UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

AN ASSORTMENT PLANNING PROCESS ANALYSIS: THE CASES OF A NORWEGIAN AND A DUTCH RETAILER

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AUTHORSHIP STATEMENT

We, the undersigned Igor Jončevski and Uroš Jarc, students of the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), authors of this written final work of studies with the title "An assortment planning process analysis: the cases of a Norwegian and a Dutch retailer", prepared under the supervision of prof. dr. Mojca Indihar Štemberger

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LIST OF ABBREVIATIONS

en. – English

no. – Norwegian

AI – artificial intelligence

AOP – Automatic order processing

CDT - customer decision tree

CPG – consumer-packaged goods

CPI – compound performance indicator

DC – distribution center

DOS – days of supply

EDW – enterprise data warehouse

FMCG – fast-moving consumer goods

GM – general merchandising

GSO – GOLD Store operation

HQ - headquarters

IIS – Internet Information Services

ITIL – Information Technology Infrastructure Library

KPI – key performance indicator

MDM – master data management

NPI – New product introduction

PIM – Product information management

POS – point-of-sale

SaaS – software-as-a-service

SFTP – secure file transfer protocol

SKU – stock keeping unit

SQL – structured query language

TPG – The Partnering Group

INTRODUCTION

Companies in the 21st century, be they manufacturers, distributors, or retailers, are facing increasing and fiercer competition in global and local markets. The market has become saturated with big systems, big companies that have emerged as a result of merging smaller companies. Due to their continued globalization and struggle to stay on the market, they have surrendered or sold themselves to larger systems, which were stronger and, as such, could withstand increasing competition on the market (Bristol, 2018 b).

The concept of category management has evolved in response to the downturn, which is showing a decline in consumption, lower purchasing power, excess production capacity, competition, and lower sales prices. Category management is a beneficial part of management that allows a trading company to define, what are the customer's wishes, needs, expectations, and requirements. Properly implemented, it helps to maximize company profitability and customer satisfaction. With a correctly executed process, category management obtains vital facts about the behavior of the market, the customer, the retailer, and the supplier, at the level of individual product groups. With this information, we receive a quality set of information, which helps us make better business decisions (Arh, 2006).

Category management is a concept where product groups act as strategic business units. It forms the basis for competitive advantage. With a properly executed concept, we gain the knowledge to adapt quickly to changes in the market. Only in this way can we market the right products at the right time, in the right direction, in order to meet our wishes and needs customers and increase the profitability of the company (Bandyopadhyay, Rominger, & Basaviah, 2009).

The beginnings of category management date back to 1990, and from this year onwards, a real revolution in knowledge in this field has been observed. At the time, it represented a revolution, especially on the part of retailers, the awareness of the importance of cooperation with all partners, and the re-emphasizing of the importance of the consumer and his desires. Managing a brand is about finding out what the consumer wants and is looking for, and more satisfying than the competition. However, to achieve this, you need to know the basics of category management and the eight steps to achieve it (Citeman, 2010).

Traditional category management obviously focuses on the product, in which product movement (in time and in location) is used as a proxy for client selection and client demand. The underlying assumption that distributors and service providers are working with is that shoppers are going to purchase what distributors sell. However, because retailers all over the world know that shoppers are not as passive as they are once assumed–they don't just want good-priced goods; they want solutions to their lifestyle needs. It's no longer a matter of what distributors and their partners would like to sell, but where and how they want to purchase it (Bandyopadhyay, Rominger, & Basaviah, 2009).

Sophisticated analysis and virtualization methods in the next-generation category management allow distributors to achieve strategic distinction by enabling them to move further from a highly competitive/low-dividing value offer that focuses on price and convenience and offers a compelling shopping experience. Retailers will be able to create more focused category plans, test these plans using client behavior insights, implement them more effectively, build a platform for better collaboration with providers, and ultimately maximize the profitability and growth potential of each store (Rigby, 2012).

Technology is engaged in all aspects of retail business, and category management is no exception. In category management, technology's function is to optimize categories by size, product mix, and inventory levels at the shop/cluster stage. New techniques, such as cloud and artificial intelligence (hereafter: AI), contribute to enhancing dexterity and scalability in turn time. Increased visibility and understanding of client requests and the associated supply mapping is the fundamental principle of implementing technology. In addition, along with various solutions to category management, proposals can be provided on assortment, marketing, pricing, space, and promotions (Michaud, 2018).

The purpose of the thesis is to evaluate the assortment procedures used by distinct distributors from different countries. Our assessment will be used primarily to build our internal company knowledge on the subject of different assortment processes, which may differ from one country to another and from one retail branch to another. This subject was selected as we want to deepen our existing knowledge of the various assortment processes in use, which will help with our understanding of operations with other retailers, which we will encounter in our work within our company.

The goals of this thesis are:

- Reviewing existing literature and researches on the topic of category management, trends related to this branch and challenges encountered by retailers
- Opening discussions with representatives of both retailers, to acquire knowledge on current and desired processes related to assortment
- Comparing both assortments processes to point out the differences between them and potentially discover opportunities

We used various methods to facilitate the creation of the thesis. We started with the theoretical part, where we described category management in general, its trends, and everyday challenges. This was accomplished by reviewing the existing literature. We continued by describing one of the tools available on the market, which is used to support category management processes. Both things were accomplished by reviewing secondary literature from foreign sources and various researches on the topic, as well as using internal material.

The knowledge we have both gathered during our own studies, accompanied by our accumulated experience while working on various projects (of different software modules - related to category management) with different clients, countries, and continents, was also utilized for the creation of the thesis.

The second part of the thesis is empirical. Discussions with resources from both retailers were performed in order to gather relevant information on the assortment processes within the companies, what were the key users' expectations and if they have been met, high points, low points, and general feedback.

This thesis is divided into 4 chapters. After the introduction, we focus on expanding our knowledge of category management, what challenges are retailers up against in this day and age, expand a bit on what are the trends in category management, and how is that branch broadening and developing. In the second chapter, we talk about the traditional approach to category management and touch on best-practice approaches. In addition, there are two sections where, in more detail, we describe the architecture of the cloud-based category management suite offered by the company we are employed in, and we also describe each tool in the suite.

Chapter 3 starts with a short overview of the methodology we used, as well a description of the retailers we are analyzing. We also talk about their strategy and vision. Afterward, we describe in detail their assortment processes and also subprocesses, which are part of the assortment definition process. At the end of each of these chapters, we offer our opinion on how both retailers can improve their assortment process.

In chapter 4, we draw a parallel between their strategy and vision and their assortment processes and try to ascertain if their assortment definition processes are compliant. We also compare both processes and point out the similarities and the differences between them and try to figure out if both retailers are following some of the best-practice approaches. At the end of this chapter, we offer our opinion on how both retailers can improve their assortment process.

In the end, we finish with the conclusion, where we summarize the thesis and point out the benefits of it. We also point out our contribution and how can we, and people in retail in general, benefit from it.

1 CATEGORY MANAGEMENT

Category management can be defined as a series of activities, combined with the understanding of the shopper's needs and wishes, as well as activities that enable the right product to be provided at the right time and at a reasonable price (ECR Europe, 1996).

Category management is (Rebernik, 2014):

- A joint process between and retailer and the manufacturer, in which categories are defined as strategic business units with the intention of improving the business result by focusing on the satisfaction of the customer.
- A functional process, in which manufacturers are driven by the market, or more precisely, by the consumer.
- A concept of closer, long-term collaboration between the retailer and the manufacturer
- A philosophy that takes into account the so-called 'back to basics' principles and is more or less an evolutionary management approach. It is completely oriented towards a state of awareness that the only possibility for success is knowing the needs of the customer

At its most fundamental dimension, category management can be considered as a process that is used to create an extensive plan for addressing the needs of shoppers in a predominant way and creating powerful business results, both for manufacturers and retailers. Many consider category management to be a holistic approach that creates a point by point plan, which is based on insights, facts, sound methodologies, and proven models of success (Category Management Association, 2016).

