the data, whereby the focus can shift to identifying and discussing exceptions and concrete directions for improvement. Therefore, an automated, standardised and uncontested IS process can improve SC performances by focusing on the information deployment. In addition, it is stated that the quality of the shared information affects applicability, hence transparency about the information quality is essential. Finally, structural IS could create a continuous incentive for the supplier to look for and implement improvements. When information is exchanged more ad hoc, this incentive is based on the moment of sharing information versus the continuous search for improvements. Thus, structural IS could cause a shift from a reactive to a proactive improvement process.

3.2.2.2 Information sharing aspects

The interview results regarding information sharing for suppliers with different shelf lives show a clear division in the desired types of information. Forecast sharing can be considered the most basic information in collaboration. Forecast sharing can be split into two types of forecast sharing, long and short term. Suppliers can use short-term forecasts to align their production planning. Long-term forecasts could be used to improve the procurement of raw materials, capacity planning, and personnel planning of the supplier. Suppliers of products with a short and medium shelf life expressed the need for daily forecast sharing with the desired horizon of two to four weeks. Besides, suppliers of products with a long shelf life expressed the need for daily or weekly forecast sharing with the desired forecast horizon of four to eight weeks. A horizon of six to twelve weeks is indicated for the long-term forecast, in which no clear distinction can be made between suppliers. In addition to sharing the forecast, the importance of timely sharing commercial and promotional decisions influencing consumer demand is addressed. Whether an order or consumer demand forecast is preferred depends on the extent the consumer demand is disrupted by, for example, order batching and waste. When the consumer demand can easily be translated into expected order, sharing consumer demand forecasts should be useful. Otherwise, the consumer demand forecast is not very useful. Concluding, when forecast information is shared, the user's needs and the objectives of the shared forecast must be taken into account.

In addition to forecast sharing, inventory information can be identified as the next type of desired information. A major part of the interviewees indicated that DC inventory information could be effective to prioritise the production and delivery of certain products. Sharing DC inventory enables the supplier to estimate which products are in the greatest need. An enhanced prioritisation could reduce the out of stocks by employing echelon inventories for replenishment. Moreover, safety stocks could be reduced when safety stocks in the SC are comprehensible because the levels and locations of the safety stocks can be calibrated. Primarily suppliers of products with short and medium shelf lives indicated the need for store inventory information.

Sharing additional information, like point of sales (POS) data, is classified as the final desired type of information. It is possible to respond quickly to changes in consumer demand by using POS data. Additionally, POS data could be classified as the purest and undistorted form of demand data. However, disruptions and adjustments to the POS data make it difficult for upstream suppliers to estimate further orders. Finally, POS data is useful as input for analyses to create valuable insight. Nevertheless, the retailer might decide to acquire these insights himself instead of outsourcing to the supplier. In conclusion, sharing and analysing POS data has great potential and is the purest demand data. However, its applicability in the short term seems minimal due to the disruptive factors. In the shorter term, however, it will be possible to share valuable insights from the analysis of POS data with suppliers.

3.2.2.3 Objectives of collaboration

Interviewees mentioned the importance of aligned objectives and priorities. Currently, the retailer's and supplier's interests can conflict, making it harder to optimise SC performances. An example from several interviews is that the retailer evaluates the supplier's performance mainly on complete and on-time delivery. As a logical consequence, suppliers may hold larger safety stocks at the expense of freshness for perishable products. An important note when determining joint KPIs is that all parties involved could influence the performance of the KPIs. All participants must agree on the measuring method and norms of the KPIs, so the use is unambiguous. In addition, the interviewees mentioned that having joint KPIs contributes to a common focus to achieve the same goals.

Almost all interviewees noted the consumer service level as an important joint KPI. Using the consumer service level as a joint KPI could cause the SC to focus on enhancing the consumer service level instead of each echelon trying to improve their performance. In an ideal state, improving customer satisfaction and demand should be the ultimate goal of the entire SC, to which individual interests are subordinate. In addition, some interviewees mentioned differentiation of the service level so that all SC members focus on the same products with the highest priority. Furthermore, waste is emphasised as a common KPI by perishable products suppliers. A more interesting difference is that a majority of the supplier of non-perishable products expect that complete and on-time delivery remains essential KPIs, in contrast to suppliers of perishable products who mentioned (joint) forecast accuracy as an important KPI. This difference could be explained by the slightly greater importance of an accurate forecast for perishables. It is important to note that suppliers of non-perishable products recognize the importance of forecast accuracy, but have not explicitly named them as a KPI.

3.2.3 Benchmarking

A majority of interviewees reported experience with SCC. The current collaboration is considered intensive, advanced, and pleasant compared to other retailers. However, most suppliers of non-perishable products indicated that IS with other retailers is more sophisticated because forecast and inventory information is automatically shared and better aligned with the supplier's needs. A few interviewees indicated receiving POS data as well. Therefore, collaboration with other retailers is often based on intensive IS rather than intensive personal contact. Nonetheless, there is a suspicion that such an intensive form of IS has been mainly established with larger retailers. Some interviewees mentioned that a retailer invested in a VMI collaboration years ago, including the necessary information exchange, and is well advanced now. However, multiple suppliers of perishable and non-perishable products mentioned that a VMI collaboration is less applicable for products with short shelf lives. However, this difference is less evident for suppliers of products with a short or medium shelf life. A majority of these suppliers indicate that the IS process is roughly similar. Finally, mainly suppliers of perishable products mentioned that the opportunity of stores to adjust orders complicates such data-driven collaboration due to the split in store and DC replenishment and the human factors influencing these processes. In conclusion, compared to other retailers, the information exchange with suppliers of perishable products has been further developed but is comparably intensive for products with a shorter shelf life.

From the interviews, it can be stated that the performance of both collaboration forms does not differ significantly. The interviewees indicated that intensive contact compensates for the lack of structural IS. However, such intensive collaboration requires an investment of many labour hours. In addition, experience is crucial since unexpected patterns and problems are early identified and solved based on experience. Furthermore, a positive aspect of a collaboration with intensive contact is flexibility. Interviewees indicated that it is possible to respond quickly to unexpected problems and changes in demand when there is intensive contact because it is easier to contact the relevant people and a certain level of trust is present. Altogether, collaboration based on data sharing can provide the fundamentals for enhancement because the focus can be on improvement, whereas collaboration based on contact can keep performance high in uncertain times.

3.2.4 Influential factors

During the interviews, some factors are identified which could influence the effectiveness or necessity of SCC. However, drawing generic conclusions is more difficult because interviewees are focused on the added value of collaborations for their products, making it hard to compare answers. Since all interviewees regard intensive collaboration as an opportunity, it can be assumed that collaboration has added value to all types of products and SC characteristics. Regardless, three influential factors are identified.

First, suppliers of products with long shelf lives mainly indicated the added value of an intensive collaboration for products with unstable demand or relatively low volumes. Intensive collaboration adds less value for products with relatively high and stable demand since it is easier to forecast demand resulting in high performances. According to these suppliers, unstable demand is mainly caused by promotions. However, since an everyday low pricing principle is used by the retailer, the number and impact of promotions could be questioned. Additionally, seasonality is addressed as another factor causing unstable demand. Therefore, the performance of products with strong seasonal patterns could be enhanced by intensive SCC. Finally, scarcity and complexity in the SC could increase the desire for more intensive SCC. For example, longer lead times in the supply could increase uncertainties and, accordingly, the added value of SCC.

Second, short and medium shelf life product suppliers indicated that intensive SCC adds more value for perishable than for non-perishables. The interviewed supplier who supplies both shelf-stable and perishable products acknowledges the additional added value of perishable products. Perishable suppliers indicated that the added value could be estimated based on the impact of the collaboration in terms of potential benefits. This impact could be estimated based on products values, sales volumes, vulnerability, and assortment importance.

Finally, it could be concluded that SCC adds more value to private label than premium products. Two causes for this difference are identified. First, private label products are exclusively produced for one retailer. Therefore, the potential sales market is smaller for private label than premium products. This tightness in the sales market could result in less flexible SCs, which are less likely to respond to unexpected changes in demand. Second, it could be easier for private label products to accomplish sufficient trust and transparency required for intensive collaboration. For example, it could be easier to establish transparency about costs and margins for private label than premium products. An important note is that this influence depends on the extent suppliers deliver predominantly private label versus premium products.

3.3 Supply chain collaboration model

The results from the interviews, as presented in Section 3.2, can be combined to create an SCC model with different levels. Since the main focus in the interviews was on improving the IS process, the different collaboration levels are mainly based on these results. Table 3.2 shows the type of information shared, intended information use, the potential benefits of the collaboration, and the corresponding KPIs of each collaboration level. As displayed in this table, four collaboration levels are defined where level one represents the least and level four the most intensive collaboration form. The classic supplier-retailer relationship, in which the retailer only places orders with the supplier after which the supplier tries to deliver them as agreed, is not included in the model. This classic relationship is excluded because such a relationship does not seem to be contemporary since forecast information is often shared in the run-up to promotions.

Several important aspects conducted from the interviews apply to all collaboration levels, which are discussed first. The current manual and hence labour-intensive information sharing process must be replaced by a systematic process reducing the labour intensity to establish a data-driven collaboration with more suppliers. Moreover, it could create unambiguously IS eliminating the discussion about the reliability and correctness of the data, which enhance the usability. Hereby, the focus could be on applying the sharing information in the daily operations and discussing exceptions to improve the forecast, operational processes, and data analysis. In addition, the retailer and supplier must coordinate the measuring method and norms of the KPIs to achieve general acceptance so that the KPI can be used to align attention.

In the first collaboration level, a short-term forecast is the only information shared with the supplier. Although this collaboration initially seems relatively simple, effective execution and implementation are more challenging than previously thought. From the interviews, it can be concluded that a successful implementation of a shared forecast is not a trivial task. Accordingly, the retailer must provide additional information to assist the supplier in using the forecast. First, the frequency of sharing, horizon, and aggregation level of the forecast must be aligned with the supplier's needs. Second, decisions affecting the forecast should timely be shared with the suppliers or included in the retailer's forecast. Thirdly, the retailer must be transparent about the forecast's accuracy, as it affects the applicability. Altogether, an accurate forecast in line with the supplier's needs including important complementary information must be shared. The supplier can match their production and transportation planning with the shared forecast. A better coordinated production and transport process can result in enhanced delivery performance. A recurring element during the interviews, but out of scope for this study, were transport processes. However, as it was a recurring element during the interviews, it is mentioned but not considered in the remaining of this research. Since the impact and insights of the supplier on downstream processes are limited, the main goal of this collaboration should be complete and on-time delivery.

Table 3.2: Supply chain collaboration model

	Collaboration level			
	1	**2**	**3**	**4**
Information sharing				
Short term forecast	X	X	X	X
Long term forecast		X	X	X
Inventory			X	X
Point of sales				X
Intended data usage				
Alignment of production process	X	X	X	X
Alignment of transportation process	X	X	X	X
Alignment of procurement of raw materials		X	X	X
Alignment of personnel planning		X	X	X
Product prioritisation			X	X
Quick response to demand patterns				X
Common analysis possibilities				X
Benefits				
Improved deliveries performance	X	X	X	X
Efficient inventory management			X	X
Efficient supply chain management				X
KPIs				
Delivery performance (complete and on-time)	X	X		
Consumer service level			X	X

The second level of collaboration extends the first level by sharing a long-term forecast with the supplier. The same points of interest as for the short-term forecast apply to the long-term forecast. So, the frequency of sharing, the level of aggregation and the horizon of the long-term forecast should also be tailored to the supplier's needs. It is plausible that the accuracy decreases for a longer-term forecast, where a higher aggregation level improves the accuracy. Since a higher level of aggregation can suffice for the long-term forecast, the required forecast accuracy can be achieved. As a result, transparency on forecast accuracy is needed. The long-term processes mentioned in the interviews are raw material procurement, capacity planning, and personnel planning. As the addition of sharing a long-term forecast does not influence the supplier's impact on downstream processes, the collaboration goal is unchanged. Finally, the implementation of this level is likely to be similar to the first level as only an additional forecast is shared. As the use and benefits are different from the first level, the forecast sharing levels are split.

The third collaboration level includes inventory information sharing, in addition to the short and long term forecast. Whether sharing DC and store inventory is required depends on the supplier's products type. Based on the interview results, it could be stated that suppliers of short shelf life products have a higher need for downstream information because of the difficulty in holding safety stocks. Suppliers of nonperishable items mainly mentioned their desire for DC inventory level as keeping a safety stock at the DC should be sufficient to supply the stores in time. Again, the frequency of sharing the inventory information should be aligned with the supplier. Sharing inventory information enables the supplier to estimate the products with the greatest need and give these products priority. In addition, the supplier can better assess when orders of which size will be placed, enabling replenishment based on echelon inventory. Additional information, like desired stock level, should be shared to make the inventory information valuable. Sharing inventory information also opens the dialogue to discuss the location and size of safety stocks. In contrast to the retailer, the supplier focuses purely on its products, which are considerably fewer in number, thus putting more emphasis on each product that could uncover potential improvements more quickly. Moreover, sharing inventory information provides the supplier with more downstream insights, whereby the focus can be on improving the service level. The aim of collaboration could be to improve the service level to the consumer. As a result, the ideal SC goal of improving customer availability will be pursued more widely throughout the chain.

The fourth collaboration level can be classified as a collaboration with complete transparency in data and information. With the addition of sharing POS data, the supplier possesses the rawest form of demand information. For POS data as well, sharing frequency and aggregation level must be synchronised with the supplier. In addition, the supplier must be aware of the retailer's forecast and replenishment processes. When many processes and human impact affect the translation of POS data into orders, the usefulness will decrease. This decrease could be explained by the complexity of assessing the effect of change in demand on the orders. POS data can be used to respond quickly to demand changes by, for example, adjusting the production process or proactively replenishing stocks to prevent shortages. Besides, the supplier could perform some analysis with the POS data to gain profound insights. The retailer could benefit from these insights when they are shared and aligned with the retailer's focus. However, these analyses also bring threats, as the purpose of the analysis could not be aligned or insights are passed on to competing retailers. Therefore, the collaboration must be based on a strategic partnership with a high degree of trust and transparency. Finally, such collaboration could aim to remove most of the company borders to achieve the highest goal of maximising customer service level.

Once the levels of collaboration have been defined, it must be determined with which supplier each level adds the most value. As concluded in Section 3.2.4, it is hard to make recommendations on the most suitable collaboration level for each type of supplier. This difficulty is due to the many different arguments for establishing intensive collaboration. However, it is possible to offer some guidelines that the retailer can use to determine which collaboration is appropriate:

- The desired flexibility in switching suppliers can help determine the appropriate level of collaboration. Retailers may desire certain flexibility in selecting suppliers for some product types to keep purchase prices as low as possible. When high flexibility is desired, it is harder to establish a relative intensive collaboration due to the lack of trust. Moreover, setting up a deep partnership is an intensive process that requires several investments. Therefore, setting up an intensive collaboration for only a few years could not be worth the investment.
- The goals of the collaboration are important to decide on the collaboration level some goals require high levels of collaboration, while for others, like increasing delivery performance, a lower level is sufficient.
- The ease of establishing collaboration based on trust and transparency may influence the collaboration intensity. This ease is affected by the extent a supplier exclusively supplies a single retailer. When a supplier only delivers to a single retailer, it may be easier to establish a higher degree of trust because the risk of sensitive data passing on to another retailer via the supplier is reduced. In addition, it may be easier to achieve a higher degree of transparency for private label products.
- The potential impact of an intensive collaboration could be advantageous to decide on the appropriate collaboration level. Five factors affecting the collaboration impact can

be conducted from the interviews, which are: sales volume, demand stability, product value, product vulnerability (i.e., shelf life), and product criticality. The absolute benefit of collaboration is likely to be greater for larger suppliers of products with relatively high volumes and many SKUs. Moreover, high demand uncertainty relative to the mean demand volume may be a primary driver for SCC. In addition, the impact in terms of the waste value can be determined based on product volumes, values and vulnerability. The potential benefit of collaboration for valuable products with a short shelf life, high demand, and high depreciation value is probably high. Lastly, some products may be crucial to the retailer for different reasons, making good performance desirable. An intensive collaboration can therefore be the method to realise this desired performance.

3.4 Conclusions

The exploratory research aims to gain insights into the suppliers' needs and desires and create an SCC model serving as input for the explanatory research. In this conclusion, the main findings of the exploratory research are discussed and reflected upon.

In general, the interviewees expressed their appreciation for the retailer's initiative to investigate SCC. Moreover, the interviews were experienced as open and constructive. The suppliers indicated to be satisfied with the current collaboration due to the intensive and frequent contact between several organisational levels. Structural IS takes mainly place via e-mail and primarily concerns forecast information, except for VMI suppliers with whom data is shared via an EDI linkage. Additional information is shared through intensive personal contact. Interviewees indicated that the intensive contact compensates for the lack of a data-driven collaboration and keeps performance up in uncertain times. Besides, suppliers recognised the added value in intensive forms of SCC. However, they also acknowledge the complexity of achieving intensive collaborations due to different barriers and challenges. Therefore, there seems to be an agreement about the added value of SCC, but realising and maintaining such an intensive collaboration does not appear to be a trivial task.

Some interviewees expressed the desire for a joint strategic vision for long-term collaboration, as aligning the collaboration goals is crucial in establishing an efficient collaboration. Moreover, most of the improvements identified are related to the IS process. The present data sharing process can be classified as labour-intensive, which reduces the time available for employing the shared data. Establishing a more data-driven collaboration could enable to focus on improving processes through the actual use of the shared information. Specifically, unambiguous, automated and vendor-tailored IS are identified as improvement opportunities. An unambiguous and automated form of IS could reduce the discussion on data reliability and labour intensity, allowing for improved processes utilising the shared data. In addition, emphasis is placed on aligning the shared information with the supplier's needs. Coordinating the aggregation level, frequency of sharing, and horizon are the stressed elements. Without this coordination, the usability of the shared information is limited because the shared information is unsuitable for the supplier to align processes.

In addition, different types of valuable information are addressed. Increasing in intensity, this concerns forecast, inventory, and POS information. Forecast information is the most appointed type of information used to synchronise supply and demand. Sharing forecast information enables suppliers to align their production and delivery process in the short-term and raw material procurement, personnel planning, and capacity planning in the long term. Moreover, transparency about the forecast accuracy is crucial since the accuracy directly affects the usability. In addition to forecast sharing, inventory information is classified as the second type of valuable information. Inventory information enables suppliers to prioritize products based on downstream needs and establish echelon replenishment. Sharing forecast information also opens the discussion on the levels and locations of safety stocks, which can improve the product flow. Finally, sharing POS data is the most enhanced type of information. Point of sales data enables the suppliers to respond quickly to demand patterns and perform in-depth analysis. Since POS data is valuable, a high level of trust is crucial.

A differentiation in information needs can be made between perishable and non-perishable product suppliers. Perishable product suppliers seem to have a greater need for more downstream information than non-perishable product suppliers. This difference can be explained by the greater complexity of perishable SCs, due to the difficulty of keeping inventories, which increases the need to respond promptly to demand changes. Finally, suppliers of both perishable and non-perishable products do not recognise the benefits of a VMI collaboration for products with a shorter shelf life.

To achieve a productive collaboration, the same objectives must be pursued. An appropriate form of collaboration and IS should be initiated based on the intended collaboration goals. Both suppliers and retailers must be able to influence the performance of the objectives. Non-perishable product suppliers mainly mentioned delivery performance (e.g., completeness and on-time delivery) and consumer service level as the most suitable objectives. Suppliers of perishable products classified the consumer service level, forecast accuracy and waste as relevant objectives. This classification highlights the desire of non-perishable suppliers to have more downstream information to reduce the distance to the consumer. This difference is also reflected in the division of responsibility. In general, it can be stated that suppliers of non-perishable products primarily focus on achieving sufficient availability at the DC level, and suppliers of perishable products focus more on the store level.

This research also serves the purpose of benchmarking the current collaboration. Most interviewees mentioned that the collaboration intensity depends on the retailer size. Moreover, one large retailer seems to establish a more data-driven collaboration with non-perishable suppliers. Mainly inventory and forecast information is shared in an advanced automated and unambiguous process. This data-driven character reduces the need for a contact intensive collaboration to keep the performance up. However, it can be concluded that more intensive contact is more useful during periods of uncertainty because rapid coordination is possible. The collaboration type and intensity for perishable products are roughly similar to other retailers. In conclusion, compared to other retailers, the collaboration is more data-driven with suppliers of non-perishables but similar with perishable suppliers.

Finally, factors affecting the effectiveness or necessity of SCC are identified. First, the desired flexibility in supplier selection could influence the appropriate SCC. High flexibility can make it harder to establish the necessary trust. Second, the intended goal of the collaboration could impact the intensity of the collaboration as different collaborations may serve various goals. Third, the ease with which trust and transparency can be built can influence because more intensive collaborations require higher levels of trust and transparency. Finally, the potential impact of SCC is likely to affect the appropriate SCC level. The impact of the SCC can be assessed by sales volume, demand stability, product value, product vulnerability (i.e., shelf life), and product criticality.

Chapter 4

Explanatory research

As indicated in the previous two chapters, there are many different SCC models of which the potential benefits are influenced by various factors. Therefore, it is crucial to assess the collaboration options against the various potential benefits, considering the challenges and characteristics of the products and suppliers. All interviewees recognised the potential of SCC as long as the following conditions are met: the information sharing is aligned with supplier needs, and the information is unambiguous and shared through an automated process. This chapter presents insights into the application and impact of sharing different information types on SC performances through quantitative analysis. It is crucial to address the empirical applicability of the SCC models so that they can be implemented in the fast-moving consumer goods industry. These industries are generally characterised as inflexible because products are produced in batches, the production is often forecast based, and the retailer demand is fulfilled from stock at the supplier. For perishable products, this implies that the product's shelf life is lost in the SC because products are kept in inventory. Therefore, the quantitative research of this study is focused on SCC in perishable SCs to improve the product's freshness and availability. The next section represents the method of the explanatory research phase. Afterwards, Section 4.2 outlines the conceptual model followed by the scientific model in Section 4.3. Section 4.4 presents the results from the quantitative analyses. Finally, Section 4.5 concludes the explanatory research.

4.1 Method

The method of this research is based on the research model by Mitroff et al. (1974) consisting of four iterative phases. A graphical representation of this research model is shown in Figure 4.1. In the conceptualization phase, the real-world problem is transformed into a conceptual model. In this phase, the problem parameters, variables, constraints and scope are defined. The second phase, modelling, translates the conceptual model into a scientific model. The scientific model is a quantitative model in which the causal relationships between the decision variables are mathematically defined corresponding to the real-world problem. Validation is essential in this phase to ensure that the scientific model is an accurate representation of the real world from the perspective of the intended uses of the model. Face validation is performed whereby it is checked whether the model and its behaviour are reasonable by changing some parameters (Sargent, 2010). The third phase, model solving, aims to analytically solve the scientific model. The solution is implemented in the practical situation in the fourth and final phase, the implementation phase. However, the implementation phase is beyond the scope of this project.

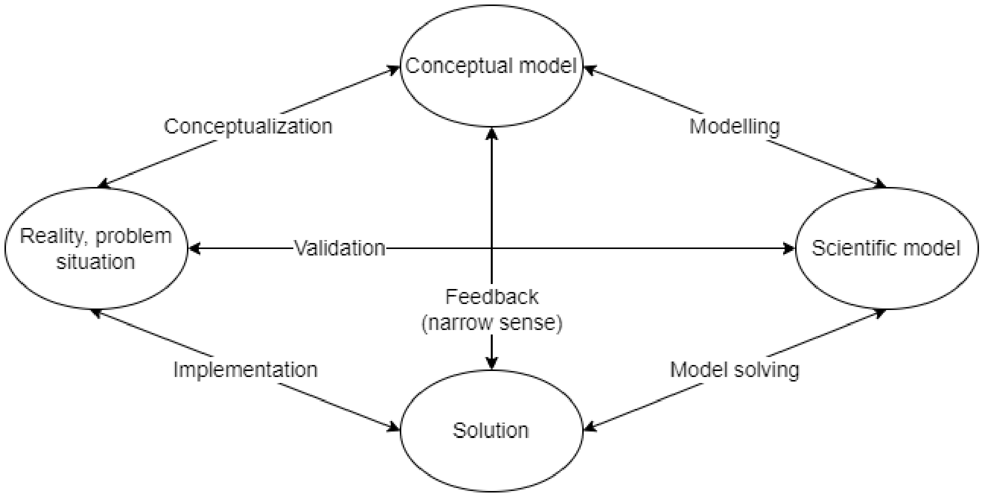

Figure 4.1: Research model by Mitroff et al. (1974)

4.2 Conceptual model

This section presents the conceptual model aiming to convey the fundamental principles and basic functionality of the system. According to the literature, collaboration in perishable SCs can enhance product availability and freshness through efficient information sharing and coordination. However, based on the literature and interviews, it can be stated that achieving efficient SCC is not a trivial task. Therefore, the explanatory research aims to investigate concrete implementations and the effects of different SCC models. These SCC models provide concrete guidelines on how information can be used and the impact of this information exchange. Accordingly, the conceptual model will be designed in different SCC models and evaluated on several performance measures. Subsequently, some independent parameters will be introduced to analyse some borderline cases concerning the effectiveness of the SCC models.

As perishable products are considered, the objective of the scenarios is to increase the freshness offered to the consumer and reduce the waste in the SC without affecting availability. Costs are not taken into account because it is difficult to determine the exact cost of, for example, losses and stock in the included tiers. In addition, the retailer's primary focus does not appear to be on reducing costs. Therefore, the proposed SCC models aim to reduce waste in the SC and increase freshness without compromising availability through improved coordination of supply and demand due to information sharing.

4.2.1 Types of information sharing

Information sharing can improve the freshness offered to the consumer and the amount of waste while maintaining availability. By sharing information, the different echelons can accurately assess needs in the SC, enabling more efficient inventory and production management (Ferguson & Ketzenberg, 2006; Ho et al., 2019). During the interviews, information sharing emerged as the preferred collaboration form, and is also the retailer's preferred form for further research. Therefore, the proposed SCC models are based on sharing information with other echelons and how this information may be used by the echelons received. Based on the literature review and interviews, two information categories can be distinguished, namely forecast and real-time information. Within these categories several types of information exchange can be identified:

Forecast information

- *Consumer demand forecast (DF) information:* The retailer can share the consumer demand forecast with upstream echelons so they can estimate the required volumes for the coming periods. This estimation allows them to tailor their production and inventory management based on the predicted consumer demand rather than the demand of the immediate downstream echelon. Moreover, promotion information can be included in the consumer demand forecast by specifying the particular promotional uplift and period. In addition, the forecast accuracy should also be shared, so that the receiving echelons can adjust their stock levels accordingly without a drop in availability (Aviv, 2001; Chen et al., 1994; Shaban et al., 2019). However, it can be difficult for receiving echelons to translate shared consumer demand into expected orders due to disruptive effects caused by, for example, waste and order batching.

- *Waste forecast (WF) information:* Besides consumer demand, waste can be seen as a second product outflow that can influence order size. Therefore, sharing expected waste can be effective in obtaining accurate insights into future downstream orders. However, only sharing expected waste seems to add little value, as the proportion of waste relative to consumer demand is usually lower. Consequently, it can be argued that waste forecast sharing can be considered complementary to consumer demand forecast sharing. An accurate estimate of expected waste requires expiration dates visibility in the inventory systems, which is generally limited. Nevertheless, the limited insights into the disturbance effect due to order batching remain unchanged.

- *Order forecast (OF) information:* To include waste and order batching in the shared information, retailers can share an order forecast. The order forecast can be based on the consumer demand forecast, estimated waste, and replenishment process, including order batching. After the first echelon has shared its order forecast, the second echelon can calculate its order forecast and share it with the next echelon and so on (Caridi et al., 2005; Du et al., 2009; Shaban et al., 2019). Order forecast sharing is emphasized during the interviews as the desired type of information sharing because it can be used directly by the upstream echelons to match demand and supply.

Real-time information

- *Inventory (I) information:* When inventory information is shared with upstream echelons, a centralized base stock policy can be established to keep the echelon inventory position constant. Therefore, inventory information includes the current and target inventory positions. Inventory information sharing provides insight into the difference between desired and current inventory levels of all downstream echelons. Based on this information, each echelon can estimate its future order volumes (Axsäter, 2015; Clark, 1958; Sari, 2008b). The effectiveness of only sharing inventory information can be questioned because upstream echelons have no insights into the expected future demand of downstream echelons. Additionally, when insights into the expiration dates in the inventory system are acquired, sharing the age-dependent inventory state can generate additional insights into the expected waste, whereby orders could be increased or advanced.

- *Point of sales (POS) information:* By sharing real-time POS data, upstream echelons can respond quickly to changes in demand and evaluate the forecast in real-time and act accordingly. Moreover, as POS data is the rawest and undistorted form of demand data, it can reduce disturbances in the SC (Borade et al., 2013; Sari, 2008b). However, the retailer considers POS data to be rather valuable information (Helvoort van, 2014), so the necessary level of trust is crucial.

- *Waste (W) information:* By sharing information on waste, a full understanding of the product outflow could be obtained. As waste is mainly a smaller part of the product outflow than demand, waste sharing itself does not seem to have significant added value.

4.2.2 Supply chain collaboration scenarios

The previous section introduced the types of information retailers can share with upstream echelons and their potential applications. This section presents the types of information shared in each SCC scenario analysed in this research. As briefly described above some combinations of information exchange are excluded because they are empirically illogical or are assumed not to improve performance. Table 4.1 provides an overview of the information types exchanged in each scenario. In each of the scenarios information is shared with all echelons with the exception of the fourth scenario.

Table 4.1: Overview of shared information per scenario

Scenario	**Repl. policy**	**Promo plan**	**DF**	**WF**	**OF**	**I**
Baseline	(R,s,nQ)	X	-	-	-	-
1	EWA	X	-	-	-	-
2	EWA	X	X	-	-	-
3	EWA	X	X	X	-	-
4	EWA	X	-	-	X	-
5	Echelon based EWA	X	X	X	-	X

Note: Repl. policy = Replenishment policy of echelons; DF = Consumer demand forecast information; WF = Waste forecast information; OF = Order forecast information; I = Inventory information

The current situation (i.e., traditional SC) will be modelled as a baseline to asses the effect of each scenario. Each echelon uses a pull driven local inventory replenishment policy whereby demand is fulfilled from stock. Each echelon maintains inventory, including the safety stock as a buffer for fluctuations in orders, affecting the product's shelf life. The (R, s, nQ) replenishment policy is used in all echelons in the baseline scenario. Finally, the promotion plan is shared with the upstream echelon members so that they can timely anticipate upcoming promotions.

Since waste is one of the model's performance measures and a crucial factor in perishable SCs, an age-based replenishment policy will be implemented in the first scenario. Therefore, the Estimated Withdrawal & Aging replenishment (EWA) policy, as introduced by Broekmeulen & van Donselaar (2009), will be implemented in all scenarios. A simulation study found the EWA policy the best performing periodic review policy for perishable products (Lowalekar & Ravichandran, 2015). Note that any form of expiration date visibility is required to implement the EWA policy. A detailed description of the (R, s, nQ) and EWA replenishment policies is provided in Section 4.3.2. Since the implementation of the EWA policy may be challenging in the medium term, the impact of the scenarios with a (R,s,nQ) replenishment policy at the DC and supplier will be analysed.

In the second scenario, the impact of sharing consumer demand forecast information is assessed. In this scenario, all echelons can base their reorder levels upon the consumer demand forecast instead of on incoming orders which could be distorted due to the demand signal processing at downstream echelons. The shared consumer demand forecast is incorporated in the reorder level of the upstream echelon by determining the reorder level based on the consumer demand forecast. This scenario is derived from the information exchange SCC model of Shaban et al. (2019), in which the added value of consumer demand forecast sharing is demonstrated in a non-perishable SC without order batching. As discussed, the waste and order batching could depress the performance of this scenario. However, it is interesting to investigate under which circumstances the mere sharing of a consumer demand forecast can improve performance and whether it adds value.

In the third scenario, the effect of sharing the expected amount of waste, in addition to the consumer demand forecast, is analysed. As discussed above, the amount of waste can significantly impact the second scenario, as waste is not included in the consumer demand forecast but could increase orders. Waste is included in the replenishment policy by adding the estimated amount of waste to the consumer demand forecast.

In the fourth scenario, the applicability of order forecast sharing is analysed. Since the order forecast includes the consumer demand forecast and waste estimation, sharing these forecasts becomes irrelevant. The first echelon (retail stores) estimates its order size based on the consumer demand forecast, waste estimation, and replenishment process. After the stores shared their order forecast, the DC can calculate its order forecast and share it with the supplier. It is assumed that the computation time is sufficient for each echelon to employ the shared order forecast. In addition, order forecast sharing is emphasized during the interviews and by the retailer as the desired information sharing because it can be used directly by the upstream echelons to match demand and supply and its ease of implementation. This scenario is derived from the research of Shaban et al. (2019), who concluded that consumer demand forecasts sharing outperforms order forecast sharing in a non-perishable SC without order batching.

The fifth scenario evaluates the usefulness of sharing real-time inventory information with consumer forecasting and waste estimation. Based on this information sharing, upstream echelons can consider echelon instead of local inventories and reorder levels during replenisment. Echelon inventories are the sum of all downstream inventory positions, and echelon reorder levels the sum of all downstream reorder levels. Since upstream echelons can estimate the orders of all downstream echelons themselves, order forecast sharing becomes irrelevant. In literature, such a replenishment system is known as echelon replenishment (Axsäter, 2015; Clark, 1958). Waste is incorporated by modifying the echelon inventory positions for the estimated outdating quantity. This method is comparable to how the EWA replenishment policy incorporates waste. A disadvantage of this scenario is that the distorting effect of order batching is not considered.

As discussed in Section 4.2.1, two other types of real-time information have been identified in addition to stock information, namely POS and waste information. POS and waste information sharing can provide upstream echelons insights into actual sales and waste volumes. Theoretical studies (e.g., (Chen et al., 2000)) show that sharing POS data can lead to a reduction in the bullwhip effect when suppliers have no prior knowledge of the demand distribution. Besides, Croson & Donohue (2003) concluded that sharing POS information could reduce some components of the bullwhip effect in a stable demand setting, namely the order oscillation of upstream members due to insights into consumer demand distribution at upstream echelons. However, the applicability of providing upstream echelons with insights into the consumer demand distributions is already assessed in the scenarios with forecast sharing. In addition, POS and waste information sharing could enable upstream echelons to evaluate pre-estimated volumes during volatile and unpredictable demand periods (e.g., unique promotions or new product introductions) and quickly respond to unforeseen demand patterns. The only non-stationary demand aspect considered in this study are promotions lasting only one week. The procurement of one-week promotions can be classified as a Newsvendor problem because the supplier cannot anticipate after sharing actual promotion POS and waste data. Finally, the interviews concludes that the need for POS data sharing is low, and suppliers indicated a clear preference for the other types of information discussed. In conclusion, this study does not include sharing real-time POS and waste information.

4.2.3 Performance measures

Each of the scenarios introduced above will be evaluated on the following performance measures:

- *Fill rate*: The fill rate, also known as On-Shelf Availability (OSA), is the long-term fraction of demand immediately delivered from stock (Donselaar van & Broekmeulen, 2014). Generally, sales are lost when consumer demand cannot be immediately delivered from the shelf. Therefore, retailers strive to fulfil all consumer demands with high product availability. However, this performance indicator is hard to measure in practice, as unsatisfied demand cannot be monitored. Therefore, the retailer applies the In-Store Availability (ISA), also known as the discrete ready rate in literature, as the availability performance indicator. Finally, the fill rate is used as a performance indicator for the delivery completeness of the DC and the supplier.

- *Discrete ready rate ($P3D$)*: The discrete ready rate, also known as $P3D$ in literature and ISA in practice, measures the probability of having positive inventory on hand just before a potential delivery moment (Donselaar van & Broekmeulen, 2014). As discussed above the retailer applies this performance indicator for the items' availability to consumers, where a norm of 95 per cent is used. Accordingly, the discrete ready rate can not be harmed in each scenario.

- *Supply chain waste fraction*: The waste fraction or relative outdating in this project is expressed as the total waste in the supply chain divided by the total consumer demand in all stores in consumer units (%SC Waste = ((SC waste/Sales)*100%). (Broekmeulen & Donselaar van, 2019). Waste occurs for each item that reaches the end of its shelf life or when the remaining shelf life is insufficient to meet the agreed minimum delivered remaining shelf life.

- *Freshness*: Since food waste mainly occurs at the consumer level, increasing product freshness is an important contributor to waste reduction. Freshness can be indicated by the average remaining shelf life in days of the products sold to the consumers (Broekmeulen & Donselaar van, 2019).

In addition to the above numerical performance indicators, the discrete ready rate and relative supply chain outdating can be visualized in Efficient Frontiers to compare the outcomes of the scenarios. An Efficient Frontier corresponds to the graph that shows the minimal expected waste increase if the discrete ready rate at the stores increases (Broekmeulen & Donselaar van, 2019).

4.2.4 Scope of the system

The performances of the proposed SCC scenarios are analysed in a divergent three-echelon SC for one perishable private label product. A private label product is selected because the majority of the perishable products are private label products, and intensive collaboration can more easily be achieved. Furthermore, one specific supplier is considered as most of the perishable private label products are supplied by specific suppliers. The retailer also aims to purchase perishable products directly from the manufacturer, resulting in more dedicated suppliers. In addition, it can be easier to establish an intensive collaboration in the medium-long term with dedicated suppliers. Finally, the supplier's production location supplies the DC based on the number of products ordered. Therefore, it is assumed that products are produced in fixed production intervals equal to the review period of the supplier's DC, in batches equal to an integer multiplication of the supplier's DC order size.

The three-echelon SC consists of multiple retailer stores, one retailer DC, and one supplier DC. The number of stores included in the model mainly influences the waste in the SC and the relative standard deviation of incoming orders in the upstream echelons. Wijshoff (2016) indicated that around 50 retail stores are sufficient for drawing conclusions for a real-world situation with more stores. However, since the number of stores has a significant impact on the results and simulation time, an analysis was performed on the effect of the number of stores on the service level of the stores, the relative SC outdating (z_{SC}), and the relative demand variability. This analysis concludes that the inclusion of 20 stores is sufficient to represent a real-world situation with more stores (Appendix C). Currently, one DC supplies more than 20 stores, so the simulation study includes one retailer DC.