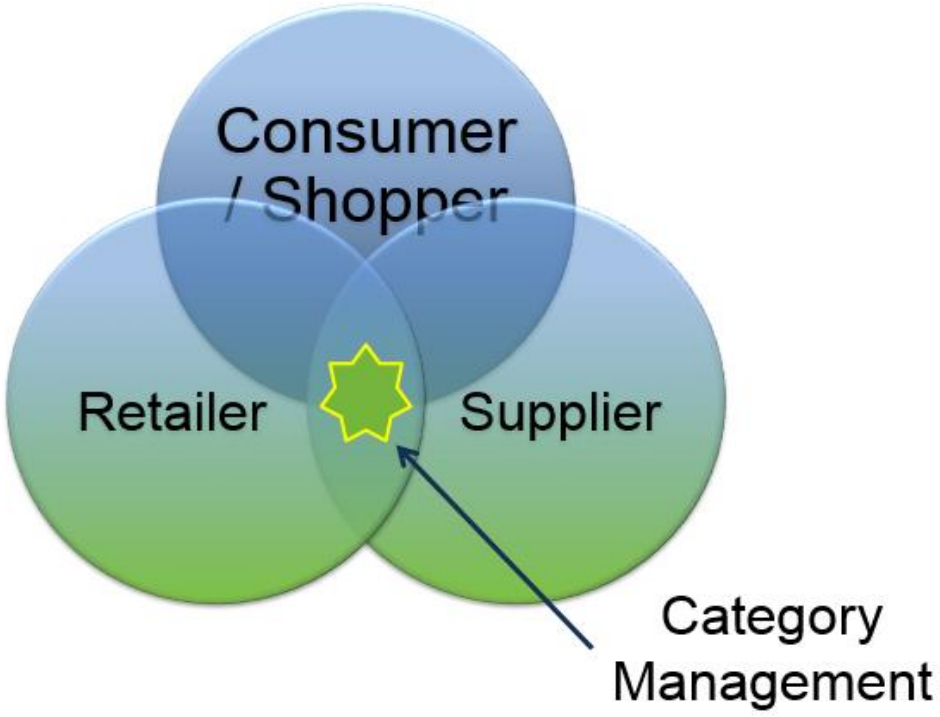
The category itself is defined as a group of products that are used by consumers to satisfy their desires. One category holds articles, for which the consumers think they are similar, structure and content-wise. Once a category is defined, it can be further divided into subcategories, which are shaped based on criteria used by the consumers to choose the products (Dupre & Gruen, 2004).

In a wider sense, category management is based on a working relationship between consumer-packaged-goods (hereafter: CPG) producers and retailers that is effective and mutually beneficial. Any veteran in the sector, however, can point out rapidly that while a cooperative relationship is desirable, developing one is a significant task. The primary obstacle is the timely and efficient execution of a common goal. The feedback method is also essential and must develop as a system that is constant, rather than discrete. In general, both retailers and CPG producers failed to come up with a truly cooperative strategy and co-existed mainly in a transactional relationship (EIQ Research Solutions, 2018).

Including shopper insights into this feature is one of the greatest improvements in category management. Information collected from inner sources (loyalty card, customer segmentation, and point-of-sale (hereafter: POS) information) and external sources (market syndicated data acquired from vendors) is processed and analyzed in order to determine specific consumer shopping patterns, which are then used to describe category features. While a number of retailers have made important progress in incorporating customer insight into this feature, others are still struggling to put their clients at the core of their development decision-making category readily and effectively (EIQ Research Solutions, 2018). According to the Category Management Association, the goals of "category management"

are to "... determine the point of optimization in pricing, promotion, shelving, and assortment to maximize profitability and shopper satisfaction."

Figure 1: Graphical representation of Category Management



Source: Symphony Retail AI (2018h).

These objectives are as important as ever to both fast-moving consumer goods (hereafter: FMCG) and general merchandising (hereafter: GM) retailers, but the category management methods of yesterday are not enough to tackle the business challenges in today's retail setting (Kilcourse, 2016).

Before category management even began, nor the manufacturer nor the retailer knew the shoppers and their needs all that well. The shopper's standpoint is vital in category management and its implementation (Dewsnap & Hart, 2004).

Retailers must be aware that the consumers' needs are two-fold because shoppers act in two different functional roles. Those are:

- The needs of a consumer;
- The needs of a buyer.

The needs of the consumer are reflected in the satisfaction that they achieve with the emotional and functional benefits they get from a product. The needs of the shopper are mainly focused on getting more for the money they pay for the product, as well as finding persuasiveness and clarity on the shelves.

Both roles are important for both the retailer and the manufacturer. The first is the one that manufacturers focus more on, because the consumer's satisfaction with the product, regardless of the benefit an individual has from it, means that the consumer will be back to buy the product again because it brings satisfaction to them. For the retailer, this role is an advantage in the sense that they get satisfied and loyal clients who will buy their product. The role of the buyer is the one that retailers focus on more. The logic behind this is that the retailers want to maximize the shopping experience by way of their pricing policy, product placement on shelves, customer satisfaction, product assortment, etc.

Customer satisfaction is essential for every organization, the reasons for that being the following (Rebernik, 2014):

- The better the supplier will fulfill or even surpass the customer's expectations, the more they would buy from them;
- A satisfied customer is the best customer, as well as the cheapest form of marketing;
- Customer satisfaction is directly proportional to the probability of a repeated purchase;
- Organizations, which want to dominate the market are forced to follow the customers' expectations.

Customer dissatisfaction is also vital for every organization, and the reasons for that are (Rebernik, 2014):

- 96% of dissatisfied customers do not complain about unsuitable products or services;
- 90% of dissatisfied customers will never go back to shop somewhere, where they have been disappointed before;
- 13% of dissatisfied customers will tell at least 20 other individuals about the unpleasant experience.

The reasons we pointed out should be considered because shoppers and their satisfaction are things worth paying attention to. The problem with which retailers and manufacturers are faced today is a drop in sales, but because they are either ignorant or not informed adequately about customer dissatisfaction, they are left wondering as to why things are the way they are.

1.1 Category Management: yesterday, today and tomorrow

Category management started as a process that allowed retailers to handle product categories as separate business units. The original version consisted of 8 steps, beginning with the definition of a category, and finishing up with a review. In between these two steps, a category plan was developed and implemented (Karolefski & Heller, 2006).

Many progressive manufacturers and retailers became aware that there is valuable information to be extracted from POS systems. A lot of questions were on their mind:

- Could they create different stocking schemes for different stores?
- Could analyzing sales data give information as to how to customize the look of the shelf for different stores?
- Could they be able to attract and keep shoppers with higher spending limits?

The answer to these questions was yes. All this and more could be achieved with category management. Category management was first introduced by The Partnering Group (hereafter: TPG), which is a consulting company, at the beginning of the 1990s. Some of the larger retailers at the time implemented category management and were soon full of advice and support. Very quickly, category management became a necessity for manufacturers and retailers alike.

Nowadays, TPG's process is considered to be the traditional form of category management. It consisted of eight steps (Karolefski & Heller, 2006):

- Category definition;
- Category role;
- Category assessment;
- Category scorecard;
- Category strategies;
- Category tactics;
- Plan implementation;
- Category review.

The first version of category management initiated a revolution in retail businesses, where a large number of retailers used category management principles in the way they operated. As time passed, many retailers found the process to be too complicated, not only to follow but to implement as well. Primary reasons were the level of detail and the number of variables that needed to be included for it to work, which made it unmanageable and lengthy. Too many services such as logistics and finance were required to coordinate in order for it work as it was intended. Manufacturers also experienced problems when sales personnel tried to get on top of the complexities of category management. This was a big problem since their main task was to develop ties and move products, and not category planning and analyzing. This resulted in manufacturers creating dedicated category management teams, where analysts were there to support the sales department. Even in those times, training someone and giving them the reigns for a whole category was a big task.

Traditional category management is clearly product-oriented, where the movement of the product (time-wise and location-wise) is used as a proxy for customer choice and demand across. The fundamental hypothesis with which both retailers and suppliers work is that shoppers will buy what retailers will sell. However, as retailers around the world have come to know that shoppers are no longer as passive as they were once assumed to be – they do not just want products with reasonable prices, they want alternatives to their lifestyle

requirements. What retailers and their associates want to sell is no longer a question, but what, where, and how shoppers want to buy (Kilcourse, 2016).

Over the years, category management has developed into different custom versions of it, each consisting of fewer steps. However, to this day, many businesses do still start with the traditional process, with the initial purpose and spirit remaining a part of it. Nowadays, category management is more than a manner of managing each category as a separate business entity. It has become a necessity for every retailer because if performed in the right way, it can provide a definite competitive advantage. In the merchandising world, the companies that can combine data, perspective, and the know-how on merchandising, are the ones that come out on top, and category management provides just that (Karolefski & Heller, 2006).

Next-gen category management with sophisticated analytics and virtualization techniques enables retailers to attain strategic differentiation by allowing them to move further from an extremely competitive/low differentiating value offering, which focuses on cost and comfort and provides a convincing shopping experience. Retailers will be able to create more concentrated and localized category plans quicker, test said plans using customer behavioral insights, roll them out more efficiently, create a platform for better cooperation with suppliers, and eventually maximize each store's profitability and development potential (Kilcourse, 2016).

1.2 Key Challenges For Retail

The mantra that 'the customer is always right' has been considered to be valid for a long time now. However, nowadays, consumers have all of the power in their own hands, because they have a lot of alternatives when buying products, and not just a couple like it was before. The number of retailers, as well as the information that is put forth to customers, has really expanded recently. The result of this is that shoppers spend plenty of time on research, all the while considering the complete shopping experience. All types of retailers are affected by shopper choosiness, and awareness since even wealthier customers are taking the time to do their research before making a purchase (eTail, 2019).

Since the expectations of the shoppers are continually changing, retailers must make sure that they are in the loop as to what are the new trends in order to tackle the challenges they are facing in satisfying picky customers.

We live in a time where every piece of information is easily accessible, both for retailers and for customers. Utilizing the customer data that is available, retailers can think of new and more innovative ways in order to get the customers coming back for more. However, this can be a double-edged sword because there is also plenty of data that is available to the customers as well (eTail, 2019).

The following are some of the key challenges that are common for most retailers around the world and need to be addressed in a proper way. They are:

- the Millennial market;
- the conscious consumer;
- environmental awareness;
- clear packaging;
- changing consumer habits and preferences.

1.2.1 The Millennial Market

Millennials are people who are born between 1980 to 2000, 'digitally fluent', having matured with all kinds of technology and expect to have it at their disposal in every of their life. The mobile phones are especially important to this group of people, given that we live in the age of social media, where sharing your life is a thing that everyone does. For example, the United Kingdom's 14 million-strong millennial population is more likely to start and end their journey on their smartphones than any other age group, who have begun turning their mobile devices into a handheld wallet (Promo Marketing, 2019).

In order to retain millennial shoppers, it is paramount for retailers to improve the payment experience for them by setting up self-check-out counters and the possibility of using contemporary payment technologies. Striving for perfection from a technological standpoint is crucial because millennials consider this to be the norm, and they expect to have it available at every corner. Retailers must be able to provide simplified and user-friendly services if they want to keep their focus on the millennial shoppers (Promo Marketing, 2019).

However, that is not all there is to the challenge. Whether this is going to happen in the actual store or online, retailers must think of a personalized shopping experience. Millennials are selective, and they are looking for someone who will be able to understand their preferences and make suggestions that will be adapted to their needs. In other words, they want a shopping experience that centers around them, and that makes them feel valued. To achieve this, retailers need to understand how they are currently processing the available customer data and what are they doing with it, and find a way to use said data to provide a more personalized in-store experience (Promo Marketing, 2019).

1.2.2 The Conscious Consumer

In the past years, retail practices have taken grossly affected the environment as manufactures tried to incorporate quicker and cheaper methods of providing customers with products. The retail manufacturing industry is the second most polluting one, after the oil industry. However, the millennial generation is propagating increased awareness on the

topic, which has paved the way for the conscious customer to emerge (Promo Marketing, 2019).

Conscious customers are the ones that look at the big picture, big picture being to think about various aspects of the business and the products (e.g., is the product environmentally friendly). In the end, people try to make the best possible decision on what to buy, while at the same time trying to resolve the negative impact that consumption has on the world these days (Promo Marketing, 2019).

Another thing that conscious consumers concern themselves with is the way how people are being targeted, both through article positioning and advertising. As both services and products keep expanding in order to represent the mixed cultural composition of the population, we can effectively witness the attempts that advertising makes to celebrate differences as the only norm there can be. In other words, they are falling in line with Omni-culturalism. This development of things shows that brands need to find a way to engage consumers and their identity in a non-traditional way (e.g., race, gender …) (Promo Marketing, 2019).

1.2.3 Environmental Awareness

One of the main changes in consumer demand recently is retailers embracing the so-called eco-friendly packaging and processes. The expectation for this is to grow exponentially, with the focus being set on two main areas as retailers try to attract Millennial and Generation Z consumers, which are people born between mid-1990 to early 2000s (Butcher, 2019).

A lot of documentaries speak about raising awareness of the effect that plastics have on the environment. This also triggered plenty of protests and boycotting products with inadequate packaging. That resulted in a number of retailers offering customers the possibility to return packaging that is difficult to recycle. The result of this has seen a number of schemes established to enable customers to return complex packaging, which is difficult for recycling plants to process. Brands like Pringles and Walkers gave in to the pressure and are now accepting packagings in certain stores. However, consumers need to be diligent and make an effort. Otherwise, all this will be viewed as a marketing scheme and a ploy (Butcher, 2019).

Designing eco-friendly packaging which keeps the contents fresh and are entirely recyclable, is not an easy task. However, retailers can team up with manufacturers and suppliers in order to come up with an innovative solution to environmental challenges. This would mean that millennials would like one more reason to shop there, which gives retailers a significant advantage. In the last two years, a number of retailers have already announced that they will try to create more recyclable packaging (Butcher, 2019).

1.2.4 Clear Packaging

Nowadays, plenty of people have already or have the intention to switch to veganism, meaning practicing a diet free from animal products. That is why many retailers are launching their own range of vegan products in order to try and attract consumers like these. However, starting new product lines is a challenge for retailers and suppliers alike. This can be seen in the case of Marks & Spencer, who did it earlier this year and had trouble and received critiques about the lack of information on the packaging (Butcher, 2019).

New legislatures dictate the content of the packaging labels. Since packaging needs to contain a lot of information, retailers have to collaborate really closely with their suppliers in order to get to the level where the labels on their products are meeting the health and safety standards, as well as the content is evident. With that being said, brands need to deliver precise data and to simplify the message they want to provide (Butcher, 2019).

1.2.5 Changing Consumer Habits and Preferences

Today's consumers expect to be able to purchase anything at any given time, anywhere, and at a reasonable price. Millennials are particularly picky and have higher expectations than any other demographic group. They (Kuijpers, Simmons, & Wamelen, 2019):

- want to know how their food is made;
- want to know where their food comes from;
- expect companies to be aware of the environment and the society they live in;
- expect companies to offer sustainable products;
- are drawn to online shopping because it is convenient.

Since Millennials are the first generation, which is less wealthy than their parents, they also expect discounts and package deals when buying products. Taking all this into account, retailers are trying hard to meet all of the above expectations, but without having to raise the prices of the products (Kuijpers, Simmons, & Wamelen, 2019).

Another demographic category that also has high purchasing power is the Baby-boomers category. These are people born between 1946 and 1964. Although Baby boomers are an essential base for retailers, they present additional challenges to tackle. First, they are slightly different than elderly generations from before, in the sense that they are more comfortable with technology, many are single, they decide to retire later, and they are concerned about wellness and health. They are also more open to trying new products and experiences and value the customer service that they get in the store. Again, the retailers' task is to adapt. Grocers have to adjust their product pallet and keep their prices as low as possible (Kuijpers, Simmons, & Wamelen, 2019).

No matter how many demographics we describe and analyze, the one thing they all will have in common is that they are not prone to cooking. Surveys have shown that more than 50% of American millennials seldom cook meals at home. Instead, what they all do is opt for ready-made meals, which can be bought at most larger stores at reasonable prices. Because of the high-paced life, especially in Europe and the United States of America, the percentage of food-at-home consumption is declining, and the foodservice one is rising. It is expected that the revenue that the food-service generates will surpass the revenue that food-at-home sales generate (Kuijpers, Simmons, & Wamelen, 2019).

1.3 Trends in Category Management

The retail sector today is much more fragmented and competitive than it was ever before. Multiple store formats and an arsenal of digital tools are to blame for the buyers' enhanced awareness of shopping decisions. There is also a growth of digital channels. This is especially true for groceries, where big players such as Amazon and Walmart continue to feed into traditional chains (Symphony Retail AI, EIQ Research Solutions, 2018).

There is also a diverse landscape, with a lot of different types of families, different lifestyles, and very different requirements than the ones that dominated past generations. This is further compounded by an ever-growing ethnic population with a distinct advantage in each region, from language and food to shopping and financial status. When we factor in the countless malls that attract the youthful Millenniums in flocks, the result is an environment that is always on the move.

Retailers are currently operating domestic and global chains. Their client base is now on the move, is ethnically and economically varied, and their channel affinities are continually evolving. Therefore, grocery retailers have created progressively advanced methods of matching products to individuals and have become pioneers in collecting and applying consumer data to merchandise mixes (Symphony Retail AI, EIQ Research Solutions, 2018).