In the considered environment, a non-stationary stochastic demand is assumed due to the presence of promotions. Promotion periods are included to assess the applicability of the SCC models in periods of uncertain and variable consumer demand. During promotions, the average consumer demand is increased by a Lift Factor with an uncertainty factor. Based on the promo planning, it was concluded that perishables are promoted on average every eight weeks. Furthermore, one-week promotions are considered, as they impact the SC the most. In addition, the considered consumer demand does not include weekly or seasonal patterns. This assumption can be justified by the limited impact on the week pattern on the amount of waste relative to the fill rate (Bastiaansen, 2019; Weteling, 2013). Moreover, fixed shelf lives delivered by the DC manufacturer are assumed. Within grocery retailing, this includes products with a predetermined expiration date like dairy, meat, and cold cuts (Kiil et al., 2018). Besides, unmet consumer demand is considered lost, meaning lost sales are assumed in the stores. When the upstream echelons cannot satisfy demand completely, the inventory position of the downstream echelon is corrected by the number of undelivered products. So, undelivered products can be ordered in the next review cycle. Finally, order batching with fixed case pack sizes and deterministic constant positive lead times and review periods are assumed.

4.3 Scientific model

This section presents the scientific model based on the conceptual model described in the previous section. A simulation study will be performed to compare the performance of the defined scenarios and to analyse the influence of some independent parameters on this performance. This section discusses the simulation characteristics.

4.3.1 Input parameters

As shown in the literature review and the exploratory research, different SC characteristics can influence the performance of the scenarios. This dependency makes it interesting to analyse which scenario adds the most value under which conditions. The effect of the following input parameters on the performance measures will be evaluated:

- *Safety factor*: The reorder levels of the echelons could be adjusted via the safety factor, aiming to achieve the intended service levels. The reorder levels also affect the waste and freshness. Therefore, varying these parameters is needed to define the expected waste increase if the fill rate increases, which is necessary for determining the Efficient Frontier.
- *Mean demand*: Based on the literature review and empirical insights, the case pack size and shelf life relative to the average demand are expected to affect the performance indicators (Broekmeulen & Donselaar van, 2019; Ketzenberg & Ferguson, 2008). Broekmeulen & Donselaar van (2019) introduced the Fresh Case Cover (FCC) as a concept to quantify the improvement potential. The FCC is defined as the case pack size divided by the average demand during the store shelf life. Under constant deterministic demand, waste will only occur if the case pack size is not sold before the end of the shelf life. The impact of the disruptive effect of the case pack size and shelf life on the scenario performance is analysed by increasing and decreasing the average consumer demand by 50% during regular and promotional periods.
- *Replenishment policy*: As discussed in section 4.2.2, the implementation of the EWA policy at the upstream echelons may be challenging in the medium term. Therefore, the effect of the EWA policy is analysed by adopting the (R,s,nQ) replenishment strategy in the DC and the supplier instead of the EWA policy.

In addition to these variable input parameters, some fixed input parameters exists. Appendix D provides an overview of all input parameters. A fixed lead time and review period of one day is assumed for all echelons. The case pack size of the stores and DC are determined based on empirical data from the retailer and are 5 and 48 consumer units, respectively. In the absence of information on the supplier's pack size, it is assumed that they produce in batches equal to the DC's case pack size. In addition, the FIFO withdrawal fraction at the stores is 0.45 based on the study of Barratt & Oliveira (2001). Finally, the DC and supplier adopt a FIFO policy.

Consumer demand is generated by a discrete demand distribution fitted on empirical sales data of an ordinary product within the research scope. Stores are clustered to keep the number of safety factor combinations manageable. The Elbow method is used to determine the number of clusters, resulting in three clusters. Afterwards, k-means clustering is used to cluster the stores based on the mean demand during regular and promotion periods. These methods are commonly used in cluster analysis (Everitt et al., 2011). Table 4.2 shows the number of stores included of each cluster and the demand characteristics of each cluster per store. This table shows that ten small, eight medium and two large stores are included in the model. Moreover, the average total consumer demand during regular periods equals 99 and during promotions equals 224. The complete cluster analysis is presented in Appendix E. Finally, a discrete demand distribution is fitted for regular and promo sales periods per cluster on the corresponding mean demand and standard deviations by the fitting procedure of Adan et al. (1995).

Table 4.2: Demand characteristics per store in each store type

Store type	**# stores**	**μ reg. dem.**	**σ reg. dem.**	**μ pro. dem.**	**σ pro. dem.**	**Lift factor**
Small	10	3.86	3.27	7.66	5.09	2.00
Medium	8	5.57	5.10	13.19	8.30	2.40
Large	2	7.92	7.72	20.96	11.95	2.71

Note: # stores = number of stores in simulation; μ reg. dem. = mean regular demand per store; μ pro. dem. = mean promo demand per store; σ reg. dem. = standard deviation of regular demand per store; σ pro. dem. = standard deviation of promo demand per store.

The impact of the promotions on the average demand, expressed in the Lift Factor, is lower than initially expected. Donselaar van et al. (2016) analysed the promotion impact on 407 perishable items in four product categories based on empirical data provided by a Dutch grocery retail chain with over 100 supermarkets. They concluded an average Lift Factor per product category between 5.6 and 13.8, which is significantly higher than the lift factor used in this study. Therefore, this lift factor has been validated by employing data analysis and questioning those responsible for forecasting the products in the research scope. However, the analysis of the data shows that the lift factor used in this study is reasonable, see Appendix F. This finding was also confirmed by the forecasters. An explanation is that the products in the scope are products with a relatively short shelf life, making mass buying less beneficial due to waste. In addition, the retailer applies an Every Day Low Pricing principle, which could be a possible explanation for the relatively low lift factor.

4.3.2 Replenishment policies

As described in the conceptual model, this study considers the (R, s, nQ), EWA, and echelon based EWA replenishment policies. This section discusses these replenishment policies in detail.

4.3.2.1 (R,s,nQ) policy

In the (R, s, nQ) policy, each fixed review period (R) orders of n times the base replenishment quantity (Q) are placed if the inventory position (IP) is strictly below the dynamic reorder level (s). The inventory position is the sum of the inventory on hand and in transit. The reorder level is updated dynamically by adding the safety stock (SS) to the expected demand during the lead time and review period. The safety stock is determined based on the desired service level and forecast error (Silver et al., 1998). Finally, the reorder level is rounded up to an integer value. Formula 4.1 shows the mathematical expression of the (R, s, nQ) replenishment policy.

$$s_t = SS_t + \sum_{i=t+1}^{t+L+R} \hat{D}_i \quad \text{where } SS_t = k * \sigma \tag{4.1}$$

In formula 4.1, $\sum_{i=t+1}^{t+L+R} \hat{D}_i$ is the demand forecast during an interval of $R + L$ periods, σ is the standard deviation of the $R + L$ period forecast error, and k is a constant chosen to meet the desired service level (i.e., safety factor). The number of case packs ordered is chosen such that the IP_t just after a replenishment is greater or equal than s_t, but strictly less than $s_t + Q$. If IP_t is defined as the inventory position at day t just before placing an order, n_t is determined by formula 4.2 (Broekmeulen & van Donselaar, 2009).

$$n_t = \begin{cases} \left\lceil \dfrac{s_t - IP_t}{Q} \right\rceil, & \text{if } IP_t < s_t, \\ 0, & \text{otherwise.} \end{cases} \tag{4.2}$$

4.3.2.2 EWA policy

In addition to the (R,s,nQ) policy, the EWA policy incorporates the expected amount of products outdating $(\hat{O})$ by increasing the order quantity based on the expected amount of products outdating (Broekmeulen & van Donselaar, 2009). Formula 4.3 shows the mathematical expression of the EWA policy.

$$n_t = \begin{cases} \left\lceil \dfrac{s_t - IP_t + \sum_{i=t+1}^{t+L+R-1} \hat{O}_i}{Q} \right\rceil, & \text{if } IP_t - \sum_{i=t+1}^{t+L+R-1} \hat{O}_i < s_t, \\ 0, & \text{otherwise.} \end{cases} \tag{4.3}$$

In formula 4.3, $\hat{O}_i$ is the estimated amount of outdating. Since the outdating on the $(L+R)$th period does not affect the ability to meet demand during that day, the outdating is estimated over $L+R-1$ periods. Finally, the expected estimated amount of outdating is determined via recursive equations using the age distribution of the inventory and the withdrawal behaviour (FIFO or LIFO) as discussed by Broekmeulen & van Donselaar (2009). This procedure consists of three steps, starting with $i = t+1$. First, the estimated FIFO and LIFO withdrawal is determined in period i by assuming that the expected demand was equal to the actual demand in period i. Second, the estimated remaining batches available for the next period and the estimated outdating in period i is determined by assuming that the withdrawal in period i is equal to the estimated withdrawal as determined in the first step. Third, while $i < t+L+R-1$ do $i := i+1$ and continue with the first step, otherwise stop (Broekmeulen & van Donselaar, 2009).

4.3.2.3 Echelon based EWA policy

In a centralized EWA replenishment policy (i.e., echelon replenishment) each review period (R) orders of n times the base replenishment quantity (Q) are placed if the echelon inventory position ($\overline{IP^i}$) minus the expected amount of echelon outdating is strictly below the echelon reorder level ($\overline{s^i}$). The echelon inventory position of echelon i is defined as the sum of all downstream inventory positions, $\overline{IP^i_\tau} = \sum_{i=1}^{i} IP^i_\tau$. Similar is the echelon reorder level at stage i defined as the sum of all downstream inventory positions $\overline{s^i_\tau} = \sum_{i=1}^{i} s^i_\tau$ (Atan, 2017; Axsäter, 2015). With these echelon parameters, the integer multiplication of the base replenishment quantity is determined in the same way as in the local EWA policy, Equation 4.3. In this formula, the local variables are replaced by the echelon variables.

4.3.3 Solution method

The simulation study aims to guide how to integrate shared information into replenishment policies and assess the impact of this information integration. In perishable SCs, determining the reorder level involves a trade-off between availability and waste. As discussed, the implementation of each scenario cannot be at the expense of availability. Therefore, reorder levels should be set such that availability in the stores is maintained and waste and freshness are optimised for each parameter and scenario combination.

As can be deduced from the replenishment policy section (Section 4.3.2), reorder levels can be influenced by the safety factor (k) in determining the safety stock (see formula 4.1). With a higher safety stock factor, the forecast error acquires more importance resulting in higher safety stock and, consequently, higher reorder level. Since, to the best of this study's knowledge, no good working heuristic exists for optimising a divergent perishable SC with three echelons and order batching, the optimal values for k could be obtained by a full enumeration of all possible safety factors.

In a single-echelon SC without order batching, the probability of getting out of stock during a replenishment cycle is equal to the probability that the total outflow (demand plus waste) during a review interval plus lead time is at least as large as the reorder level (Silver et al., 1998).

The reorder level is based on the forecasted demand plus safety stock. Therefore, an echelon gets out of stock if the forecast error is higher than the safety stock. The safety factor can be obtained from the inverse normal distribution and the desired availability under the assumption of normally distributed forecast errors (Silver et al., 1998). It must be noted that this method is used for non-perishable products with backorders and, in this study, for perishable products with last sales. Since the inventory position is greater than or equal to the reorder level every review period, order batching will positively affect the availability assuming complete delivery by the upstream echelon. However, in a multi-echelon SC, the availability of downstream echelons may drop if upstream echelons get out of stock. This method for determining the safety stock is derived from the study of Kiil et al. (2018) who also considers a perishable SC with order batching and has been used extensively in forecast sharing studies (Kamalapur & Lyth, 2014; Sari, 2008a).

A drawback of this method for determining the safety stock is how the service level is measured. In this method, as developed by Silver et al. (1998), the service level is defined as the fraction of replenishment cycles in which a stockout does not occur, often called the cycle service or P1 service level. However, this measurement method does not correspond to the definition used in this study. As discussed in Section 4.2.3, the service level in the stores is evaluated on the P3D (or ISA) and the upstream echelons on the fill rate. Consequently, it is reasonable that the desired service levels are not exactly realised in the simulation. Therefore, different combinations of safety factors will be tested, including the extreme cases. The lower limit is when the DC and the supplier do not maintain any safety stock (k=0), and the upper limit is a target service level of 0.99 (k=2.33). The intermediate values for k at the DC and supplier are 0.84, 1.28, and 1.64. In theory, upstream echelons could also maintain a negative safety stock. However, it is unlikely that suppliers would agree to negative safety stocks in practice. After the simulation of all safety factor combinations, the combination minimizing the relative SC outdating while achieving the desired service level in the stores is determined. In addition, the relationship between the safety factors and target service levels will be investigated.

4.3.4 Events in the simulation model

This study uses discrete event simulation to explore the performance impact achieved by the SCC scenarios under different SC conditions using the simulation framework SimPy based on standard Python. The simulation model functions by events at the supplier DC, retailer DC, and the 20 retailer stores. Figure 4.2 presents each event and how they relate. The supplier's production is coloured grey in this figure because this echelon is outside the scope. The general sequence of events during a period at the stores is as follows: first, the inventory is reduced by the demand during the day, then expired products are removed from inventory, next goods arrive, and finally the orders are placed. The general sequence of events during one period at the DC and supplier is as follows: first, the order of the downstream echelon is received, next goods arrive, then expired products are removed from inventory, followed by the transshipment of goods, and finally orders are placed. Besides, one simulation period represents one day. Finally, goods are reduced with one day of reaming shelf life at the end of every period.

Preliminary results showed that the service levels of the DC and the supplier did not significantly decrease when reducing the safety factor, see Appendix G. Further analysis showed that maintaining an inventory position in the DC and at the supplier equal to predicted demand during the lead time and review period plus a safety stock was too excessive. This finding can be explained by the sequence of events in the DC and the supplier. When these echelons have to make their replenishment decisions, the order size is partly known. Therefore, only one day's demand needs to be forecasted and the forecast standard deviation can also be based on the uncertainty of one day. In the current situation, the retailer strives to realise such coordination of the ordering, production, and delivery processes. The retailer recognises the importance of this alignment, emphasised during this research as well. Since this project has a strategic horizon, the simulation study assumes that synchronisation between the moment of ordering, producing, and delivering is realised. In the remainder of the analysis, the forecast period used by the DC and the supplier to determine their reorder levels is reduced by one day.

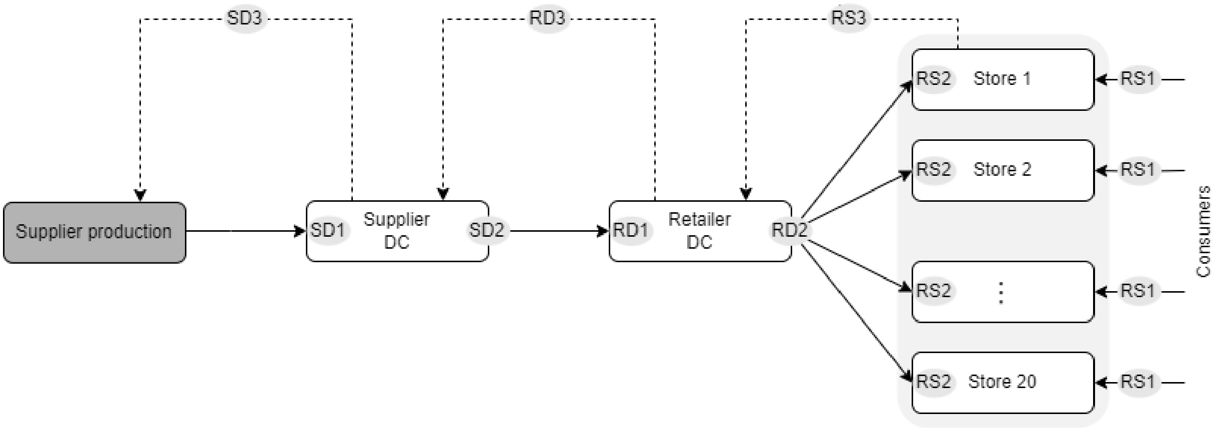

Figure 4.2: Events in simulation model

Below, all events in the simulation model, as displayed in Figure 4.2, will be explained in detail. Starting with the events in the retail stores (RS), followed by the events in the retailer DC (RD) and ending with those of the supplier DC (SD).

RS1 - Satisfy demand
At the beginning of each period, a random value for each store is sampled from the discrete distribution based on the store's cluster and the sales period, regular or promotional. Promotions occur every eight weeks and always last one week. To model promotion realistically, the effect of the promos on the mean demand is varied per promotion. Moreover, only a part of this variation is known and can be shared. Consumer demand is depleted by 45% FIFO (products with the shortest remaining shelf life), and the rest is issued LIFO (products with the longest remaining shelf life). In the simulation, 45% of the total demand, rounded to the nearest integer, is withdrawn FIFO, and the remainder from the products is withdrawn LIFO. Finally, all demand not immediately deliverable from stock is lost.

RS2 - Goods arrive and are added to inventory
After consumer demand is satisfied or lost, goods arrive and are stacked on the store's shelves one period after ordering.

RS3 - Replenishment
Before replenishment, outdating products are removed. Since the retailer applies a policy of offering products with a same-day expiry for free, products with a remaining shelf life of one day are outdated. The replenishment process starts with generating a moving average forecast on the most recent 75 periods covering the review period and lead time. In forecasting demand, perceived regular sales are used to estimate demand and determine the forecast standard deviation for regular periods and promotional sales for promo periods. Depending on the selected replenishment policy, the required number of batches is determined and ordered. The (R, s, nQ) replenishment policy is applied in the baseline scenario and the EWA policy in all other scenarios.

RD1 - Goods arrive and are added to inventory
One period after the DC has ordered, goods are delivered and added to inventory. As the DC applies a FIFO policy, delivered batches are stacked behind the existing inventory.

RD2 - Satisfy demand
Before shipment, the DC's inventory is checked for outdating to ensure that all delivered products meet the desired minimum remaining shelf life of five days when arriving at the stores.

After store orders are received, ordered products are added to the stock, and outdated products are removed, store orders are transshipped. The DC satisfy store demand according to the first-come, first-serve principle. When the DC cannot satisfy all demand, the inventory position of these stores is reduced by the undelivered products, allowing them to account for this in the next replenishment cycle. In addition, the stores whose orders were incomplete in the previous period obtain priority when the DC is unable to fully meet demand next time. Moreover, products are always shipped in one or an integer multiplication of the case pack size. Finally, a FIFO policy is applied in the DC.

RD3 - Replenishment
The SCC scenarios mainly affect the replenishment process of the DC and the supplier through the retrieved data and applied replenishment policies. First, the reorder level is updated based on the demand forecast and standard deviation of forecast errors. The data available for forecasting depends on the scenario as discussed in Section 4.2.2 and displayed in Table 4.1. The forecast standard deviation is also shared and used in determining the reorder level. The forecast and its standard deviation depend on the sales period, regular or promotion. Without forecast information sharing, the moving average forecast is made based on the observed incoming orders. It is assumed that echelons are transparent about their review periods and lead times and that promotions are communicated and considered when forecasting. As a result, the DC can determine the promotion fraction in perceived and upcoming orders and use this fraction when forecasting and determining the forecast standard deviation. Depending on the scenario, the corresponding replenishment policy is selected, and the required number of batches is ordered.

SD1 - Goods arrive and are added to inventory
Since the supplier has an unlimited source of supply, all ordered items are always delivered one period after ordering with a fixed remaining shelf life of twelve days. As the supplier applies a FIFO policy, delivered batches are stacked behind the existing inventory.

SD2 - Satisfy demand
The satisfy demand event at the supplier is similar to that of the DC. Before goods are transshipped to the DC, outdating is removed from inventory. At the supplier, goods are outdated if the remaining shelf life of nine days, so the DC receives goods with a minimum remaining shelf life of eight days. Afterwards, DC orders are transshipped. If the supplier cannot fulfil all demand, the DC's inventory position is reduced by the undelivered products, allowing them to account for the next replenishment cycle. Finally, products will always be shipped in an integer multiplication of the case pack size and a FIFO withdrawal policy is assumed at the supplier.

SD3 - Replenishment
The replenishment process described for the DC also applies to the supplier. First, the supplier's reorder level is updated based on the moving average forecast and corresponding forecast standard deviation drawn upon the available information in each scenario. Second, the required number of batches is determined based on the selected replenishment policy.

4.3.5 Simulation properties

Since the simulation study aims to optimize the echelon outdating while maintaining availability, these two variables are most important when defining the warm-up period, simulation length, and the number of runs. Appendix H shows the performed analysis to determine these simulation properties.

- *Warm-up period*: The warm-up period is the period that the simulation will run before starting to collect results. This period allows simulation aspects to get into conditions that are typical of normal running conditions in the considered environment (Boon et al., 2019). The warm-up period is determined based on the number of products in the system, the echelon's inventory levels, and reorder levels of each echelon. These parameters are used because they reflect the available stock and the stability of the forecast and its standard deviation. Eventually, the warm-up period is set at 40 weeks.
- *Simulation length*: The simulation has no predetermined endpoint, so the simulation length must be determined. Given that a longer simulation yields better results with improved statistical significance, the minimum required duration is the point in time when customer service and relative SC outdating converge. It is assumed that a simulation length of two years is sufficient to obtain reliable results.
- *Number of runs*: To obtain a $(1-\alpha)\%$ confidence interval, the number of replications n has to satisfy inequality 4.4. In this inequality, $z_{\alpha/2}$ is 1.96 based on a 95% confidence interval, σ is the standard deviation, and ϵ is the desired error term. Since no initial guess for the value of σ is available, the two-step approach is applied (Boon et al., 2019). First, a short, initial simulation with a relatively small number of runs is performed to estimate the standard deviations of the discrete ready rate in the stores and relative SC outdating. Afterwards, the estimated standard deviation is used in the inequality. Ultimately, the simulation is repeated 30 times for each parameter combination.

$$n > \left(\frac{z_{\alpha/2} \cdot \sigma}{\varepsilon}\right)^2 \tag{4.4}$$

4.3.6 Model validation

The validation of the simulation model is twofold. First, the simulation is validated by comparing the simulation results of multiple KPIs with analytical results in a single echelon perishable SC. Second, the simulation of the multi-echelon perishable SC is validated by face validation.

The performances on different KPIs in the stores are validated by comparing these performances with the DoBr tool. The DoBr tool is an analytical model to calculate the performance on several KPIs under predefined SC characteristics serving as a calculation tool for the analytical expressions in Donselaar van & Broekmeulen (2014). In this validation, the effect of the upstream echelons is muted. In addition, this validation aims to check whether the simulation model has correctly calculated the KPIs, implements all processes as planned, and responds accurately to different parameter values. This validation can be found in Appendix I and confirms that the simulation model is an accurate representation of the conceptual model use.

Since there is no verified analytical model for a multi-echelon perishable SC, the complete model is validated via the face validation method as described by Sargent (2010). This validation method evaluates whether the model's behaviour is reasonable and possesses sufficient accuracy for the scenarios and various input parameters. First, the general SC processes, such as replenishment, demand handling and KPI calculation, are modelled generically such that each echelon in the simulation uses the same function. With the numerical validation of the single-echelon SC, these functions are also validated for the upstream echelons. In addition, the results of the three-echelon system with high stocks and long shelf life resemble those of the validated one-echelon system. Second, the behaviour and primary requirements of the model under different parameters are numerically and visually assessed. For example, the inventory on hand in each echelon can never be negative, the outdating can never exceed the inventory on hand, the relationship between the reorder level and the achieved service levels is as expected, and echelons can never transship more than their inventory on hand. Third, the sequence of simulation events within and between echelons is checked. Finally, the different scenarios were validated by comparing their behaviours and results.

4.4 Results

This section presents the simulation results for the different scenarios and input parameters. First, Section 4.4.1 compares the scenarios' performances. Then, the results of increasing and decreasing consumer demand are discussed in Section 4.4.2. Section 4.4.3 presents the results when the DC and supplier use the (R, s, nQ) instead of the EWA replenishment policy. Finally, Section 4.4.4 presents the results of the analysis regarding the impact of the upstream service levels on the SC performances.

4.4.1 Scenario analysis

As previously mentioned, the proposed SCC models aim to reduce waste in the entire SC and increase freshness without compromising availability by sharing different types of information in each scenario. These scenarios are evaluated based on the performance measures presented in Section 4.2.3. First, the performance of each scenario is assessed in the current situation, where the retailer applies a P3D norm of 95%. In contrast to the current situation, no minimum fill rate was applied to either the DC or the supplier because it is assumed that the entire SC strives to improve customer service at minimum waste during collaborations. A detailed analysis of the impact of the desired service levels in the DC and at the supplier on the performance indicators is presented in Section 4.4.4. The combination of target service levels across all echelons was examined to minimise relative SC outdating and still provide the desired in-store availability for each scenario. Since a discrete ready rate of exactly 95% is not present in most simulations, interpolation on the waste fraction and freshness is used to compare the scenarios at a constant availability level. Exponential interpolation is adopted for the waste fraction due to the curve of the Efficient Frontier, and linear interpolation for the delivered freshness based on preliminary results.

Order forecast sharing and echelon replenishment improve relative SC outdating and freshness, whereas POS forecast sharing and EWA implementations mainly enhance the relative SC outdating. Table 4.3 shows the performances of each scenario on the relative SC outdating and freshness of the delivered product to the customers in days in the current situation. This table shows that the EWA implementations primarily reduce the relative SC outdating. As expected, all forms of information sharing further improve performance. However, POS forecast sharing mainly improves the relative SC outdating while freshness remains roughly the same compared to the baseline scenario. Complementing the POS forecast with the expected outdating does not yield the expected improvements, which can be caused by each echelon already accounting for expected outdating by applying the EWA replenishment policy. Finally, order forecast sharing and a centralized EWA policy perform best on both performance indicators in the current situation, with the centralized EWA policy slightly outperforming the order forecast sharing.

Table 4.3: Performance of each scenario in current situation

Scenario	**Baseline**	**1**	**2**	**3**	**4**	**5**
Relative SC outdating	8.17%	7.82%	7.01%	7.01%	6.74%	6.49%
Freshness	6.28	6.26	6.27	6.27	6.50	6.57

Currently, there is discussion at the retailer whether one in-store availability norm for all products is optimal or differentiation is needed to reduce waste and increase freshness while maintaining or even increasing the aggregate in-store availability. Efficient Frontiers represents the trade-off between product availability and SC waste in each scenario (Broekmeulen & Donselaar van, 2019). A scenario outperforms another when its Efficient Frontier is below that of another, meaning that it can achieve the same service level at a lower relative SC outdating. In addition, the freshness and in-store availability are compared by plotting the freshness delivered to the consumers in days to the discrete ready rate in the stores. One scenario outperforms another when the line is above it, as higher freshness can be achieved with the same store availability.

Information sharing and EWA implementations improve the Efficient Frontier compared to the baseline scenario, while order forecast sharing and echelon based EWA also improve freshness. Figure 4.3 displays the Efficient Frontiers of all scenarios. This figure shows that EWA implementations result in a slight improvement in the efficient frontier, which is in line with expectations. Furthermore, it can be observed that information sharing results in the largest improvement, but the differences between the scenarios are small. In addition, Figure 4.4 illustrates the freshness delivered to the customer against the stores' discrete ready rate for all scenarios. This figure shows that scenarios four and five outperform all other scenarios, both performing roughly similarly. This difference can be explained by improved alignment of supply and demand in the SC, which leads to similar performance with reduced inventories, thus improving freshness. Concluding, primarily information sharing enhances the trade-off between the relative SC outdating and in-store availability. Additionally, order forecast sharing and a centralised replenishment policy improve the balance between freshness and in-store availability.

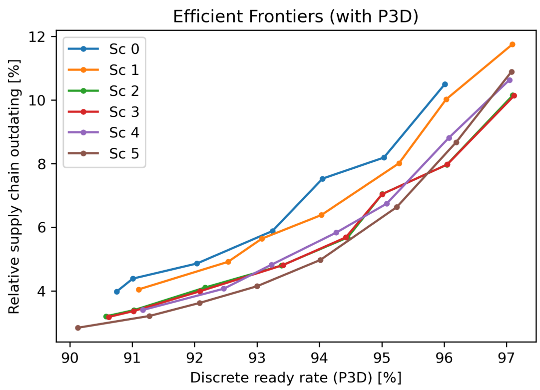

Figure 4.3: Efficient Frontiers

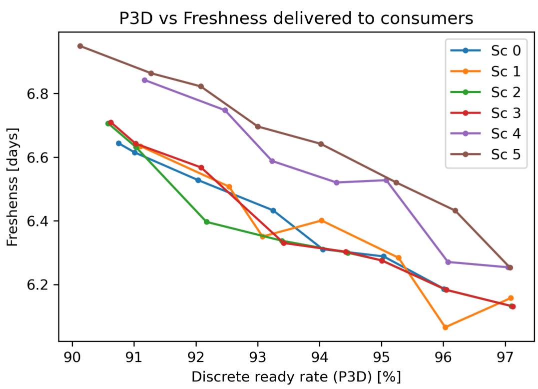

Figure 4.4: P3D versus freshness

4.4.2 Demand adjustment

To analyse the impact of the disruptive effect of order batching and outdating on the scenarios, the average demand was increased and decreased by 50% during both the promotional and regular sales periods. Again, the performances of the scenarios are evaluated first in the current situation with a P3D norm of 95%. Afterwards, the trade-offs between the relative SC outdating and freshness, and the in-store availability are considered.

The implementation of the EWA policy and all types of information sharing becomes more profitable relative to the baseline situation under reduced average demand compared to the original demand situation. Table 4.4 shows the performances of each scenario on the relative SC outdating and freshness of the delivered product to the customers in the current situation with decreased demand. This table shows that all scenarios outperform the baseline scenario. Moreover, it can be seen that order forecast sharing results in the greatest improvement of all scenarios in relative SC outdating and a considerable improvement in freshness. The echelon based EWA replenishment policy realizes the greatest enhancement in terms of freshness. Finally, the relative differences between the scenarios increase compared to the unadjusted demand. This observation can be explained by the greater added value of information sharing when the disruptive effects in the SC increase.

Table 4.4: Relative SC outdating and freshness decreased demand

Scenario	**Baseline**	**1**	**2**	**3**	**4**	**5**
Relative SC outdating	12.17%	10.63%	9.68%	9.68%	7.69%	8.60%
Freshness	5.62	5.75	5.69	5.69	6.24	6.33

Under increased demand, all scenarios show improved performances compared to the baseline scenario. Table 4.5 shows the performances of each scenario on the relative SC outdating and freshness of the delivered product to the consumers in the current situation with increased demand. This table shows that EWA implementations enhance the relative SC outdating and freshness delivered to the consumers. Moreover, all types of information sharing improve the performances, where the centralized EWA policy yields the greatest benefits. Besides, it is remarkable that POS forecast sharing performs better than order forecast sharing on relative SC outdating. Finally, it can be argued that information sharing has a greater positive effect when the disruptive effect in the SC are stronger under decreased demand.

Table 4.5: Relative SC outdating and freshness increased demand

Scenario	**Baseline**	**1**	**2**	**3**	**4**	**5**
Relative SC outdating	7.37%	6.58%	5.70%	5.70%	5.96%	5.43%
Freshness	6.34	6.40	6.33	6.33	6.55	6.57

The Efficient Frontiers shows that the impact of the disruptions in the SC due to order batching and shelf life affects the favourable SCC scenario. Figures 4.5 and 4.6 display the Efficient Frontiers under decreased and increased demand of all scenarios. Under decreased demand, order forecast sharing and the centralised EWA policy perform best. However, the performance of POS forecast sharing expands under increased demand. The peak of scenario four in Figure 4.5 can be explained by the fact that only a limited number of combinations of target service levels achieve the high desired service level, leaving only a combination with a high relative SC outdating. Testing more combinations probably results in a point on the Efficient Frontier, which is more in line with the other points. Furthermore, Figure 4.6 shows that the performances of all forms of information sharing are approximately comparable. It can even be argued that order forecast sharing performs slightly less than the other information sharing scenarios. The baseline scenario performs worst, and the EWA implementations achieve a small improvement but still perform worse than the information sharing scenarios. The differences in the preferred scenario for demand conditions may be explained by order forecast sharing and a centralised EWA policy being more resilient to SC disruptions than POS forecast sharing, even when supplemented with expected waste. Under increased demand, the effect of these distortions is lower, improving the performance of POS forecast sharing.

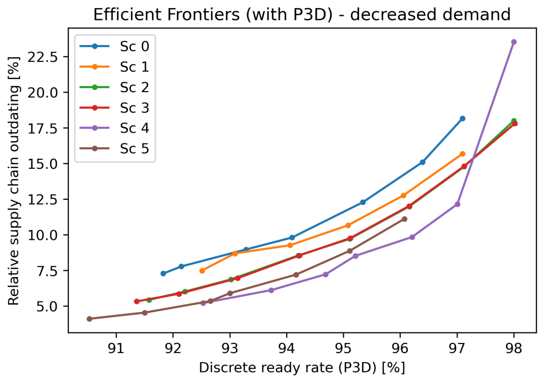

Figure 4.5: Efficient Frontiers decreased demand

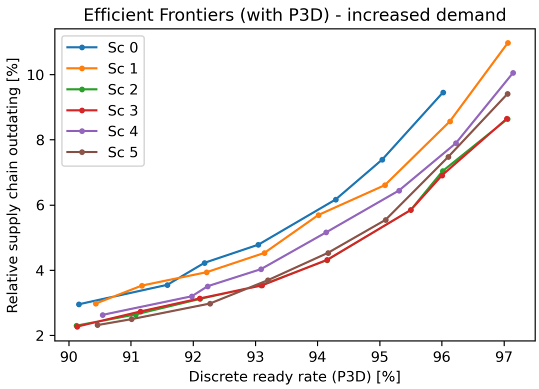

Figure 4.6: Efficient Frontiers increased demand

Order forecast sharing and echelon based EWA replenishment outperform the other scenarios in terms of freshness delivered to the customers under both demand conditions, as displayed in Figures 4.7 and 4.8. These figures display the freshness delivered to the customer against the stores' discrete ready rate for all scenarios under decreased and increased demand. Finally, these figures show that the positive impact of scenarios four and five are higher under decreased than increased demand. The improved coordination in the SC may explain this difference in performance.

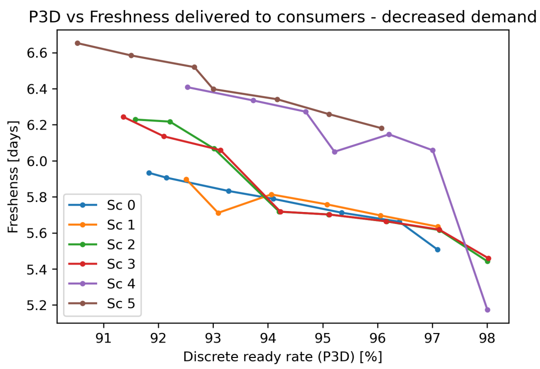

Figure 4.7: P3D versus freshness decreased demand

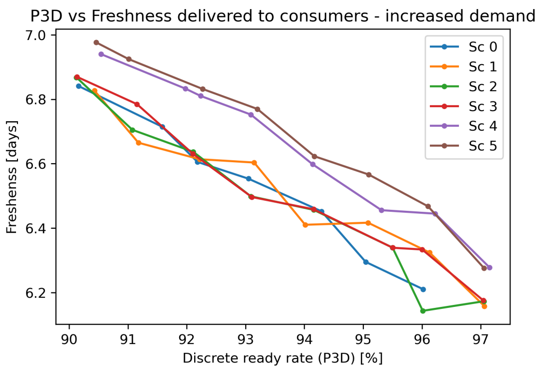

Figure 4.8: P3D versus freshness increased demand

4.4.3 Without EWA replenishment at DC and supplier

Since implementing the EWA policy at the DC and supplier could be challenging, the effect of employing the (R, s, nQ), instead of the EWA policy, in these echelons on the scenarios performances are analysed. This analysis is only performed under the original consumer demand situation, as in Section 4.4.1. As in the previous two sections, first, the scenario performance in the current situation will be evaluated, followed by the Efficient Frontiers and P3D versus freshness trade-offs.

The interrelationships between the scenarios do not change significantly compared to the situation with EWA implementations in the upstream echelons. Table 4.6 shows the relative SC outdating and freshness delivered to the consumers without upstream EWA implementations. This table shows that the relative SC outdating and delivered freshness in each scenario is approximately comparable to the situation with upstream EWA implementations. In addition, the relative SC outdating is generally a bit higher without upstream EWA implementations than with upstream EWA implementations. In summary, upstream EWA implementations do not significantly affect the relative SC outdating and delivered freshness and do not affect the relative differences between the scenarios.

Table 4.6: Relative SC outdating and freshness without EWA at upstream echelons

Scenario	**Baseline**	**1**	**2**	**3**	**4**	**5**
Relative SC outdating	8.20%	7.86%	6.98%	6.98%	6.61%	6.53%
Freshness stores	6.28	6.26	6.26	6.26	6.52	6.54

Based on the Efficient Frontiers and in-store availability versus the delivered freshness, the same conclusions as for the current situation could be drawn regarding the impact of upstream EWA implementations. Figures 4.9 and 4.10 shows the Efficient Frontiers and freshness delivered to the consumers versus the stores availability without upstream EWA implementations. These figures show that the preferred scenarios remain the same compared to the results with upstream EWA implementations. However, it can be stated that the differences between the scenarios have become slightly smaller.