In order to attract different kinds of shoppers, suppliers and retailers alike are in need of real-time information about the shoppers. However, the development of different systems, sensors, and machine-to-machine communications have led to big data sets, and manipulating them represents significant logistical problems for businesses using on-line data management instruments or traditional data processing apps. In addition, many companies are having issues with hiring personnel. They need to introduce complicated technology instruments, analyze the information, and make practical suggestions (Symphony Retail AI, EIQ Research Solutions, 2018).

In order to navigate through the mess, a lot of successful high-volume retailers and CPG organizations have started using AI. AI systems replicate human behavior in the easiest possible way in order to increase productivity and improve company efficiency. Machine learning, natural language processing, and robotics are all part of AI applications.

Technology can be found in every aspect of retail, and category management is no exception. When it comes to category management, the role of technology is to find a way to optimize categories on a shop, cluster, product, and even inventory level. Technologies of the newer era, such as cloud and AI, by combining multiple datasets, help to improve turn-around time by increasing dexterity and scalability.

'Deep learning' is a class of machine learning algorithms. By combining enormous computer energy and infinite data sets, deep learning can extract multiple layers of high-level features from raw data. Just like humans, deep learning algorithms have the ability to learn from mistakes and correct them, so that it does not come to that again (Fahimi, 2018).

The ultimate goal of implementing technology is to provide greater visibility, as well as understanding customer needs and corresponding supply mapping. Additionally, category management can benefit from proposals on assortment, advertising, prices, promotions, and space (EIQ Research Solutions, 2018).

While creating a basis for planning, traditional data takes into account the historical shopping behavior of customers. However, this data is considered past tense since it is not validated against real-time measurable actions that reflect changing trends. The lifestyles and behaviors of consumers are always changing. For instance, a community that was once home to many families with young children could now have more so-called empty nesters. This would mean much less demand for snacks and lunch boxes for children and more demand for larger food packages. However, relying solely on historical information will restrict the capability of a retailer to realize these changes promptly. Generally speaking, retailers collect a lot of data, but when it comes to consolidating it in an understandable way, they often face problems in doing it quickly and at a lower cost. According to EIQ Research's 2018 study (EIQ Research Solutions, 2018), 50% of retailers are dealing with incomplete or inconsistent data, while more than half lack the skillset needed to analyze it. With this lack of talent accessible, retailers are looking for machine-first methods that will allow them to do more with the same number of employees. Most retailers do not like sharing data with suppliers, and vice versa, although both sides may have information that could be useful to the other side. While experts in the field praise the advantages of sharing, the discussion over how this situation can be changed has been raging for years. Grocers tend to depend strongly on the expertise and information supplied by experienced managers with whom they have continuing and good-standing relationships. There is no doubt that these vendors are specialists in their categories, but their input on the topic it nearly not enough. However, if their information is coupled with other customer metrics and evaluated using the appropriate technology, the result can better fulfill both current demand and their shoppers' preferences for future item attributes (Symphony Retail AI, EIQ Research Solutions, 2018).

AI applications fall under three key areas (Symphony Retail AI, EIQ Research Solutions, 2018).

Machine learning, which uses machines to evaluate significant quantities of information and 'learn' using rule-based algorithms that define patterns and trends. For instance, in terms of their shopping patterns and other practices, machine learning can efficiently merge 100,000 + data points from 75 million clients.

Natural language processing is the capability of a machine to comprehend, evaluate, and generate human speech. A computer listens the written or spoken natural language of a person, understands the context, and responds by creating a natural language to interact back (as opposed to a computer language such as Java or Structured Query Language (hereafter: SQL)). Using natural language processing, retailers can request comprehensive information about a particular store, product, method of shipping, or another topic without even getting near or touching a computer.

Robotics includes full-scale automation of tasks, generally performed by people. For instance, warehouse picking and packing can be done by robots.

Changing existing grocers' procedures and practices take time. However, since AI recommendations are given priority and have highly predictable outcomes, they are a more reliable measure of financial return. This enables retailers and suppliers to continually improve their category optimization processes and challenge currently applied techniques. When put on top of assortment planning and optimization, AI, by analyzing significant amounts of data, can provide a profound and extensive understanding of real-time consumer purchasing trends. This includes the retailer's own data, as well as external data, which can range from generic weather information and holidays to demographics and social media. The outcome is a neural network providing a much more precise assortment forecast than traditional approaches of calendar review (Symphony Retail AI, EIQ Research Solutions, 2018).

AI allows both manufacturers and retailers to automatically gather customer-specific insights and predict future actions based on patterns discovered from said customer data. AI uses predictive models to understand customer motivations, desires, and actions by analyzing both digital and physical channels. This allows suppliers and retailers to strengthen numerous functions, such as implementing customized advertising campaigns and improving attempts to promote trade. In addition, AI can automate stock needs forecasting, predict stock incidences more accurately, and ultimately help to optimize supply chains (Symphony Retail AI, EIQ Research Solutions, 2018).

2 TOOLS SUPPORTING CATEGORY MANAGEMENT PROCESS

The evolving retail business landscape puts higher pressure on retailers to maximize their retail stores' earnings from every inch. Shoppers are more sophisticated than ever before. Today's client is walking through the door, waiting for an extremely customized shopping

experience that enables them to discover the correct item at the correct location at the right price. In a historically difficult and evolving economic environment, retailers need to discover a way to fulfill increased standards for personalized customer service and enhance the profitability of their shops (Oracle Retail, 2009b).

Space is one of the most significant assets of a retailer and how well this asset is used can result in either client and margin erosion or client retention and maximization of margins. The strong reaction clients have when the design of a store is not what they expect is one of the primary reasons that space usage is so crucial. Maximum space usage is a challenging job for most distributors. This is often owing to a lack of knowledge about execution specific to the store. The outcome is a non-compliance of store-level space, which is the mis or non-alignment of store-specific space execution with objectives of corporate-driven category and space efficiency. Compliance with total space has long been the retailers ‘ objective, but it is considered extremely hard to accomplish, with expensive inefficiencies to perform and monitor (Oracle Retail, 2009b).

2.1 Traditional Approach and Next-generation Workflows

Historically, the process of optimizing assortment had strongly relied on POS and syndicated data sources. This type of data has constraints as it does not always consider demographic modifications, preferences, social sentiment, and other variables that can provide an all-round view of shopper behavior (Symphony Retail AI, EIQ Research Solutions, 2018).

Traditional ways of planning and optimizing assortment don’t always tent to be timely or cost-effective relative to altering consumer needs. More and more retailers are looking into AI as a solution, which is capable of (Symphony Retail AI, EIQ Research Solutions, 2018):

- Providing a timely, through and through knowledge of shopping habits for consumers;
- Constantly refining, updating, and analyzing real-time data samples and making product suggestions based on what works;
- Curate micro assortments and define precise stock levels with appropriate adjacencies of item and category, and lucrative promotions, efficient pricing, and appropriate category/product adjacencies.

The rapid increase of cloud computing today enables big data and AI to provide grocers with the chance and power to make the method of assortment management and optimization even more timely, perfectly aligned with customer requirements and behaviors, and eventually, more lucrative. These advanced solutions provide a better understanding of what consumers purchase, why the decision to purchase it, and how they decide to purchase it. They support the retailer’s knowledge of how and when these variables change and what affects the many business changes. AI-enabled solutions and systems at their easiest stage imitate human behavior in smart ways that can enhance productivity and optimize efficiency. AI enables retailers to automatically and predictively collect insight from shoppers. This allows them to

assess and predict the future behavior of consumers based on both past buying habits and future market trends reactions. It also utilizes predictive models to better comprehend wishes, motivations, and actions by distributors and vendors. This enhances many features, including the capacity to produce real-time shopper-focused, trend-right assortments to best satisfy and anticipate the near-term and future requirements of clients across all categories (Symphony Retail AI, EIQ Research Solutions, 2018).

The growing demand from customers for locally sourced products is welcome as it improves choice, interest in the category and can provide real differentiation versus rivalry. Managing this growing number of providers needs flexible and scalable alternatives that enable cooperation and sharing of information when necessary. There are two main aspects to consider when choosing an end-to-end solution for category planning (Symphony Retail AI, 2018a):

- A cloud-based, single-platform solution that not only promotes such cooperative projects but also enables retailers to cooperate with other departments within their company. Moreover, leveraging techniques that assist them in identifying possibilities faster and quickly implement them makes sense;
- Artificial intelligence should be a critical component of your assessment. To carry out duties that have traditionally needed large human resources, AI utilizes technology with sophisticated analytical capacities such as machine learning. It enables us to speed up strategy, decision-making, and execution considerably, allowing organizations to perform extremely complicated duties quickly, anticipate, and react more quickly to market requirements and fresh trends.