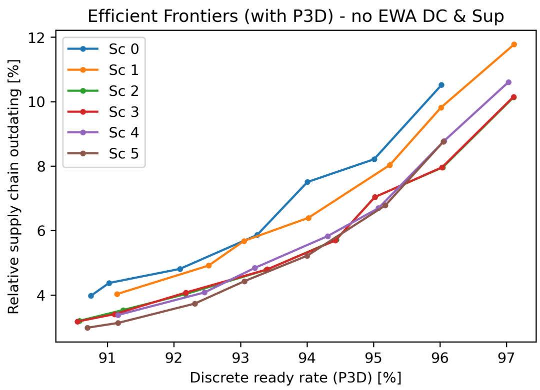

Figure 4.9: Efficient Frontiers no EWA

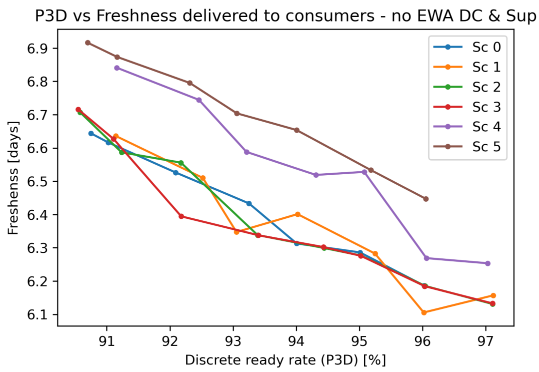

Figure 4.10: P3D versus freshness no EWA

4.4.4 Impact of DC's and supplier's target service level

During the analysis of the preliminary results, it appeared that the target service levels in the DC and at the supplier seemed to have more impact on the relative SC outdating and freshness delivered to the consumer than on the achieved availability in the stores. Since these results are in line with the current discussion between retailer and supplier regarding the trade-off between delivery completeness and freshness or waste and were also mentioned several times during the interviews, this impact was further analyzed.

First, the relationship between the safety factors (k) in each echelon and the performance measures is examined by calculating the Pearson correlations. The Pearson coefficient is a measure of the strength and direction of the linear association between two variables with no assumption of causality (Montgomery & Runger, 2013). Pearson correlations provide an impression of the significance and direction of the relationships between the safety factors and the performance measures. The correlations are calculated for each scenario for all safety factor combinations.

The correlations confirm the suspicion that the safety factors of the upstream echelons have a stronger impact on freshness and relative SC outdating than on availability in the stores. Table 4.7 presents the Pearson correlations and level of significance between the target service levels in each echelon and the in-store availability, relative SC outdating, and freshness. Since scenarios two and three showed almost similar results, they are merged to increase readability. This table shows that the impact of supplier safety factor on availability is low while its impact on performance indicators is high for all scenarios, excluding scenarios two and three. Except for scenarios two, three, and five, these conclusions also apply for the DC. This conclusion shows the opportunity to improve freshness and relative SC outdating without compromising availability by reducing the DC's and supplier's safety factors. However, the impact of this reduction must be examined for each collaboration.

Table 4.7: Pearson correlations between echelons' target service levels and P3D stores, relative SC outdating (z_{SC}), and freshness

	Scenario 0			**Scenario 1**			**Scenario 2/3**			**Scenario 4**			**Scenario 5**		
	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh
S0	0.73**	0.41**	-0.34**	0.74**	0.41**	-0.35**	0.48**	0.43**	-0.25**	0.74**	0.31**	-0.24**	0.64**	0.48**	-0.48**
S1	0.62**	0.52**	-0.28**	0.62**	0.54**	-0.29**	0.34**	0.54**	-0.12**	0.62**	0.4**	-0.19**	0.48**	0.62**	-0.32**
S2	0.16**	0.2**	-0.07**	0.16**	0.2**	-0.07**	0.07**	0.21**	0.0	0.16**	0.15**	-0.05**	0.1**	0.24**	-0.05**
DC	0.14**	0.34**	-0.55**	0.16**	0.33**	-0.54**	0.3**	0.27**	-0.44**	0.14**	0.36**	-0.5**	0.55**	0.27**	-0.36**
Sup	-0.0	0.31**	-0.55**	0.02**	0.3**	-0.55**	0.46**	0.42**	-0.69**	0.04**	0.53**	-0.73**	0.13**	0.28**	-0.62**

Note: ** Correlation is significant at the 0.01 level (2-tailed); * Correlation is significant at the 0.05 level (2-tailed)

Since a significant relationship between the DC's and supplier's safety factors and the performance indicators has been indicated, the impact between these variables is examined. Therefore, the average availability in the stores, relative SC outdating and freshness delivered to the consumer from all unique safety factor combinations are calculated for the DC and supplier for each scenario. Table 4.8 shows the impact of the DC's safety factor on the performance measures and Table 4.9 of the supplier.

From Table 4.8 it can be seen that the in-store availability hardly increases in the baseline scenario and scenarios one and four. However, the relative SC outdating increased and freshness delivered to the consumers decreased when the DC's safety factor increases. These findings imply that increasing safety stock levels in the DC does not necessarily improve customer availability but does result in reduced freshness and increased relative outdating. For the other scenarios (two, three and five), this effect seems to be less significant. There is still a reasonable increase in availability for these scenarios, while the performance reduction on freshness and relative SC outdating is less significant. Finally, these observations are consistent with those based on the correlations discussed above.

Table 4.8: Impact of DC's safety factor on P3D stores, relative SC outdating, and freshness

	Scenario 0			Scenario 1			Scenario 2/3			Scenario 4			Scenario 5		
k	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh
0	0.937	0.083	6.211	0.942	0.085	6.198	0.929	0.062	6.393	0.944	0.092	6.215	0.917	0.055	6.638
0.84	0.941	0.096	6.059	0.947	0.098	6.050	0.942	0.071	6.272	0.948	0.106	6.059	0.931	0.061	6.590
1.28	0.942	0.103	5.976	0.948	0.105	5.968	0.944	0.074	6.215	0.949	0.116	5.957	0.937	0.064	6.552
1.64	0.942	0.109	5.902	0.948	0.111	5.898	0.944	0.076	6.170	0.949	0.125	5.864	0.940	0.066	6.515
2.33	0.942	0.120	5.775	0.949	0.122	5.779	0.945	0.081	6.086	0.949	0.145	5.681	0.945	0.071	6.434

Whereas an increase in the safety factor at the DC still had some impact on availability in the stores, this is not the case with the supplier. Table 4.9 shows that an increase in the supplier's safety factor results in a reduction of freshness and relative outdating, while availability hardly increases in all scenarios. The degree to which this performance declines seems to vary per scenario. For example, the relative SC outdating in scenario four compared to scenario five increases more intense when the supplier's safety factor increases. Finally, these observations are again consistent with those based on the correlations.

Table 4.9: Impact of supplier's safety factor on P3D stores, relative SC outdating, and freshness

	Scenario 0			Scenario 1			Scenario 2/3			Scenario 4			Scenario 5		
k	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh	P3D	z_{SC}	Fresh
0	0.941	0.087	6.186	0.946	0.089	6.176	0.922	0.056	6.509	0.946	0.078	6.373	0.930	0.055	6.713
0.84	0.942	0.092	6.131	0.947	0.094	6.124	0.945	0.072	6.237	0.948	0.104	6.024	0.934	0.061	6.605
1.28	0.941	0.102	5.983	0.947	0.104	5.975	0.946	0.074	6.213	0.948	0.116	5.956	0.935	0.064	6.542
1.64	0.941	0.109	5.854	0.947	0.112	5.848	0.946	0.075	6.198	0.948	0.132	5.749	0.936	0.066	6.487
2.33	0.940	0.120	5.768	0.947	0.122	5.769	0.945	0.086	5.981	0.948	0.155	5.674	0.936	0.072	6.382

4.5 Conclusions

The simulation study aims to gain insights into the applicability and potential of different forms of information sharing in a perishable divergent SC. This conclusion discusses and reflects on the results obtained from the simulation study.

Based on the results presented, it can be stated that order forecast sharing is generally the most appropriate and beneficial SCC model. The relative SC outdating can be improved without collaboration by implementing the EWA replenishment policy mainly in the stores. However, the application of the EWA has minimal impact on the freshness delivered to the consumer. Furthermore, the performances of order forecast sharing and centralised EWA replenishment policy are approximately similar under the evaluated conditions (current situation, demand adjustment and upstream replenishment policy). POS forecast sharing becomes attractive when consumer demand is sufficiently high to reduce the disruptive effects of order batching and outdating, as shown in the increased demand adjustment situation. Supplementing the POS forecast with the estimated outdating does not improve performances. The freshness delivered to the consumer enhances with order forecast sharing and centralised EWA replenishment but remains about the same with POS forecast sharing compared to the current situation. In addition, the difference in relative SC outdating between POS forecast sharing, order forecast sharing, and centralised EWA replenishment is minimal when targeting high service levels. Therefore, order forecast sharing or centralized EWA replenishment is preferred over POS forecast sharing. Moreover, the interviews conclude that sharing order forecasts is preferred by suppliers and that the retailer also prefers this form of information sharing. Besides, the echelon based EWA replenishment outperforms order forecast sharing in some situations but requires more adaptation of current processes, making this scenario inferior to order forecast sharing.

From the results of adjusting the consumer demand, it is concluded that the average demand, and thus the disruptions of order batching and product shelf life, impact the applicability and benefits of the SCC models. When average demand increases, and thus the disruption of order batching and product shelving decreases, the added value of SCC decreases, and vice versa. However, the results demonstrate that each collaborative model improves SC performances. Since the achievement of efficient collaboration is not a trivial task, it can be argued that careful consideration should be given to which suppliers are preferred for which collaboration form. Finally, the simulation results without upstream EWA implementation show that upstream EWA implementations do not yield significant performance improvements. This finding can be explained by the fact that most of the waste in the SC is depreciated in stores, making upstream EWA implementations less valuable. Implementing the EWA replenishment policy in the stores reduces SC outdating and can thus improve this performance without the need for collaboration.

Finally, the analysis of the impact of the DCs and supplier safety factors shows potential in reducing upstream safety stocks. Reducing these stocks can result in less waste throughout the SC and deliver fresher products to consumers without compromising the service in the stores. However, implementing this kind of change in practice requires a shift in the evaluation of suppliers. Currently, many suppliers are evaluated based on their delivery completeness and on-time delivery. However, this evaluation matrix reduces the freshness of the delivered products because suppliers maintain safety stocks to comply with the delivery standards set. The same shift in KPIs was emphasised during the interviews when discussing intensified collaboration. These original performance indicators could be supplemented by a KPI for the delivered freshness, instead of agreeing on a minimum freshness delivered. When more intensive collaboration is achieved, the relative outdating in the entire SC and the freshness delivered to the consumer could be used as KPI.

Chapter 5

Conclusions and recommendations

This concluding chapter presents the conclusions and recommendations of the research. First, the research is concluded by answering the research question in Section 5.1. Then, in Section 5.2, the recommendations to Jumbo are presented. The scientific contribution of the research is discussed in Section 5.3 Finally, the limitations of the research and possible future research directions are presented in Section 5.4.

5.1 Conclusions

This study aimed to help Jumbo develop a vision on how to intensify collaboration in their SC by delivering concrete guidelines on how the collaboration could be intensified and what the impact of intensified collaboration would be. Therefore, the research question was formulated as follows:

Which supply chain collaboration model should be used to efficiently improve supply chain performance considering different supply chain conditions (e.g., perishability, demand variability, case pack sizes)?

Five sub-research questions were formulated to answer the main research question. The first sub-research question focused on the existing supply chain collaboration (SCC) models and conditions influencing the potential of these models. The literature review concluded that several SCC techniques are developed in past decades, but most emphasis is placed on information sharing (IS), vendor managed inventory (VMI), and collaborative planning, forecasting, and replenishment (CPFR). CPFR is the most comprehensive collaboration framework, thereby offering the greatest potential benefits for the entire SC. However, based on practical experience CPFR also appears difficult to realise due to various implementation barriers like trust, proper information sharing, and integration of improved forecasts in daily operations. In addition, the comprehensiveness of CPFR also causes the concept to become vaguer, hindering practical implementation. Finally, it can be concluded from the literature review that the effect of collaboration is enhanced in uncertain situations with higher costs, such as longer lead times, higher demand variability, and higher holding and backorder costs.

The second sub-research question concerned the requirements and desires of the supply chain (SC) members considering different SCC models. A wide range of suppliers was interviewed to obtain these insights. In general, the interviewees indicated to be satisfied with the current collaboration and acknowledged the added value of SCC. Moreover, interviewees characterise the current collaboration as labour-intensive and mainly address data-related improvements.

Besides, it is crucial to align the goals and define associated key performance indicators (KPIs) that all parties can control, including the measurement and evaluation method. Furthermore, an unambiguous, automated, standardized, and vendor-tailored information sharing system is required to enable the supplier to align processes on shared information. Suppliers classified forecast, inventory, and point of sales (POS) information as valuable information, ascending in intensity.

The third sub-research question focused on the quantitative modelling of different SCC models. Based on the literature review and exploratory research, six SCC scenarios were evaluated that differ in replenishment strategy and shared information through a discrete event simulation. These scenarios were assessed in a divergent three-echelon SC for a perishable with fixed shelf life under non-stationary demand due to promotions, order batching and lost sales. The simulation study aimed to optimise SC waste and freshness while maintaining in-store availability. Finally, the performances of the SCC scenarios are assessed under adjusted demand to assess the influence of the disruptive effects of order batching and shelf life on their performances. Additionally, the effect of upstream EWA implementations was examined.

The fourth sub-research question focused on quantitatively identifying the optimal SCC model under different SC conditions. Implementations of the EWA policy, mainly in the stores, reduced SC outdating but has a limited effect on the freshness delivered to the consumer. In the current situation and with reduced demand, order forecast sharing and centralised EWA policies perform equally well. Under increased consumer demand, the performance of POS forecast sharing enhances. Extending this POS forecast with expected outdating has a limited effect. POS forecast sharing does not improve freshness, while order forecast sharing and centralised EWA policies do. Since order forecast sharing is preferred by the supplier and retailer and easier to implement, order forecast sharing is the preferred SCC model. Furthermore, the positive impact of SCC grows as the disruptive effects caused by order batching and shelf life increase. Finally, the upstream implementation of the EWA policy has a limited effect on the performance.

The fifth sub-research question focused on the quantitative impact of implementing collaboration in the SC on performances under different SC conditions. The quantitative impact is assessed in the current situation, where a service level of 95 per cent is targeted. In the current situation, the EWA implementation reduces the relative SC outdating by 4.3%, the centralised replenishment policy enhances the relative SC outdating by 20.6% and the delivered freshness to the consumer by 4.6%, and order forecast sharing with EWA enhances the relative SC outdating by 17.5% and the delivered freshness by 3.5%. However, under reduced demand, these differences are even higher: the EWA implementation enhances the relative SC outdating by 12.7%, and the centralized replenishment policy improves the relative SC outdating by 29.3% and the delivered freshness to the consumer by 12.6%. Moreover, order forecast sharing enhances the relative SC outdating by 36.8% and the freshness by 11.0%. In conclusion, these three SCC models lead to significant improvements in a three-echelon perishable SC, positively affected by disruptive SC effects.

In conclusion, collaboration in the supply chain positively influences supply chain performance. A productive collaboration requires an alignment of vision and goals. Moreover, an unambiguous, automated, standardized, and vendor-tailored information sharing system is needed. Additionally, mutual trust and transparency about information quality and accuracy are essential. Finally, order forecast sharing is identified as the preferred form of information sharing.

5.2 Recommendations

The recommendations resulting from this study are discussed in this section. This study aimed to provide Jumbo with concrete guidelines on intensifying collaboration in their SC. Practical recommendations on SCC are derived from the exploratory research, supplemented by the explanatory research to determine the applicability and benefits of perishable SCs.

Before initiating collaborations, Jumbo should create a detailed understanding of what they want to achieve with which type of supplier. The desired degree of flexibility in supplier selection, the intended goal of the collaboration, the ease of establishing intensive collaboration, and the potential impact are four factors that can assist with the consideration of supplier selection. After the retailer has clarified what they want to achieve with which suppliers, the supplier can be involved. In collaborations, both parties must perceive the added value. As aligning the collaboration goals is crucial in establishing efficient collaborations, a joint strategic vision must be developed during the initialisation phase. From this vision, concrete collaboration objectives must be aligned and translated into KPIs that can be pursued and influenced by all parties. All parties must agree on the measurement and evaluation of these KPIs methods and must be able to affect the KPI performances by initiating improvement initiatives.

Once a detailed collaboration vision has been developed, the type of information that needs to be shared to achieve the intended objectives can be determined. The intensity of information sharing depends on the intended purpose and type of supplier. However, the information sharing process is independent of the intended purpose. The current information sharing process is perceived as inefficient because it is labour-intensive due to the many manual operations and is not aligned with the supplier's needs. As a result, the shared information cannot be fully utilised to improve and align processes. In particular, establishing an unambiguous, automated, standardised, and supplier-tailored information sharing process is identified as a required improvement. In addition, different types of valuable information are addressed. Suppliers classified forecast, inventory, and point of sales (POS) information as valuable information, ascending in intensity. Forecast information is the most appointed type of information used to synchronise supply and demand. Transparency about forecast accuracy is crucial because it directly affects the usability of the shared forecast. Inventory information enables suppliers to prioritize products based on downstream needs and opens the discussion on the levels and locations of safety stocks. Finally, POS data sharing enables suppliers to respond quickly to changing demand patterns and perform in-depth analysis but is the least addressed because exploitation is complicated by SC disruptions.

When intensive collaboration is desired, it is recommended to initiate order forecast sharing, whereby transparency regarding the standard deviation is required. Order forecast sharing has the highest potential to reduce relative outdating in the SC while increasing the freshness delivered to the consumers without reducing availability. Besides, order forecasting sharing is preferred by the supplier and the retailer because limited sensitive information needs to be shared. Moreover, suppliers can use this forecast to synchronise their processes with the expected demand of the direct downstream echelon. It is also advisable to initiate collaborations for products or product groups with the highest potential benefits. The Fresh Case Cover can be used to easily quantify the improvement potential in food waste and freshness, as defined in Broekmeulen & Donselaar van (2019). Finally, it is recommended to implement the EWA replenishment policy in the stores. However, this implementation requires any form of expiration data visibility, which must be established first. Without the implementation of item-level expiration date visibility, EWA replenishment can be achieved when the DC informs the store of the actual shelf life per delivery.

5.3 Scientific contribution

This section discusses the scientific contributions of this research in the field of supply chain collaboration.

The qualitative research is an extension of the existing literature on SCC by adding in-depth empirical insights into the requirements, desires, and barriers of upstream SC members in fast-moving consumer goods. Besides, aspects are identified which could support retailers in their decision process when determining the appropriate collaboration model. Moreover, the qualitative research adds an understanding of the magnitude and dimensions of SCC, merged into an SCC model. This model could help retailers initiate and implement collaboration successfully by aligning the required information sharing, intended information usage, envisaged benefits, and associated KPIs. Altogether, these findings extend the literature by making SCC models concrete and tangible and providing guidelines on how the appropriate SCC model can be determined, initiated, and implemented.

As emphasised in the literature (Hollmann et al., 2015; Nimmy et al., 2019), this research endorses the importance of a thorough information sharing process. The exploratory research helps to determine crucial factors of a comprehensive information sharing process. These insights assist in establishing a robust information sharing process and technology serving as a basis for effective collaboration.

In addition, this research contributes to the existing literature by quantifying the potential improvements of multiple forms of information sharing in relative SC outdating and freshness delivered to the consumer in a divergent three echelon perishable supply chain with order batching and inclusion of promotion periods. This study indicated that sharing order forecasts significantly improve the performance of the SC. In addition, this research shows that sharing a consumer demand forecast does not improve performance, which can be explained by the distorted effect of order batching. Adding estimated outdating does not increase the performance of consumer demand forecast sharing either. Finally, this study supports the added value of the EWA replenishment policy, as repeatedly demonstrated in the literature.