Localization is the main goal of most high-volume retailers today, and even though that is not necessarily their approach, having the correct product that is always in stock to meet the requirements of your most precious shoppers will promote sustainable sales efficiency on the shelf. With an assortment optimization solution and an associated strategy that places client requirements and conduct at the core of your decision making, retailers can most efficiently manage the product blend. This method goes hand in hand with retailers merchandising attempts to guarantee in-store communication and execution of planning and policies efficiently (Robinson, 2019).

Based on ad hoc analysis from syndicated sources provided by the data service providers such as IRI and Nielsen, the assortment choices were usually taken through an unstructured business process, and the end product mix was visualized in the resulting planogram. The end result was a long assortment of tails (products that are only available in a few stores). The solutions that followed were forced to manage the assortment tail and to calculate sales for the new product mix. But, in order to achieve the best results, they forced an endless test-and-mistake game. Furthermore, most of these models were black-box in its nature, and retailers had no way of understanding why they achieved your outcomes or set their strategies and goals to represent the appropriate category tactics (Robinson, 2019).

Not every category and product have the same strategies. In general, categories called "Routine" are used to generate quantity and return on transactions. "Destination" categories are often regarded as must-win or client excitement transactions. Categories of "Comfort" can be used to improve the picture of the retailer. Finally, the categories "Season" are used to create excitement and profit. Legacy optimization solutions often handled all product areas as if they had the same function and would often lack ideal outcomes because of these suggestions (Robinson, 2019).

The following points are to be considered when retailers are evaluating a solution for assortment optimization (Robinson, 2019):

- Best-practice approach: There are many category management frameworks that are intended to make the method more effective for category managers, but those that are most effective focus more on the end client and their shopping preferences and behavior rather than being product-centric. Look for a solution that allows an attitude to best practice;
- Consumer Decision Tree: Whether you've used formal research techniques to create customer choice trees – or if it's years of collective experience – today's assortment solutions can and should leverage this precious understanding and provide this data with a structured repository;
- Category Assessment: To understand missed opportunities and under / over performing product segments, a historical perspective on performance and market comparison is important. Based on this understanding, support for category evaluation can lead you to redefine the category–consider, for example, the trend of organic items;
- Objective Driven: Retailers should look for a solution to guide the outcomes and drive the significant metric(s) for them, i.e., loyalty, profit, volume. As the next step, users should look for a suggested assortment combination that will maximize their goals. Retailers should have findings delivered rapidly and effectively. To reflect distinct strategies for each product section or shop cluster, there should be some flexibility to set distinct targets for each product group or geography;
- Localized results: Delivering suggestions for localized assortment is mandatory. In order to do this at a shop or cluster level, the solution should be flexible and scalable;
- Inventory model: It is essential that the analyzes take into account thresholds for case pack, presentation quantities, and supply days;
- Control churn: For minor reviews, this feature is required to restrict the number of items that have been affected;
- Must stock and must not stock items: This is preferably notified by an automated data feed – offering the capacity to make key items compulsory, limit the accessibility of regional products, or restrict forbidden items. This requires to be supported by your solution at the store and cluster level;

- Transferable demand: The software should offer a feature to be able to model family information in relation to all other products in the assortment in order to calculate the real incrementality of each product;
- Forecast data: All products under account should have a predicted quantity of sales if real sales are not accessible. Ideally, it's a prediction at the store level;
- Artificial intelligence: AI is the recent innovation in optimizing the assortment. It is possible to use machine learning to evaluate big data sources and recognize trends and patterns;
- Space aware assortment: It is critical to understand your available marketable shelf space. The real item capability – calculating for distinct techniques of merchandising and stacking for each individual product is also critical;
- Understanding the results: Reporting and analytical opinions should be easily accessible for the optimization of both pre and post assortment. This involves scorecards, distribution reports. In addition, retailers should be able to have visibility in the system logic to validate why each assortment choice was made in the event outcomes are unexpected;
- Output: It is essential for retailers to have an effective way of handing over the assortment choices to the merchandising team. For each cluster or store, this must include the adds/deletes/retains;
- Collaboration: There may be cooperation with inner stakeholders, including approval measures, depending on the retailer's category management process. It may also include cooperation with both upstream and downstream internal stakeholders. Ensure that cooperation has been integrated into your solution;
- Track execution: Tracking real outcomes against predictions offers better performance and better insight for future optimization.

The above points should be considered by retailers when evaluating solutions for assortment optimization.

2.2 Benefits of Using End-to-end Solutions

By centralizing decision-making processes based on the aggregation of company-wide information and linking this insight to key performance indicators (hereafter: KPI), Category Managers can make cleverer and more strategic decisions for each shop and customer group. Based on results of EIQ research (Symphony Retail AI, 2018e), it was discovered that while currently 90% of retailers use on-premise solutions, they intend to migrate to Software-as-a-Service (hereafter: SaaS) model within the next 2 years. In their omnipresent channel or unified trade activities, they will be better prepared to assimilate information from all the databases and then to scale and update it at will. With the implementation of new techniques such as AI and machine training, they can predict large and subtle changes in behavior, in real-time (Robinson, 2018c).

It would be a critical measure of future achievement of how well a supplier or retailer manages and acts on the client's information at its disposal. To achieve this, a single 360-degree client perspective has to be established, and market trends quickly identified that have a true impact on the shop, the category, or the product level. This can only happen through scalable, hyper-efficient, and localized analyses, which have come about now with a new approach to category planning through machine learning and artificial intelligence capacities (Robinson, 2018c).

There is not much doubt anymore about the fact that retailers and consumer packaged goods (CPG) suppliers need real-time and deep expertise to attract and retain diverse buyers and, most importantly – keep them coming back to their stores. But with the emergence of different systems, sensors, and machine-to-machine communications, the information sets have become so big that for businesses using traditional data management applications or companies burdened with inaccurate or obsolete heritage information, these are important logistical challenges. This is emphasized by the problems with hiring resources, with relevant skills in implementing complicated technological instruments, analyzing the information, and making efficient suggestions (Michaud, 2018).

A lot of effective high-volume retailers and CPG organizations switched to AI to navigate the muddle in reaction. AI machines or systems at the simplest level imitate human behavior in smart ways that can increase productivity and optimize company efficiency. And while machine learning first became a scientific discipline in the late 1990s, it did not take off seriously until the 2000s, when development was driven by access to enormous quantities of real-time information and the emergence of algorithms that make sense of that information for efficient production (Michaud, 2018).

Applying AI in shops makes it simple to handle assortment planning, supply chain activities, and product development, where an ongoing forecasting loop adjusts stock levels continuously. This relieves inconsistent buying, overstocking, understocking, and consequent erosion of the margin. It also generates happy, faithful clients who keep returning because of more relevant assortments and fresh items (Michaud, 2018).

For instance, AI-activated customization can boost income by 5% to 15% and boost marketing expenditure effectiveness by up to 30%. According to EIQ Research (Symphony Retail AI, 2018e), two out of three CPG businesses will use AI to power pricing and promotion optimization over the next 24 months when it comes to trade promotion leadership, and nearly three out of four distributors will use AI to handle merchandising choices and customer insight (Michaud, 2018).

Although retail acceptance of AI is somewhat frictional, it is reaching its tipping point. With more distributors and CPG firms deploying AI-powered apps, others will see the advantages of related efficiency gains and more private customer interactions. They will also investigate its ability to keep up and compete. It may have taken some time to reach this point of

inflection, but it will not be long before these days seem like a remote history (Michaud, 2018).

AI-enabled apps have the biggest advantage of being able to detect trends or anomalies among these trillions of information points in order to predict future conduct more quickly and precisely than any human operator. They can project results and guide marketing choices based on any mixture of prospective inputs, such as a targeted discount for a particular product or the introduction of an alternative private label to a low-margin provider item (Symphony Retail AI, 2018l).

No one could predict when a customer who has never purchased a sports drink or a drink would be prepared to join the category in a conventional merchandising model. But AI — activated category management solutions allocated the resulting objective of growing sports — drinking sales can identify behavioral patterns for sports — drinking customers in other categories that clarify who to target and what to transform them categories that clarify who to target and what to do to transform them (Symphony Retail AI, 2018l).

Category managers and other merchandising experts can assess important issues such as (Symphony Retail AI, 2018l):

- How does category X perform in separate stores?
- What are the performance developments in category X?
- What do clients buy as opposed to X products?
- How did X-category promotions perform at each shop this week?

Once these responses are disclosed, focused, localized assortments that generate a greater connection between the retailer and the community as a whole become simpler to produce. Curated local assortments driven by AI enable retailers to guarantee that they offer products that are most important to their customers' preferences while ensuring a retailer's optimized, stable source of revenue (Symphony Retail AI, 2018l).

Today, physical retailing is all about establishing a rewarding, data-based shop environment-driving customer engagement policies leading to long-term loyalty. It is no longer the exclusive domain of customized digital marketing or curated assortments, nor is it any longer acceptable to generate deals that support company objectives simply by forcing them to feed reluctant shoppers. A basic mandate now exists for shops to have a 360-degree knowledge of their consumption and to know exactly how to behave on that data. Fortunately, when AI arrives, it becomes simple to synthesize and act on the ideas shared by clients at every touchpoint. And this will generate fresh relevance and strength in a data store-oriented digital economy (Symphony Retail AI, 2018l).

While the competitive environment for category planning is wide, many suppliers within have tended to concentrate on providing point-specific alternatives, rather than adopting a holistic strategy to category assessment, planning, and implementation. Times have altered,

and these traditional methods have often ignored the wider responsibilities that category leadership now expects, including category strategy, floor space distribution, financial budgeting, assortment planning, planogramming, self-label development, and joint supplier business planning (Symphony Retail AI, 2018a).

Add to this today's extremely educated shopper who is likely to shop across various stores and who has high expectations of accessibility, and it becomes essential that distributors and suppliers of CPG invest in category scheduling solutions that link their business with the client.

Key benefits of adopting a customer - connected category planning perspective (Symphony Retail AI, 2018a):

- Workflow-enabled apps can decrease category planning administrative expenses;
- Assortments that are guaranteed to fit into specific areas considerably enhance the effectiveness of shelf storage, product accessibility, and on-going forecasting / replacement;
- Reviewing the distribution of shelf space is an outstanding chance to improve accessibility and reduce revenues lost;
- Understanding the impacts of transferable demand for products added to a category is critical to understanding the effect of cannibalization or incremental sales. In addition to providing insight into where sales of products removed will now appear in the assortment;
- Fine – Tuned store clusters by category reflecting shopper behavior produce sales uplifts and inform the optimization process of the assortment.

2.3 The Architecture of the Cloud-based Category Management Solution

This section details the System Architecture of the Category Management solution. It covers the platform used for the applications in the Category management suite, as well as the Azure Cloud Infrastructure used for these applications. Additionally, it also covers the responsibilities of the Cloud Services team and Security Management.

2.3.1 System Architecture

The Category Management solution is designed to run on the Microsoft Azure cloud platform. The applications are built using Microsoft .NET, along with Microsoft SQL Server and Microsoft Azure Services. Some components also use Java and Delphi programming languages. There is also one component that uses Yellowbrick technology to access the enterprise data warehouse (Symphony Retail AI, 2018h).

The R&D team has four environments, Development, Quality Assurance, User Acceptance Test, and Production at its disposal. All the environments are the same type of architecture. The only difference is the database, which in environments Development and Quality Assurance is scarcer, compared to the other two environments (Symphony Retail AI, 2018h).

2.3.2 High-Level Architecture

This section explains a high-level architecture for the Category Management solutions, deployed in the Microsoft Azure Cloud. Each customer environment is operated within its own Microsoft Subscription/Resource Group. Each dedicated Customer Resource Group has its own domain management and Network Security Groups, which ensures that only authorized users have access to this domain. The Network Security Groups provide for the separation of the application tiers and provide firewall control to ensure that the whole architecture is secure from outside access (Symphony Retail AI, 2018h).

Within the Web-Tier sit the Web and Report Servers, which are virtual machines that run Microsoft Internet Information Services (hereafter: IIS). The database tier runs the SQL Server, which houses the databases. The Authentication tier houses the domain controllers (Symphony Retail AI, 2018h).

The Web tier is architected to use Microsoft Azure Availability Sets. This provides for high availability, load balancing across multiple servers, and it ensures that there is no single point of failure for any of the web servers. An Azure Load Balancer directs the web traffic to the available healthy servers and uses IP affinity to keep a user's session tied to one of the web servers (Symphony Retail AI, 2018h).

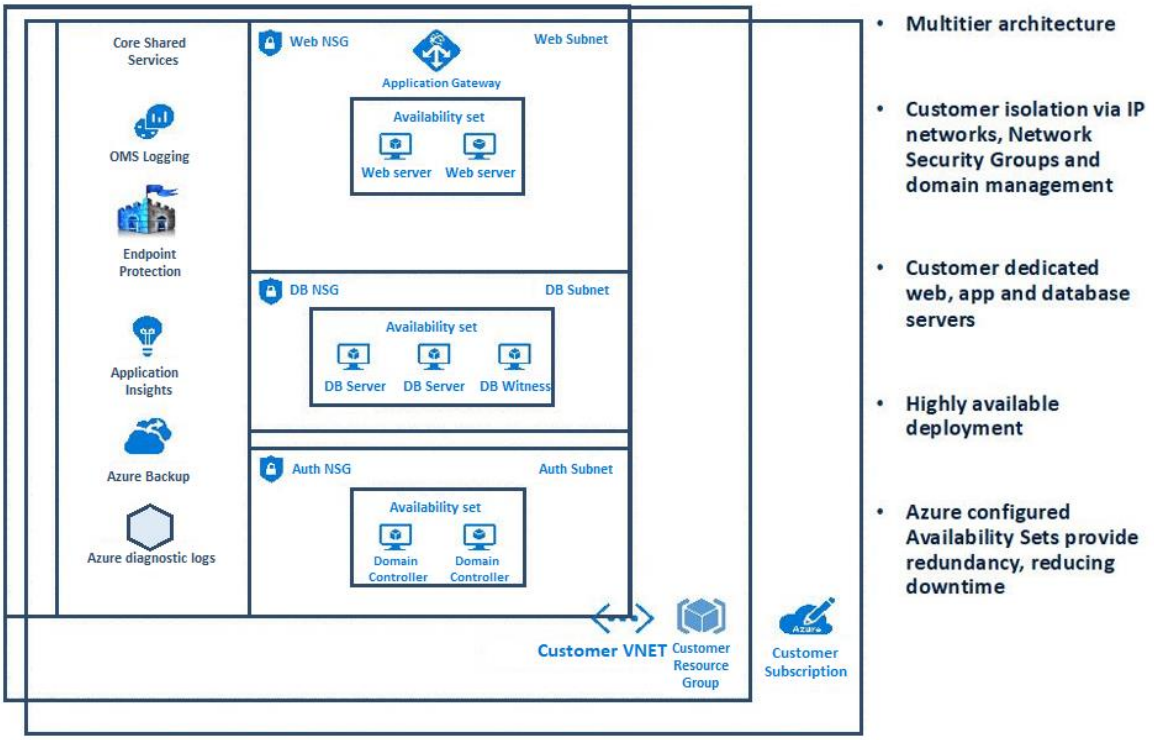
The Authentication tier also has fault tolerance with a primary and secondary domain controller. The Category management suite supports multiple ways of User Authentication, which include Active Directory, Active Directory Federation Services, and Security Assertion Markup Language 2.0. Currently, most customers authenticate using Active Directory. The system supports Single Sign-On for users (Symphony Retail AI, 2018h).

2.3.3 Integration Architecture with Enterprise Data Warehouse

The Category management system, in part, integrates with a system from an internal subsidiary, to get Loyalty Metrics and Transferable Demand Metrics from the enterprise data warehouse (hereafter: EDW) that resides in Yellowbrick database servers.

The Yellowbrick server houses the raw transactional data. The Category management solutions make requests to this server to retrieve Loyalty Metrics and Transferable Demand Metrics during project creation time if this option is configured for the Assortment optimization application (Symphony Retail AI, 2018h).

Figure 2: High-level architecture



Source: Symphony Retail AI (2018h).

Connectivity between the Azure environment and the data center in the past was via a secure VPN connection across the internet. That has recently been changed to use Microsoft Express Route, which again is secure, but is more robust and enables the servers in the data center to appear as servers with the domain in Azure. The Virtual Private Network connection is kept in place for now as a secondary pathway, should Express Route have an issue (Symphony Retail AI, 2018h).