5.4 Limitations and further research

This section discusses the limitations of this research and potential directions for further research in the domain of supply chain collaboration.

All interviewed suppliers were located in the Netherlands and were familiar with Dutch culture. Only one interviewee reported international experience with supply chain collaboration. However, differences in culture and dynamics of these supply chains may influence the results of the interviews. Cultural differences and different dynamics in the supply chain can influence the results. Accordingly, it may be interesting to conduct further research into the needs of international suppliers and to what extent cultural differences can affect collaboration. In addition, it may be interesting to interview more respondents from each or more distinct supplier categories to increase the generalisation of the findings. This study mainly categorised suppliers by shelf life and product type (private label or A-brand). However, there are many different ways in which suppliers can be categorised, which can provide interesting additional insights. Therefore, an opportunity for further research might be to use statistical qualitative analysis to identify the differences between several types of suppliers and to develop a framework based on the requirements and desires per type of supplier.

The optimisation method of the decision variables in the simulation study can be seen as a limitation of this research. In this study, the decision variables are optimised based on an enumeration of a limited set of possible variable values. A complete enumeration of all possible values or a different optimisation method could lead to different results. This limitation creates an opportunity to further investigate collaborations in perishable supply chains using a different optimisation method.

The scope of the simulation study may be a limitation of the explanatory research phase. The simulation study evaluates the effect of the collaboration models in a supply chain of one perishable product from one dedicated supplier with a daily and unlimited production process. Extending this scope can lead to relevant new insights. The inclusion of multiple different products and transport and production capacities can result in other preferred collaboration models. In addition, including multiple retailers can result in interesting additional insights because the supplier can use different SCC models with each retailer, which could impact the performance of each retailer. Furthermore, analysing the effect promotions and the promotion frequency have on the performance of the SCC models would be interesting for further research. If a significant relationship is found this could help the retailer to determine the desired form of collaboration per supplier. Besides, further analysis of the effect of case pack size and shelf life on the SCC model performances may also help differentiate between product groups. Finally, it may be interesting to analyse the effect of a less flexible production process on the performance of the SCC models. In conclusion, once a broader scope has been analysed, a framework can be developed to indicate which SCC model is preferable under which SC conditions.

In future research, the concept of point of sales data sharing in a multi-echelon perishable supply chain could be investigated. Literature suggests that POS information sharing could enhance SC performances by quickly obtaining accurate insights into the underlying demand patterns (Croson & Donohue, 2003; Sari, 2008b). However, based on the interviews and practical applications, realising this potential seems challenging (Accenture, 2001, 2002). Therefore, the concept of sharing POS information and its added value can be an interesting topic for further research.

Finally, further research is needed to determine the optimal distribution of the safety stock and the associated safety factors. This research shows that reducing upstream safety stock can positively impact the performance of a perishable supply chain. However, further in-depth analysis is required to determine the impact of various factors on this distribution. Therefore, further research into the level and location of safety factors in a collaborative perishable supply chain may be of interest.

Bibliography

Accenture (2001). A Guide to CPFR Implementation. Tech. rep., ECR Europe, Brussels, Belguim. 11, 50

Accenture (2002). European CPFR Insights. Tech. rep., ECR Europe, Brussels, Belguim. 11, 50

Adan, I., Eenige van, M., & Resing, J. (1995). Fitting discrete distributions on the first two moments. *Probability in the Engineering and Informational Sciences*, *9*(4), 623–632. 31

Alsaawi, A. (2014). A Critical Review of Qualitative Interviews. *European Journal of Business and Social Sciences*, *3*(4), 149–156. 12

Atan, Z. (2017). Lecture nodes 1CM100 Multi Echelon Inventory Management. Tech. rep., Eindhoven University of Technology, Eindhoven. 33

Audy, J. F., Lehoux, N., D'Amours, S., & Rönnqvist, M. (2012). A framework for an efficient implementation of logistics collaborations. *International Transactions in Operational Research*, *19*(5), 633–657. 9

Aviv, Y. (2001). The effect of collaborative forecasting on supply chain performance. *Management Science*, *47*(10), 1326–1343. 8, 26

Axsäter, S. (2015). *Inventory Control*. Springer, 3 ed. 26, 28, 33

Barratt, M., & Oliveira, A. (2001). Exploring the experiences of collaborative planning initiatives. *International Journal of Physical Distribution and Logistics Management*, *31*(4), 266–289. 1, 31

Bastiaansen, G. (2019). Implementation of expiration date visibility at Jumbo Supermarkten. Tech. rep., Eindhoven University of Technology, Eindhoven. 30, 63

Boon, M., Boor, M. v. d., Leeuwarden, J. v., Mathijsen, B., Pol, J. v. d., & Resing, J. (2019). Stochastic Simulation using Python. Tech. rep., Eindhoven Univesity of Technology, Eindhoven. 37

Borade, A. B., Kannan, G., & Bansod, S. V. (2013). Analytical hierarchy process-based framework for VMI adoption. *International Journal of Production Research*, *51*(4), 963–978. 9, 26

Broekmeulen, R. A., & Donselaar van, K. H. (2019). Quantifying the potential to improve on food waste, freshness and sales for perishables in supermarkets. *International Journal of Production Economics*, *209*, 265–273. 29, 31, 39, 48

Broekmeulen, R. A., & van Donselaar, K. H. (2009). A heuristic to manage perishable inventory with batch ordering, positive lead-times, and time-varying demand. *Computers and Operations Research*, *36*(11), 3013–3018. 27, 32, 33

Caridi, M., Cigolini, R., & De Marco, D. (2005). Improving supply-chain collaboration by linking intelligent agents to CPFR. *International Journal of Production Research*, *43*(20), 4191–4218. 26

Chen, F., Drezner, Z., Ryan, J. K., & Simchi-Levi, D. (1994). *The Bullwhip Effect: Managerial Insights on the Impact of Forecasting and Information on Variability in a Supply Chain*, vol. 17. Springer, Boston, MA. 8, 26

Chen, F., Drezner, Z., Ryan, J. K., & Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times, and information. *Management Science*, *46*(3), 436–443. 28

Christopher, M. (1999). *Logistics and Supply Chain Management: Strategies for Reducing Cost and Improving Service (Second Edition)*, vol. 2. Financial Times Professional Limited. 1

Clark, A. (1958). A Dynamic, Single-Item, Multi-Echelon Inventory Model. Tech. rep., Rand Corporation, Santa Monica. 26, 28

Creswell, W. J., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative and Mixed Methods Approaches*. Los Angeles: SAGE, 5 ed. vi, x, 7, 12, 13

Croson, R., & Donohue, K. (2003). Impact of POS data sharing on supply chain management: An experimental study. *Production and Operations Management*, *12*(1), 1–11. 28, 50

Danese, P. (2011). Towards a contingency theory of collaborative planning initiatives in supply networks. *International Journal of Production Research*, *49*(4), 1081–1103. 1

Donselaar van, K. H., & Broekmeulen, R. A. C. M. (2014). Stochastic inventory models for a single item at a single location. *BETA publicatie: working papers*, *447*, 1–71. URL `https://pure.tue.nl/ws/portalfiles/portal/3784301/708391088818209.pdf` 3, 29, 37

Donselaar van, K. H., Peters, J., De Jong, A., & Broekmeulen, R. A. (2016). Analysis and forecasting of demand during promotions for perishable items. *International Journal of Production Economics*, *172*, 65–75. URL `http://dx.doi.org/10.1016/j.ijpe.2015.10.022` 32

Du, X. F., Leung, S. C., Zhang, J. L., & Lai, K. K. (2009). Procurement of agricultural products using the CPFR approach. *Supply Chain Management*, *14*(4), 253–258. 9, 26

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster Analysis: 5th Edition*. John Wiley & Sons Inc, 5 ed. 31

Fawcett, S. E., Magnan, G. M., & McCarter, M. W. (2008). a Three-Stage Implementation Model for Supply Chain Collaboration. *Journal of Business Logistics*, *29*(1), 93–112. 10

Ferguson, M., & Ketzenberg, M. E. (2006). Information Sharing to Improve Retail Product Freshness of Perishables. *Production and Operations Management*, *15*(1), 57–73. 8, 25

Fliedner, G. (2003). CPFR: An emerging supply chain tool. *Industrial Management and Data Systems*, *103*(1-2), 14–21. 10

Gavirneni, S. (2002). Information flows in capacitated supply chains with fixed ordering costs. *Management Science*, *48*(5), 644–651. 8

Gosselink, E. (2019). Improving retail product freshness of perishable goods with retailer-supplier collaboration a design for Jumbo Supermarkten B.V. Tech. Rep. September, Eindhoven University of Technology, Eindhoven. URL `https://research.tue.nl/en/studentTheses/improving-retail-product-freshness-of-perishable-goods-with-retai` 4

Haijema, R. (2013). A new class of stock-level dependent ordering policies for perishables with a short maximum shelf life. *International Journal of Production Economics*, *143*(2), 434–439. 4

Haijema, R., & Minner, S. (2016). Stock-level dependent ordering of perishables: A comparison of hybrid base-stock and constant order policies. *International Journal of Production*

Economics, *181*, 215–225.
URL `http://dx.doi.org/10.1016/j.ijpe.2015.10.013` 4

Helvoort van, N. (2014). Supplier-related replenishment improvements at Albert Heijn. Tech. rep., Eindhoven University of Technology, Eindhoven.
URL `https://research.tue.nl/en/studentTheses/supplier-related-replenishment-improvement-at-albert-heijn` 27

Hennink, M., Hutter, I., & Bailey, A. (2020). *Qualitative research methods*. London: SAGE, 2 ed. 7, 12, 13, 14

Hidayat, Y. A., Anna, I. D., & Khrisnadewi, A. (2011). The implementation of Vendor Managed Inventory in the supply chain with simple probabilistic inventory model. *MATEC Web of Conferences*, *58*, 252–256. 9

Ho, D., Kumar, A., & Shiwakoti, N. (2019). A Literature Review of Supply Chain Collaboration Mechanisms and Their Impact on Performance. *EMJ - Engineering Management Journal*, *31*(1), 47–68. 10, 25

Hollmann, R. L., Scavarda, L. F., & Thomé, A. M. T. (2015). Collaborative planning, forecasting and replenishment: a literature review. *International Journal of Productivity and Performance Management*, *64*(7), 971–993. v, 1, 9, 49

Jumbo (2020). Forecast and replenishment roadmap. Tech. rep., JUMBO SUPERMARKTEN B.V. v, 4

Jumbo (2021). Feiten en cijfers.
URL `https://www.jumbo.com/service/het-bedrijf-jumbo/feiten-en-cijfers` 2

Kamalapur, R., & Lyth, D. (2014). Benefits of CPFR Collaboration Strategy under Different Inventory Holding and Backorder Penalty Costs. *International Journal of Business and Management*, *9*(10), 1–9. 9, 34

Kamalapur, R., Lyth, D., & Houshyar, A. (2013). Benefits of Cpfr and Vmi Collaboration Strategies: a Simulation Study. *Journal of Operations and Supply Chain Management*, *6*(2), 59–73. 9

Kampen van, T. J., Donk van, D. P., & Zee van der, D. J. (2010). Safety stock or safety lead time: Coping with unreliability in demand and supply. *International Journal of Production Research*, *48*(24), 7463–7481. 8

Ketzenberg, M., & Ferguson, M. E. (2008). Managing slow-moving perishables in the grocery industry. *Production and Operations Management*, *17*(5), 513–521. 9, 31

Ketzenberg, M. E., Hall, R., Ferguson, M., & Street, W. P. (2005). Sharing Information to Manage Perishables. *College of Business, Colorade State University working paper*. 8

Kiil, K., Hvolby, H.-H., Fraser, K., Dreyer, H., & Strandhagen, J. O. (2018). Automatic replenishment of perishables in grocery retailing: The value of utilizing remaining shelf life information. *British Food Journal*, *120*(9), 2033–2046. 30, 34

Larsen, T. S., Thernøe, C., & Andresen, C. (2003). Supply chain collaboration: Theoretical perspectives and empirical evidence. *International Journal of Physical Distribution and Logistics Management*, *33*(6), 531–549. 11

Larson, P. D., & Rogers, D. S. (1998). Supply Chain Management: Definition, Growth and Approaches. *Journal of Marketing Theory and Practice*, *6*(4), 1–5. 8

Lowalekar, H., & Ravichandran, N. (2015). A combined age-and-stock-based policy for ordering blood units in hospital blood banks. *International Transactions in Operational Research*, *24*(4), 1561–1586. 27

Min, S., Roath, A. S., Daugherty, P. J., Genchev, S. E., Chen, H., Arndt, A. D., & Glenn Richey, R. (2005). Supply chain collaboration: What's happening? *The International Journal of Logistics Management*, *16*(2), 237–256. 10

Mitroff, I. I., Betz, F., Pondy, L. R., & Sagasti, F. (1974). On Managing Science in the Systems Age: Two Schemas for the Study of Science as a Whole Systems Phenomenon. *Interfaces*, *4*(3), 46–58. x, 24, 25

Montgomery, D. C., & Runger, G. C. (2013). *Applied statistics and probability for engineers*. Wiley, 6 ed. 43

Moyaux, T., Chaib-draa, B., & D'Amours, S. (2006). Supply Chain Management and Multiagent Systems: An Overview. *Multiagent based Supply Chain Management*, (pp. 1–27). 8

Niemann, W., Kotzé, T., & Jacobs, D. (2018). Collaborative planning, forecasting, and replenishment implementation: A case study of a major grocery retailer in South Africa. *South African Journal of Industrial Engineering*, *29*(4), 1–16. 9, 10

Nimmy, J., Chilkapure, A., & Pillai, M. V. (2019). Literature review on supply chain collaboration: comparison of various collaborative techniques. *Journal of Advances in Management Research*, *16*(4), 537–562. v, 1, 8, 49

Parsa, P., Shbool, M. A., Sattar, T., Rossetti, M. D., & Pohl, E. A. (2020). A Collaborative Planning Forecasting and Replenishment (CPFR) Maturity Model. *International Journal of Supply Chain Management*, *9*(6), 49–71. xi, 11

Ramanathan, U., Gunasekaran, A., & Subramanian, N. (2011). Supply chain collaboration performance metrics: A conceptual framework. *Benchmarking*, *18*(6), 856–872. 1, 8, 9

Rossman, G., & Rallis, S. (2012). *Learning in the field: An introduction to qualitative research*. Thousand Oaks: SAGE, 3 ed. 14

Sargent, R. G. (2010). Verification and validation of simulation models. In *In Proceedings of the 2010 Winter Simulation Conference*, (pp. 166–183). Baltimore, MD, USA: IEEE. 24, 37

Sari, K. (2008a). Inventory inaccuracy and performance of collaborative supply chain practices. *Industrial Management & Data Systems*, *108*(4), 495–509. 1, 8, 34

Sari, K. (2008b). On the benefits of CPFR and VMI: A comparative simulation study. *International Journal of Production Economics*, *113*(2), 575–586. 9, 26, 50

Seifert, D. (2003). *Collaborative Planning, Forecasting, and Replenishment: How to Create a Supply Chain Advantage*. New York: AMACOM, 1 ed. 11

Shaban, A., Costantino, F., Di Gravio, G., & Tronci, M. (2019). A new efficient collaboration model for multi-echelon supply chains. *Expert Systems with Applications*, *128*, 54–66. URL `https://doi.org/10.1016/j.eswa.2019.03.026` 26, 28

Shen, D., Lai, K. K., Leung, S. C., & Liang, L. (2011). Modelling and analysis of inventory replenishment for perishable agricultural products with buyer-seller collaboration. *International Journal of Systems Science*, *42*(7), 1207–1217. 9

Shen, D., Lai, K. K., & Liang, L. (2009). Inventory replenishment model for perishable products in two-level supply chain. *International Conference on Business Intelligence and Financial Engineering, BIFE*, (pp. 396–400). 9

Silver, E., Pyke, D., & Peterson, R. (1998). *Inventory management and production planning and scheduling*. New York: Wiley, 3 ed. 32, 33, 34

Simatupang, T. M., & Sridharan, R. (2002). The collaborative supply chain. *The international Journal of Logistics Management*, *13*(1), 15–30. 1

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (1999). *Designing and Managing the Supply Chain*. London: McGraw-Hill. 1

Thomé, A. M. T., Hollmann, R. L., & do Carmo, L. F. R. R. S. (2014). Research synthesis in collaborative planning forecast and replenishment. *Industrial Management and Data Systems*, *114*(6), 949–965. 9

VICS (1998). CPFR Guidelines. Tech. rep., Voluntary Interindustry Commerce Standards. 10

VICS (2004). CPFR - An Overview. Tech. rep., Voluntary Interindustry Commerce Standards. URL `https://www.gs1us.org/DesktopModules/Bring2mind/DMX/Download.aspx?Command=Core_Download&EntryId=492` v, x, 5, 9, 10

Vlist van der, P. (2007). *Synchronizing the retail supply chain (No. 110)*. Rotterdam: Erasmus Universiteit Rotterdam.
URL `http://repub.eur.nl/res/pub/10418/` 4

Waller, M., Johnson, M., & Davis, T. (1999). Vendor-managed inventory in the retail supply chain. *Journal of business logistics*, *20*(1), 183. 9

Weteling, R. (2013). Improving Freshness - the effects of week patterns and opening terms on outdating at Albert Heijn. Tech. rep., Eindhoven University of Technology, Eindhoven. 30

Wijshoff, M. (2016). Improving retail product freshness of perishable goods with strategic distribution flow management: A design for Hollander Barendrecht. Tech. rep., Eindhoven University of Technology.
URL `https://pure.tue.nl/ws/files/46946509/855864-1.pdf` 30, 61

Appendix A

Interview guide

This appendix shows the interview guide used during the interviews based on which the results of the exploratory research were obtained.

1 Introduction:

- Introducing myself:
  My name is Koen van Wershoven and I am currently working on my graduation project for the master Operations Management & Logistics at the Technical University of Eindhoven. In cooperation with Jumbo supermarkets, I will investigate how Jumbo can intensify the collaborations in their supply chain to improve the performance in the entire supply chain. The scope of the research concerns collaboration regarding forecast and replenishment processes and related information sharing. In the remainder of this interview, collaboration refers to the collaboration regarding forecast and replenishment processes and related information sharing.
- Purpose of the interview:
  The purpose of this interview is to gain insights into the current collaboration; the desired future collaboration and how this can be achieved; how Jumbo's collaboration compares to other partners; and what are influential factors on the collaboration.
- All interviews will be handled discreetly and anonymously:
  Your name will not be mentioned anywhere in my research or report. Also, the name of your company will not be mentioned anywhere during the entire process. For example, an interview will be referred to as the interview with company A.
- Recording:
  I would like to record the interview to allow for a detailed analysis and to be able to fully concentrate on the interview during the interview. Do you agree that I will record the interview from now on?

2 Current collaboration with Jumbo:

(a) How would you describe the current collaboration with Jumbo?
(b) What information is currently shared from Jumbo? (elaborate: what frequency, horizon, quality and level of detail?)
(c) How is this information currently used? (If not used, ask why this information is not currently used).