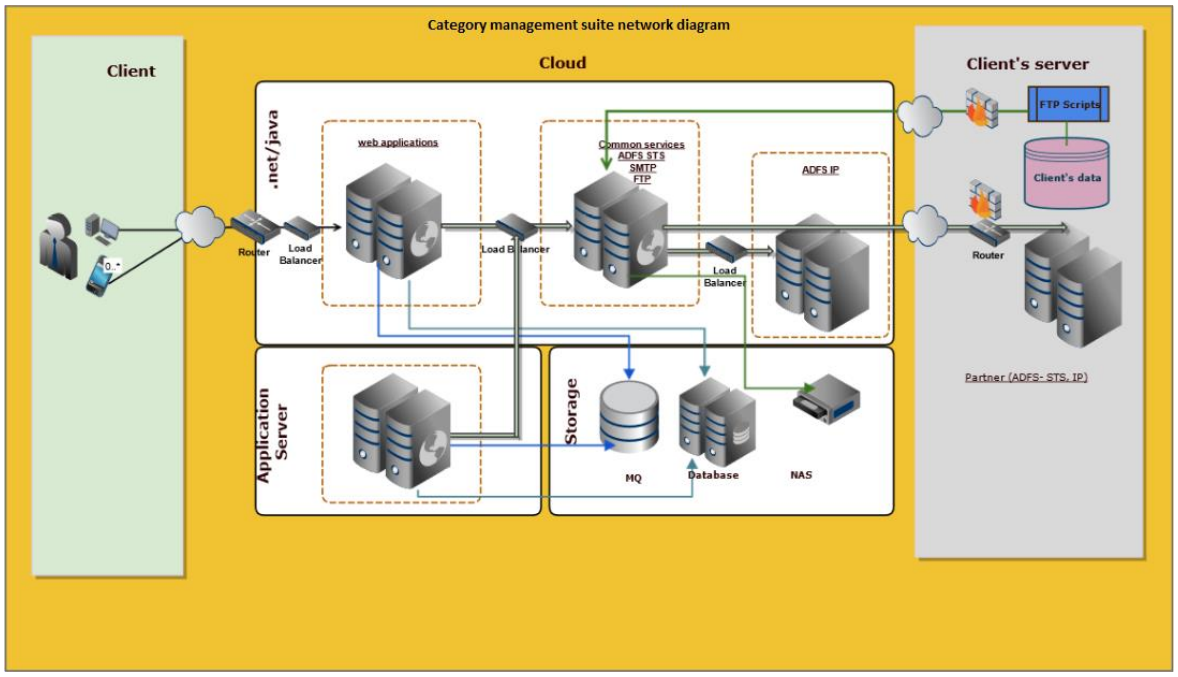
2.3.4 Network Architecture

The diagram in Figure 3 shows the high-level network architecture used for the Category management suite of applications.

In Figure 3, on one side, we can see the Client. All applications that are part of the Category Management suite are completely responsive, meaning that clients can access them using different devices, such as tablets (iOS and Android), phones, or computers. No matter the device that the clients are accessing the applications from, the monthly cost for clients is based on resource usage.

In the middle, we have the Cloud. Every part of the Category management suite is located in the cloud, and users are accessing the applications through a provided web address.

Figure 3: High-level network architecture



Source: Symphony Retail AI (2018h).

On the right side, we have the Client's external system, which is, in most cases, completely integrated with the Category Management solution.

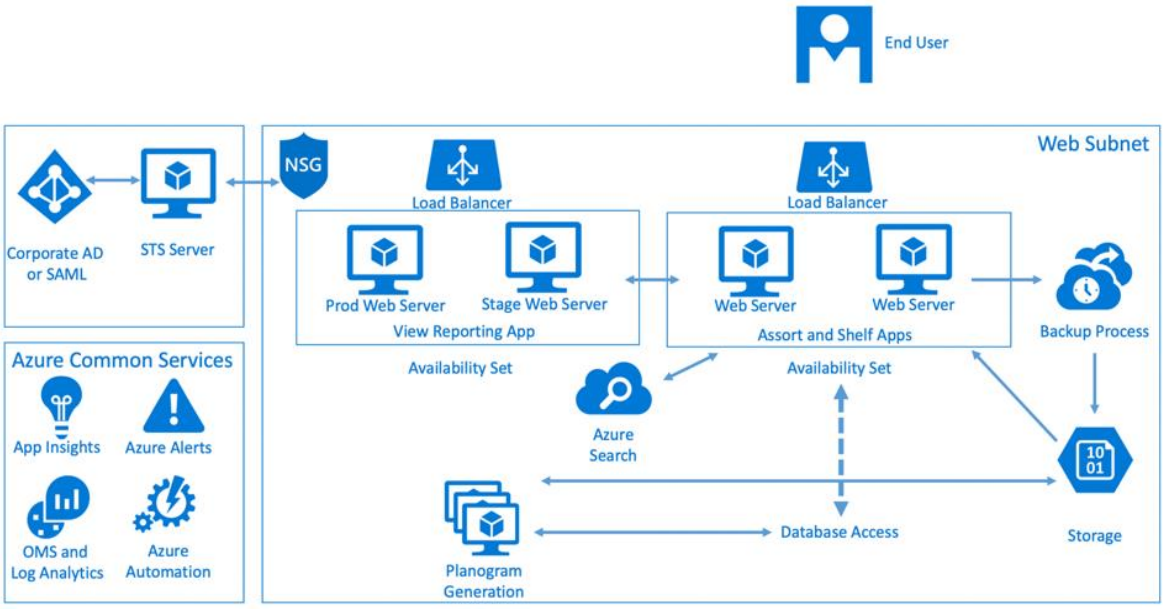
2.3.5 Web Server Tier

The Web Server Tier houses virtual machines that run Microsoft IIS and Report servers that generate planograms. The Web Servers are currently Standard D13 servers with 8 processors and 56 GB RAM and can be scaled out horizontally based on usage volume. The horizontal scaling out is presently manual, and the Load Balancer is using a proxy to direct the traffic to the correct Web Server based on IP affinity.

The intent in the future is to use auto-scaling by using health monitors to determine when additional servers need to be added to the web farm. The backup process keeps a copy of the webserver images. Web server logging is to Azure Storage (Symphony Retail AI, 2018h).

Several Azure common services are used to augment the application. The applications make use of Azure App Insights to record user interaction with the application, and alerts can be generated should any action exceed certain thresholds. Log files are analyzed to understand user access. Azure Automation is used to automate jobs such as data backup and machine sizing. Azure dashboards are used by Cloud Services to monitor the environments (Symphony Retail AI, 2018h).

Figure 4: Web Server Tier



Source: Symphony Retail AI (2018h).

The web servers provide the Application platform and use Microsoft IIS at present. This may change in the near future to use Azure Web Apps, which are more robust and scalable and easier to maintain. These web servers also contain the Assort Application, which runs on Apache Tomcat at this time, though this may change as well in the latter part of 2019 (Symphony Retail AI, 2018h).

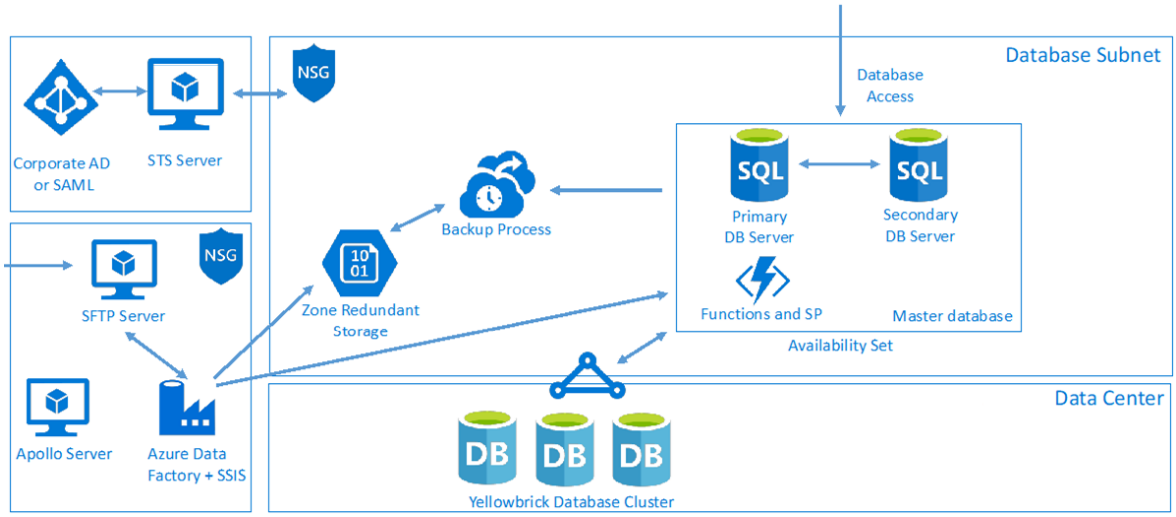
2.3.6 Database Server Tier

The database tier house the primary Category management database, which runs on SQL Server 2014 (this will be upgraded to SQL Server 2017 by the end of Q3 2019). This database houses the POS, market, planogram metadata, assortment details, store data, and product data. It is a very large database, so it has to run on high-performance servers with Premium SSD disks. The system is architected to partition and spread the data across multiple disks to achieve the best throughput of the server.