(d) What information is currently shared with Jumbo? (elaborate: what frequency, horizon, quality and level of detail?)
(e) How satisfied are you with the current collaboration with Jumbo?

3 Desired future collaboration with Jumbo:

(a) How can the current collaboration with Jumbo be improved?
(b) What are important joint key performance indicators?
(c) Which types of information are most useful to improve chain performance? (elaborate: what frequency, horizon and level of detail?)
(d) *(possible assistance question)* How would you rank the following types of information sharing in terms of usefulness for improving the supplier's processes?
  - Capacity information
  - Order forecast information (customer, shop or DC order)
  - Promotion information
  - Sales information
  - Inventory information (DC or shop)
(e) How can this information be used to improve supply chain performance?
(f) What are the most important potential benefits of improving the collaboration and information sharing with Jumbo? (elaborate: the benefits for both the supplier and Jumbo)

4 Expertise in the area of supply chain collaboration / benchmarking:

(a) To what extent does the supplier has experience with collaboration and information sharing in the supply chain with other partners?
(b) How intensive would you classify the collaboration with Jumbo compared to other partners?
(c) What are the main differences between the current collaboration with Jumbo and other partners? (elaborate: which information?)
(d) Based on your experiences, what are positive effects of collaboration in the supply chain?
(e) Based on your experiences, what are negative effects of collaborations in the supply chain?

5 Influencing factors on collaboration in the supply chain:

(a) For which type of products could collaboration in the supply chain adds the value?
(b) For which type of products does supply chain collaboration have no or less added value?
(c) What are supply chain conditions or characteristics (e.g. delivery time, minimum order quantity, variability of demand, production cycles) that may influence the effect of supply chain collaboration?

6 Closure:

(a) The forecast and replenishment mission of Jumbo reads: "Forecasting & Replenishment contributes to customer satisfaction by ensuring maximum availability, quality and freshness at optimal cost through managing the entire chain from supplier to (cold) cabinet, for bricks and clicks. How can intensified collaboration contribute to achieving this mission?
(b) Are there any other things you would like to share or emphasize?
(c) Do you have any feedback for me?

Appendix B

Interviews results

This appendix shows the results per respondent of the interviews. Tables B.1, B.2, B.3, B.4 and B.5 indicate for each respondent whether specific reference was made to a construct during an interview. These results can be considered as the raw results of the qualitative research.

Table B.1: Results interviews current collaboration

Supplier	A	B	C	D	E	F	G	H	I	J	K	L	M
Perishability	S	S	S	S	S	M	M	L	L	L	L&M	L	L
Brand	PL	PL	PL	PL	PL	PL&PR	PL&PR	PR	PR	PR	PL	PL	PL&PR
Current - General													
Satisfied with current collaboration	X	X	X	X	X	X	X	X	X	X	X	X	X
Recognises opportunities in collaboration	X	X	X	X	X	X	X	X	X	X	X	X	X
Intensive contact	X	X	X	X			X	X	X	X		X	X
Joint long-term strategic plans and goals		X	X				X	X					
Current - Information sharing													
Forecast promotion/seasonal orders		X	X	X	X	X	X	X	X	X	X	X	X
Forecast consumer demand		X	X				X		X	X	X	X	
Forecast orders		X	X	X									
DC inventory							X						
Shop orders	X	X	X	X			X						
Shop orders advice		X	X										
Point of sales data		X	X	X				X			X		
Additional information is shared through intensive contact	X	X	X				X		X		X		X

note: perishability: S-short, M-medium, L-long; brand: PL-private label, PR-premium

Table B.2: Results interviews desired collaboration

Supplier	A	B	C	D	E	F	G	H	I	J	K	L	M
Perishability	S	S	S	S	S	M	M	L	L	L	L&M	L	L
Brand	PL	PL	PL	PL	PL	PL&PR	PL&PR	PR	PR	PR	PL	PL	PL&PR
Desired - General													
Joint long-term strategic plans and goals	X				X					X		X	X
Trust and transparency in sharing problems and bottlenecks			X		X			X	X	X			
Automated, standardised and uncontested information sharing	X	X	X	X		X	X	X		X		X	
Quality of the shared data effects usability		X	X	X	X	X	X	X		X		X	
Importance and understanding of forecast accuracy	X	X	X	X	X	X	X	X		X	X	X	
Matching forecast horizon and aggregation		X	X		X		X	X	X	X		X	
Service level differentiation		X	X	X				X		X			
Transport and logistic collaboration	X				X		X					X	X
Desired - Information sharing													
Forecast consumer demand	X				X	X							
Forecast orders					X			X	X			X	
Inventory information DC	X			X	X	X		X	X	X	X	X	X
Inventory information stores	X	X			X		X		X			X	X
Point of sales	X				X		X			X		X	
Promotion information							X						X

note: perishability: S-short, M-medium, L-long; brand: PL-private label, PR-premium

Table B.3: Results interviews joint collaboration KPIs

Supplier	A	B	C	D	E	F	G	H	I	J	K	L	M
Perishability	S	S	S	S	S	M	M	L	L	L	L&M	L	L
Brand	PL	PL	PL	PL	PL	PL&PR	PL&PR	PR	PR	PR	PL	PL	PL&PR
Complete delivery								X	X	X	X	X	X
On-time delivery								X	X	X	X	X	X
Consumer service level	X	X	X	X	X		X	X	X	X	X	X	X
Waste	X	X	X	X	X	X	X						
(Joint) Forecast accuracy	X	X	X	X	X		X	X		X			
Freshness		X		X									
Promotion presentation									X				
Sustainability								X					

note: perishability: S-short, M-medium, L-long; brand: PL-private label, PR-premium

Table B.4: Results interviews benchmarking

Supplier	A	B	C	D	E	F	G	H	I	J	K	L	M
Perishability	S	S	S	S	S	M	M	L	L	L	L&M	L	L
Brand	PL	PL	PL	PL	PL	PL&PR	PL&PR	PR	PR	PR	PL	PL	PL&PR
Experience with supply chain collaboration	-	X	X	X	X	X	X	X	X	X	X	X	X
Collaboration intensity depends on the retailer's size	-	X				X		X					X
Relative intensive contact	-	X	X	X	X	X	X	X	X		X	X	X
Relative intensive and structured information sharing	-	X		X	X								
Opportunities in structured and matched information sharing	-		X			X	X	X	X		X	X	X

note: perishability: S-short, M-medium, L-long; brand: PL-private label, PR-premium

Table B.5: Results interviews influential factors

Supplier	A	B	C	D	E	F	G	H	I	J	K	L	M
Perishability	S	S	S	S	S	M	M	L	L	L	L&M	L	L
Brand	PL	PL	PL	PL	PL	PL&PR	PL&PR	PR	PR	PR	PL	PL	PL&PR
Perishability	X	X	X	X	X		X	X				X	
Seasonality / Promotions	X					X			X	X		X	X
Private label							X						X
Sales volume			X										
Product value		X	X		X								
Product volume											X		
Possibility of full transparency			X						X				
Lead times						X		X					

note: perishability: S-short, M-medium, L-long; brand: PL-private label, PR-premium

Appendix C

Impact of the number of stores in the simulation model

This appendix shows the analysis used to determine the number of stores in the simulation study. Since the number of stores included in the simulation significantly impacts the simulation time, the effect of the number of stores on the performance measures is analyzed. The effect of the number of stores on the relative demand variability (expressed in coefficient of variation), relative supply chain outdating, and the aggregate store performance (P2 and P3D) is analyzed. Since the number of stores will negatively impact the required simulation time, a trade-off must be made between the number of stores and the simulation time. These effects are analyzed based on a simulation of the baseline scenario with 30 replications and a warm-up period of 40 weeks, and a simulation time of 2 years. The results are displayed in Figure C.1.

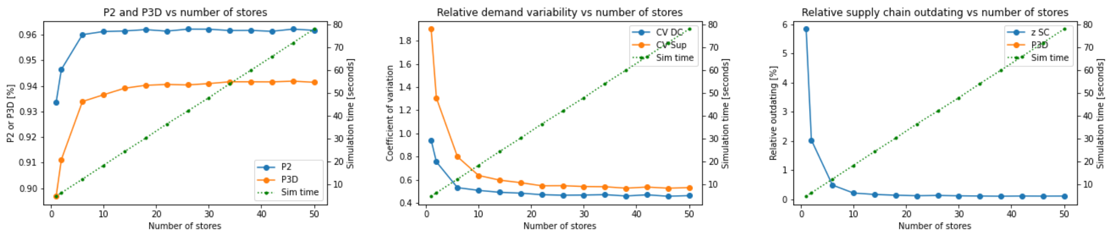

Figure C.1: Effect of the number of stores on the service level, upstream demand variability, and relative SC outdating

The number of stores significantly impacts the aggregate store performance, the relative supply chain outdating, and the relative demand variability of the DC and supplier. In contraction to the suggested inclusion of 50 stores by Wijshoff (2016), it can be concluded that 20 stores should be sufficient. Including more stores would not lead to improved results, but will increase the simulation time. Including 20, instead of 50 stores will reduce the approximate simulation time by approximately 50 seconds per simulation run. Therefore, 20 stores are included in the simulation study.

Appendix D

Input parameters simulation study

This appendix presents the input parameters of the simulation study. Table D.1 presents the input parameters regarding the simulation settings, based on the determination analysis of the simulation properties in Appendix H.

Table D.1: Input parameters - Simulation settings

Input parameters	Value(s)
Warm up time	40 weeks (280 periods)
Simulation time	2 years (728 periods)

Table D.2 shows the input parameters regarding the design of the supply chain. The number of stores included in the model is based on the analysis shown in Appendix C. The number of stores per cluster is based on the fraction of each cluster as presented in Appendix E. Finally, the initial shelf life of the products is determined based on expert interviews at the retailers since no data was available.

Table D.2: Input parameters - Supply chain design

Input parameters	Value(s)
Nr. of stores	20
Nr. of stores per category [small, medium, large]	[10, 8, 2]
Initial shelf life	12

Table D.3 provides an overview of the demand input parameters. The majority of these parameters are based on empirical sales data. The uncertainty in the Lift Factor and forecast error in the lift factor are based on expert interviews with forecasts at the retailer.

Table D.4 presents the input parameters regarding the individual echelons. The length of the lead times and review periods are defined based on the retailer's process description. The Store's en DC's case pack size is based on empirical data from all stock keeping used inside the research scope. Since no data were available about the supplier's case pack size (e.i., producing batch size), the assumption is made that these batches are equal to the DC case pack size, so they produce in integer multiplication of the pallet or pallet layer size. There is compensation for the fact that DC normally supplies more than 20 stores by dividing the average number of

Table D.3: Input parameters - Demand

Input parameters	Value(s)
Weighted mean regular demand	4.95 [3.86, 5.57, 7.92]
Weighted CV regular demand	0.89 [0.85, 0.91, 1.00]
Weighted mean promo demand	11.20 [7.66, 13.19, 20.96]
Weighted CV promo demand	0.64 [0.66, 0.63, 0.57]
Weighted lift factor	2.21 [1.98, 2.37, 2.65]
Promotion frequency	8
Uncertainty lift factor	∼U(0.85,1.15)
Forecast error lift factor	∼N(1, 0.15)

stores supplied from one DC by the number of included stores rounded up to the nearest integer multiplication of the store's case pack size. The minimum life on supply is based on empirical data. Finally, the FIFO withdrawal fraction in the stores is based on the research of Bastiaansen (2019), and a FIFO policy is assumed at the DC and the stores.

Table D.4: Input parameters - Echelons

Input parameters	Values(s)		
	Stores	DC	Supplier
Lead time	1	1	1
Review period	1	1	1
Case pack size	5	48	48
Minimum life on supply	1	6	9
Target P3D	[0.90, 0.95, 0.99]	[0.50, 0.80, 0.90, 0.95, 0.99]	[0.50, 0.80, 0.90, 0.95, 0.99]
FIFO withdrawal fraction	0.45	1.0	1.0

Appendix E

Store clustering

This appendix discusses the clustering procedure of the stores. To reduce the number of safety factors in the simulation model, the stores' demand is clustered. The elbow method is used to determine the number of clusters, and k-means clustering is used to cluster the stores. Stores are clustered based on the mean demand during 2022 during regular and promotion periods. Based on the elbow row three clusters are created, see Figure E.1. It could be stated that stores er clustered based on their size, where size is defined as the average yearly sales during promotions and regular sales periods. Besides, it can be concluded that the mean demand during promotions is approximately linear with the mean demand during promotions. Moreover, based on Figure E.2, the mean demand is approximate linear related to the demand's standard deviation per store.

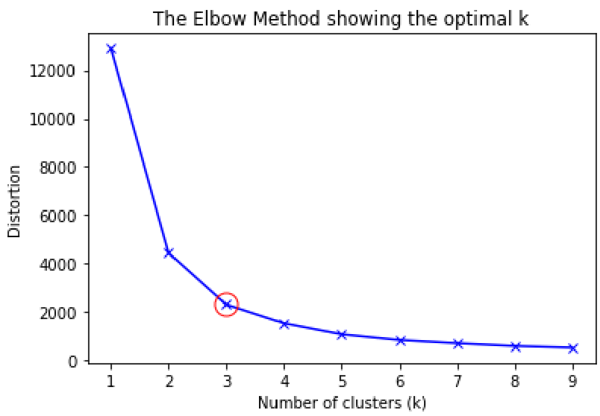

Figure E.1: Elbow method for store clustering

Table E.1 presents the deceptive statics of the clustered stores. Based on these results the proportion of large stores (cluster 0) is 0.149, of medium stores (cluster 3) 0.362, and of small stores (cluster 2) 0.489. These proportion will be used to initialize the demand distribution functions in the simulation. Therefore, 5 (4.47) large stores, 11 (10.86) medium stores, and 14 (14.67) small stores are included in the simulation.

Table E.2 shows the fitted discrete demand distribution on clustered store data. A distribution is fitted based on these results for each cluster during regular and promotion demand. All stores in each cluster have identical demand distribution functions. Therefore, all stores within

Figure E.2: Mean and standard deviation of promo and regular demand per cluster

Table E.1: Descriptive statistics of the clustered stores

Cluster	**Count**	**μ regular dem.**	**μ promo dem.**	**σ regular dem.**	**σ promo dem.**	**CV. regular dem.**	**CV. promo dem.**	**Lift Factor**
0	67	7.919	20.958	7.719	11.938	1.001	0.573	2.70634
1	220	3.861	7.660	3.270	5.089	0.851	0.665	1.99676
2	163	5.570	13.191	5.099	8.298	0.932	0.632	2.40427

one cluster have the same demand characteristics (mean and standard deviation) during promotions and regular sales periods. Using the fitting procedure of Adan result in the following promotion and regular demand distributions per cluster.

Table E.2: Fitted discrete demand distribution on clustered store data.

Regular								
Cluster	EX	CV	condition	a	dist	k	q	p
0	7.91871	1.00055	TRUE	0.87481	NB	1	0.66634	0.85586
1	3.86136	0.85075	TRUE	0.46479	NB	2	0.63816	0.62048
2	5.56973	0.93177	TRUE	0.68865	NB	1	0.34831	0.77128
Promotion								
Cluster	EX	CV	condition	a	dist	k	q	p
0	20.95774	0.57339	TRUE	0.28106	NB	3	0.25936	0.84855
1	7.65968	0.66461	TRUE	0.31116	NB	3	0.55581	0.68982
2	13.19106	0.63198	TRUE	0.32358	NB	3	0.71948	0.80084

Appendix F

Analysis of Lift Factor

This appendix presents the analysis preformed to validate the lift factor. The average lift factor is analyzed to estimate whether an product with an average lift factor is selected. This is based on two data set. First, a lager data set for a lot of promotion mechanism and product combination are analyzed. These results are shown in the Table F.1 and Figure F.1. However, since this data was prepossessed the accuracy of the data could not be verified, while it contained a relatively large number of inexplicable elements, the POS data of five SKUs are analyzed to check whether the lift analyzed lift factors where correct. The selected SKUs are from different product categories.

Table F.1: Descriptive statics regular sales, promotion sales, and the lift factor

	count	mean	std	min	25%	50%	75%	max
Regular sales	1,306	7,391	8,628	91.00	1,965	4,796	9,678	67,664
Promo sales	1,306	12,624	14,467	0.00	2,985	7,496	17,390	116,792
Lift factor	1,306	1.82	1.14	0.00	1.23	1.52	2.02	23.54

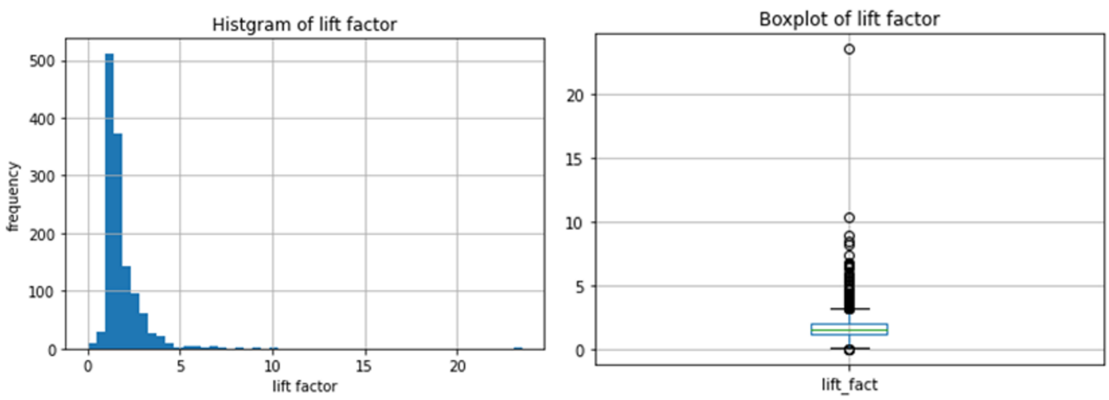

Figure F.1: Histogram and box plot of the Lift Factor

Several effects could disrupt this analysis, like incorrect promotion calendar or because local entrepreneurs extend the promotion because they still have enough stock, for instance. As discussed, the POS data of three products is analyzed in detail to verify these results. This analysis is based on POS data for one year (2021) of all available stores. During the preparation of the data, it emerged that some stores did not sell the product throughout the year; these shops were removed from the data.

Figure F.2 shows the weekly sales for each product. These figures show that several aspects could influence the Lift Factor, like no sales due to upstream delivery problems and disappointing promotion. When these periods are not considered, the Lift Factors fall in the range found earlier. Therefore, it can be concluded that the lift factor used in this research is representative for the retailer's press products. However, it can help the retailer in the future to create a better overview of the different promotions and their effect on the demand for the products in the perishable product categories.

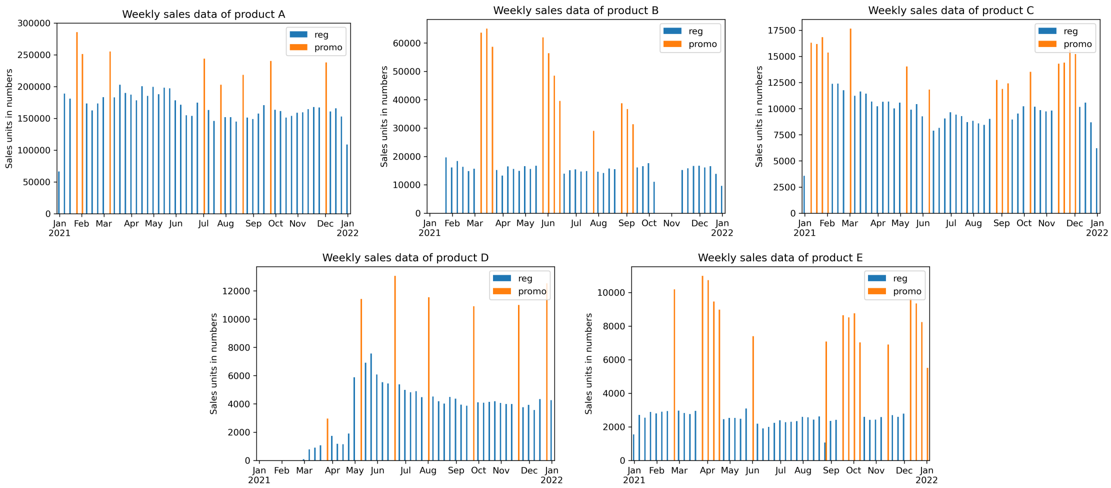

Figure F.2: Weekly sales of each products

Appendix G

Impact of the forecasting period on the service level

This appendix shows the analysis of the impact of the forecasting period on the upstream service levels. The aim of this analysis is the show that the sequence of events, in which coordination between production, delivery, ordering, and transport is assumed, the forecast period can be shortened. By this alignment, a portion of the day's demand is already known and therefore no longer needs to be predicted. This analyse is based on the baseline scenario, 30 simulation replications, a warm-up period of 40 weeks and simulation length of two years.

Figures G.1 and G.2 shows the P3D and P2 of the supplier and DC for several safety factors. From these figures, it can be concluded that even negative safety factors do not result in a significant reduction in performance. Therefore, it can be concluded that the forecast period is such a long time that the DC and supplier always have sufficient inventory to meet demand when applying realistic safety factors ($k >= 0$). Due to this forecast period, it makes no sense to optimise the safety factors of the upstream echelons because the lowest factors will always be chosen, as this does not compromise service but improves freshness and losses. Figures G.3 and G.4 shows the P3D and P2 of the supplier and DC for several safety factors with reduced forecasting periods. These figures show that this reduction results in a more realistic situation and the relation between the safety factor and realised performances. Therefore, the forecast period of the upstream echelons is reduced by one.

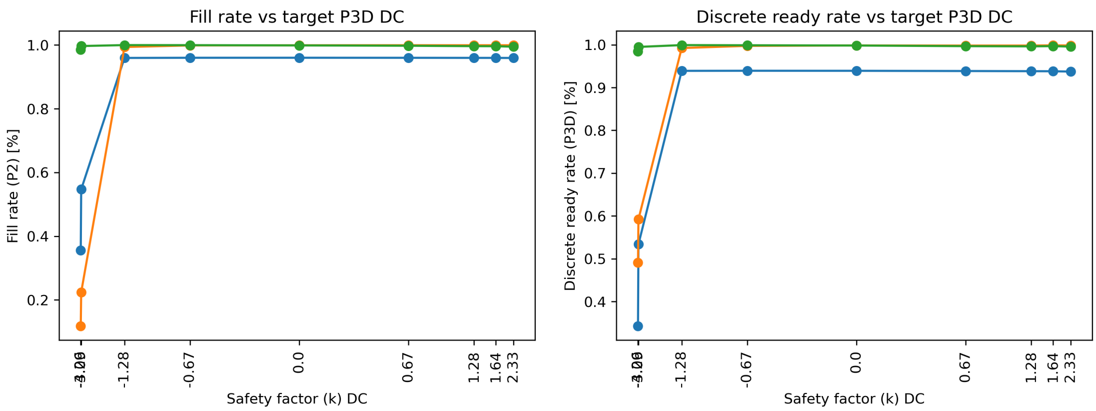

Figure G.1: Impact safety factor on service level DC with original forecasting period

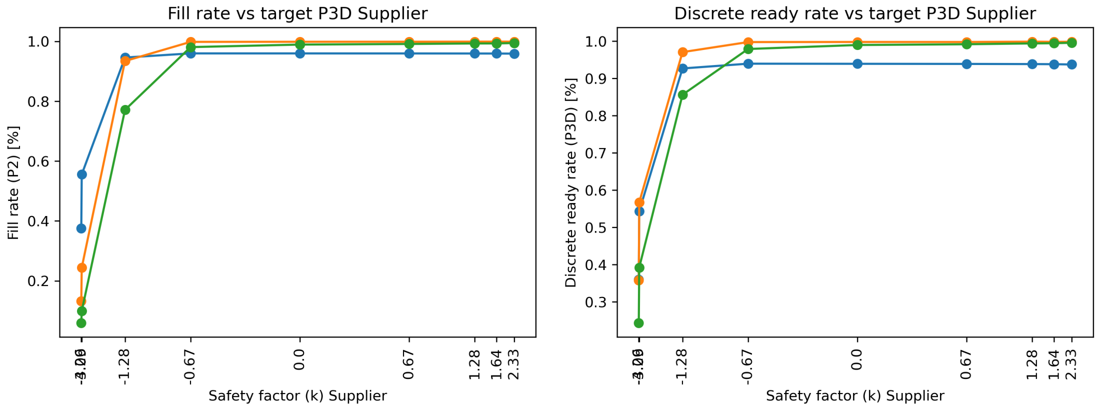

Figure G.2: Impact safety factor on service level supplier with original forecasting period

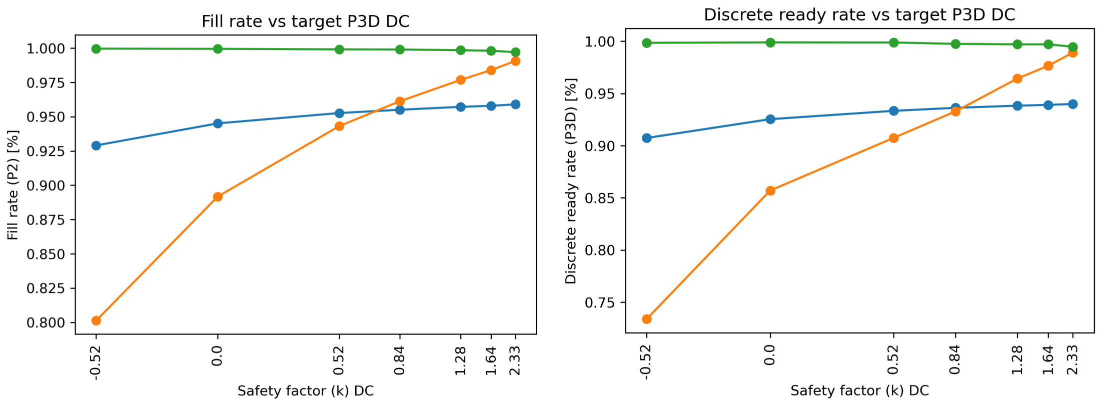

Figure G.3: Impact safety factor on service level DC with reduced forecasting period

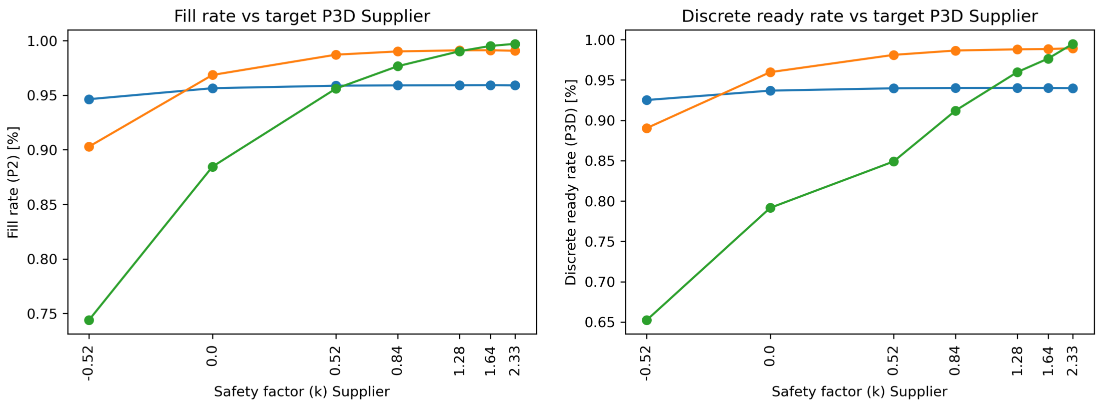

Figure G.4: Impact safety factor on service level supplier with reduced forecasting period

Appendix H

Analysis of simulation properties

This appendix presents the performed analysis that defines the three simulation properties, warm-up period, simulation length, and the number of simulation runs.

First, the warm-up time is determined. The warm-up time is the time that the simulation will run before starting to collect results. This allows simulation aspects to get into conditions that are typical of normal running conditions in the considered system. In this simulation the number of products in the system, the echelon's inventory levels, and reorder levels are used to determine the warm up time. These parameters are chosen because they represent the available inventory in each echelon and the stability of the forecast. Finally, the warm-up time is determined based on one simulation run for the baseline scenario.

Figures H.1 and H.2 show the inventory on hand in each echelon with and without promotions without a warm-up period. Based on these plots, a warm-up period of 40 weeks (280 days) is chosen. In these 40 weeks, 8 promotion periods take place. It can be observed that the system without promotions reaches a stable state after approximately 250 days. However, the inclusion of promotions leads to a longer unstable period. This longer unstable behaviour is mainly caused by the fact that there are fewer promotions than regular sales days, which means that there is less available data that can be used for predicting the average promotion demand. Concluding, a warm-up period of 40 weeks (280 days) will be used.

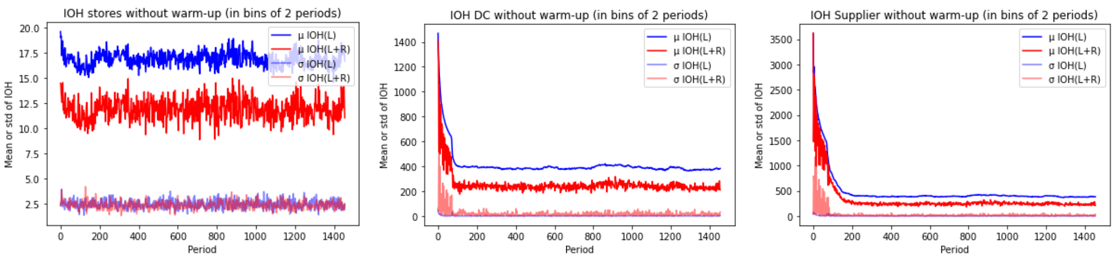

Figure H.1: Inventory on hand in each echelon without promotion and warm-up period

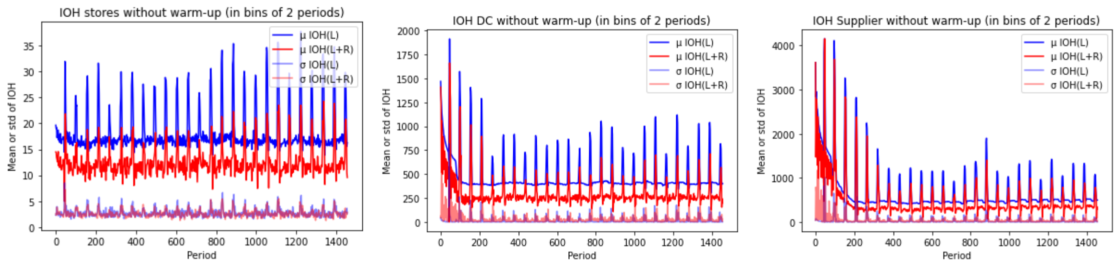

Figure H.2: Inventory on hand in each echelon with promotion and without warm-up period

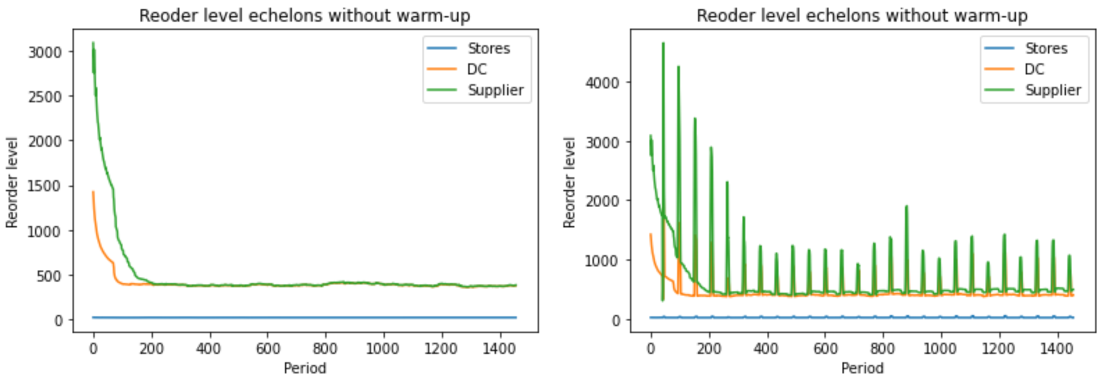

Figure H.3: Reorder level of echelons without warm-up period

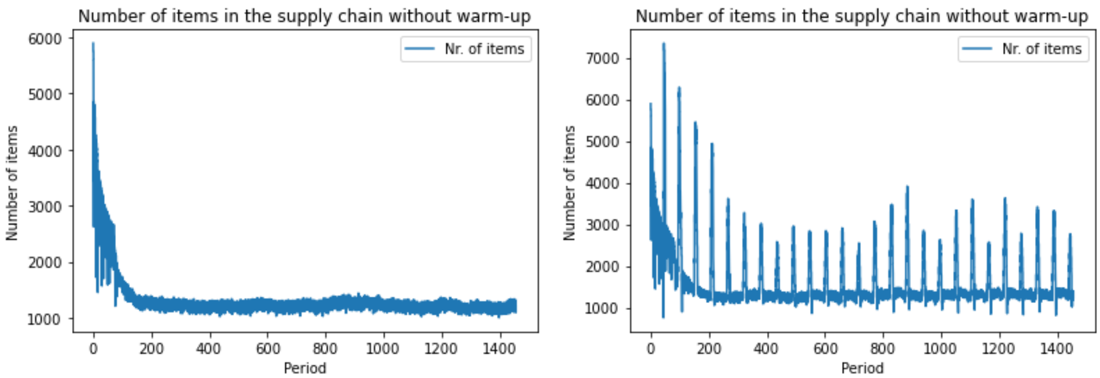

Figure H.4: Number of products in the system without warm-up

Second, the simulation length is determined. In this project, strategic supply chain implementations are considered and therefore it makes no sense to have a simulation length of less than one year. In addition, the length of the simulation rounds should be significant compared to the length of the warm-up period. Therefore, it is assumed that a simulation length equal to two years is sufficient to generate reliable results. An extension of the simulation length does not result in a significant reduction of the standard deviation between the simulation runs, but only results in a longer computation time.

Finally, the number of simulation runs is determined. Since no initial guess for the value of standard deviations is available, the two-step approach can be used. Therefore, the baseline scenario with the determined warm-up time and simulation length is executed for ten random seeds to estimate the standard deviations. Based on 10 simulation runs the estimated standard deviation of the aggregate store's discrete ready rate is 0.001 and of the relative supply chain outdating is 0.05. Therefore, to obtain a 95% confidence interval for the mean aggregate stores' discrete ready rate of half-width 0.001, the number of replications n has to be 10. However, since the standard deviation of the relative supply chain outdating is higher, a lot more replications are required to obtain the same half-width. Since the computation time in combination with the number of simulations required does not allow for more than 30 replications or for extending the simulation length, each simulation will be run 30 times.

Appendix I

Simulation validation

This appendix presents the numerical validation of the simulation by comparing the simulation results with analytical obtained results from the DoBr-tool. As this research aims to vary some input parameters this validation is performed for multiple input parameter configurations. Table I.1 provides an overview of the test input parameters.

Tables I.2 and I.3 show the absolute and absolute percentage differences between the results from the simulation and the DoBr tool. These results confirm that the simulation model is an accurate representation of the conceptual model usage.

Table I.1: Input parameter settings mode validation with DoBr tool

Parameters	**Value**
Situation	Lost sales
Lead-time	1.0
StDev lead-time	0.0
Review period	1.0
Mean period demand	3.58936755
StDev period demand	3.358783533
IOQ (case pack size)	[1,**3**,5]
MOQ	0.0
Reorder level	[10,**15**,20]
Shelf life	[3,**5**,7]
Fraction FIFO withdrawal	[0.5,0.8,**1.0**]

Note: The values in bold are the values used in the baseline scenario. Therefore, no full enumeration has taken place, but the values have been changed alternately, with the bolded values serving as the baseline.

Table I.2: Simulation comparison with DoBr tool (absolute difference)

		IOQ		Reorder level		Shelf life		FIFO fraction		
KPIs	**Base**	1	5	10	20	3	7	0.5	0.8	**Mean**
P2	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.003	0.002	0.00
P3D	0.002	0.002	0.004	0.006	0.001	0.008	0.002	0.010	0.004	0.00
E[IOH(L)]	0.010	0.010	0.028	0.007	0.015	0.008	0.011	0.015	0.030	0.01
E[IOH(R+L)]	0.020	0.020	0.042	0.036	0.026	0.022	0.019	0.011	0.060	0.03
E[OL]	0.001	0.002	0.002	0.001	0.003	0.002	0.003	0.008	0.001	0.00
E[OS]	0.014	0.025	0.005	0.014	0.035	0.023	0.028	0.050	0.043	0.03
E[supply]	0.009	0.010	0.013	0.011	0.012	0.014	0.009	0.005	0.030	0.01
E[Z]	0.000	0.000	0.000	0.001	0.002	0.002	0.000	0.004	0.005	0.00
Mean	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	

Table I.3: Simulation comparison with DoBr tool (percentage absolute difference)

		IOQ		Reorder level		Shelf life		FIFO fraction		
KPIs	**Base**	1	5	10	20	3	7	0.5	0.8	**Mean**
P2	0.16%	0.19%	0.08%	0.15%	0.12%	0.09%	0.15%	0.28%	0.24%	0.16%
P3D	0.16%	0.17%	0.44%	0.70%	0.11%	0.93%	0.17%	1.12%	0.42%	0.47%
E[IOH(L)]	0.08%	0.09%	0.22%	0.09%	0.08%	0.07%	0.09%	0.12%	0.24%	0.12%
E[IOH(R+L)]	0.23%	0.27%	0.46%	0.77%	0.21%	0.30%	0.23%	0.14%	0.73%	0.37%
E[OL]	0.08%	0.18%	0.32%	0.09%	0.32%	0.23%	0.35%	1.03%	0.12%	0.30%
E[OS]	0.28%	0.58%	0.07%	0.29%	0.63%	0.42%	0.54%	0.92%	0.82%	0.51%
E[supply]	0.24%	0.27%	0.33%	0.34%	0.26%	0.30%	0.23%	0.11%	0.75%	0.31%
E[Z]	0.33%	0.46%	0.42%	2.44%	0.85%	0.72%	0.48%	2.35%	4.62%	1.41%
Mean	0.20%	0.28%	0.29%	0.61%	0.32%	0.38%	0.28%	0.76%	0.99%	