The database makes heavy use of stored procedures for data processing and recently has been making use of Azure Functions to offload the database system. Azure functions are serverless and very scalable, thus enabling big improvements in processing time and reducing the load on the database server. Data ingestion is via a secure file transfer protocol (hereafter: SFTP) server and then is processed using either Azure Data Factory (Data Flow) or SQL Server Integration Services (Symphony Retail AI, 2018h).

Data ingested is backed up to Azure Zone redundant storage and loaded into the database server. This typically does not happen during daytime operational hours and will normally occur over a weekend or at night (Symphony Retail AI, 2018h).

Figure 5: Database Server Tier



Source: Symphony Retail AI (2018h).

2.3.7 Cloud Infrastructure Management

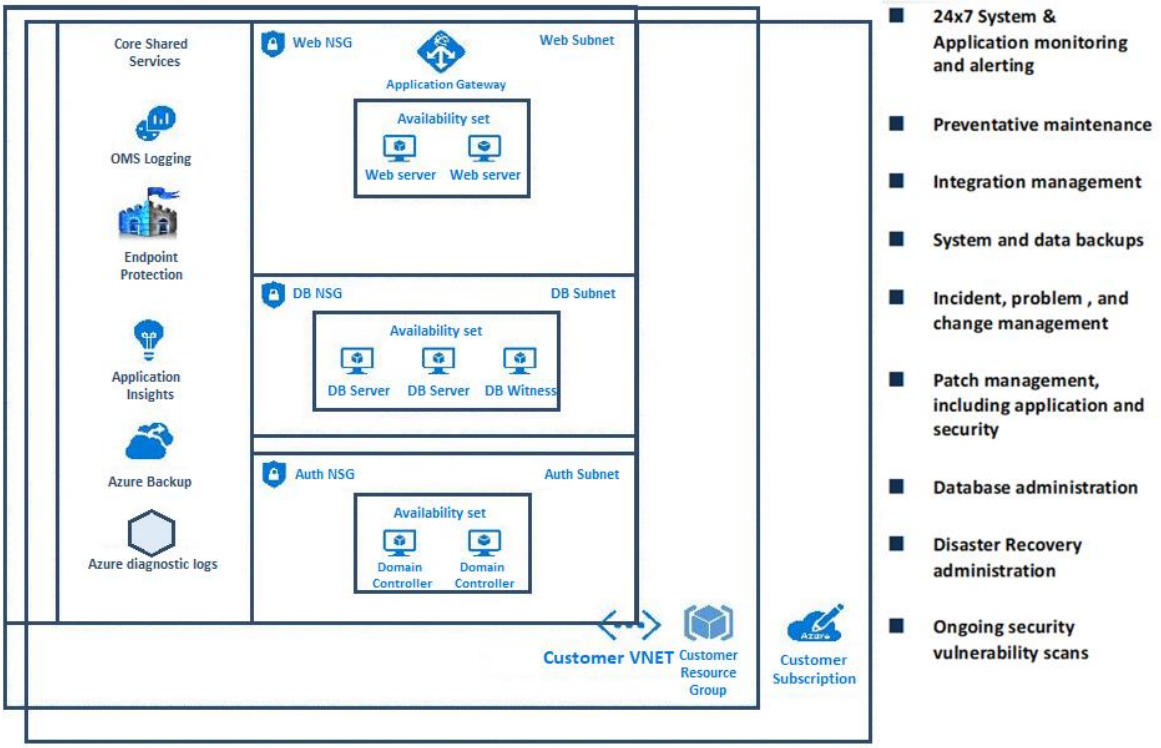
The Cloud Services Team manages the Azure Cloud Infrastructure and all the other Data Centers for the Symphony Retail AI applications. This includes all the standard Information Technology Infrastructure Library (hereafter: ITIL) tasks to ensure a safe, managed environment for customers' data. Cloud Services has a 24x7 helpdesk and cloud operations center to monitor and resolve any issues across the enterprise. This includes Application Monitoring, Preventive Maintenance, System and Data backups, Incident resolution, Patch Management, Database Management, and Security Scans (Symphony Retail AI, 2018h).

The Cloud Infrastructure Team provides service management for the environment. This includes monitoring and alerting system health, setting up and executing backup processes, and controlling security tasks. Cloud Services covers (Symphony Retail AI, 2018h):

- Infrastructure and Alert Monitoring: The Cloud Services team uses various Azure services to monitor devices and services with the infrastructure. The software applications are enabled with Application Insights, which provides for monitoring and alerts when services do not respond within reasonable time constraints. The web servers log all events, and these are monitored. Monitoring and alerting are managed through the Monitor Dashboard;
- High Availability and Backups: The Cloud Services team sets up all servers to use Azure Backup to take snapshot images of the virtual machines. They setup Availability Sets of

servers that are zone or geo-redundant to provide for high availability. Azure storage accounts are provisioned either locally or globally redundant, depending on the priority of the data being stored. Backup processes are also enabled for databases. These are executed using scripts that perform a weekly full backup of the database and daily incrementals. The default retention period is 30 days;

Figure 6: Cloud infrastructure management



Source: Symphony Retail AI (2018h).

– Security Management: processes are in place to monitor server access and quickly determine if there are any attempts of unauthorized access. Currently, the systems log access, and these are audited. In the future, Cloud Services is looking at using the Web Application Firewall to strengthen the security position. Also, virus protection and malware protection are performed across all systems.

The Cloud Services team also performs vulnerability scans across the whole environment to make sure the systems are hardened to ensure resilience (Symphony Retail AI, 2018h):

– Vulnerability and Risk Assessment: performing vulnerability scanning and auditing to provide consistent metrics regarding vulnerability as a factor of the determination of the loss event frequency. These factors are weighed against a business defined impact analysis of key assets to measure risk. This ISO 27005 compliant process measures technical, procedural, and operational risk to internal information and systems. This

metric is used to determine mitigation prioritization and guide a strategic response to any threat to business;
- Penetration testing: conducted periodically by 3rd party specialists. Testing reports are available on request

2.4 Description of Different Modules Used in the Category Management Solution

Although the process of space planning is full of problems and inefficiencies, many distributors have become accustomed to them and have accepted as the best that can be accomplished in a deeply faulty process.

Company headquarters and shops have known for years that when they reach the shop, space plans created at headquarters are seldom performed precisely as planned. Simply put, the route toward attaining store-specific plans and overall compliance is not evident, and most distributors do not have the instruments to make it possible.

You can start to comprehend when and where the method breaks down by looking at each of the following steps along the route (Symphony Retail AI, 2018l):

- Step 1: Store-specific assortments – You must first guarantee that you develop local assortments using store-specific demand before you can even get to the stage of creating an executable plan;
- Step 2: Store-Specific Planograms – Once store-specific assortments are available, you need to guarantee that you are developing planograms for each store's real fixing and space limitations. Although this has historically been a retailer challenge, technology has proven itself in this regard;
- Step 3: Store-Specific Floor Plans – Retailers must move away from the development of prototype store layouts to develop, execute, and maintain store-specific plans (with the exception of discount retailers). While this has also been a challenge historically, there is technology to assist distributors in accomplishing this step;
- Step 4: Collaborating & Communicating – Once you have store-specific assortments, floor plans, and planograms, you need a technique for collaborating and communicating between corporate headquarters, shops, and even suppliers while offering real-time visibility throughout the process;
- Step 5: Enable the store to make smart decisions and give them a voice. To be effective, retailers need to tap the store's understanding. Not only do they need to allow them to provide insight into the upfront planning process, but they also need to create smart choices during execution, rather than making changes blindly, with little visibility to the general plan effect;
- Step 6: Stores Need to Provide Visibility Back to Corporate Headquarters – Stores need a method to collaborate and provide visibility on store-level changes. Plans need to be

updated and reused the next time around, rather than using the "start from scratch" strategy to history;

- Step 7: Corporate Headquarters Needs to be Armed with Proper Technology — Corporate headquarters must have the correct systems in place to have real-time visibility to track, handle, and respond to critical corporate space plans non-compliance. The key to keeping compliance is exceptionally managing, monitoring it efficiently, and responding to important fields of non-compliance. It is important to have the right technology in place to allow this monitoring.

The process that follows the above steps meets customers' localized requirements by breaking out of its silo the traditional spatial planning method and incorporating it completely across shops and corporate headquarters. Corporate headquarters can deliver store-specific macro space plans and micro planograms in real-time through a dynamic centralized database, while shops can create notes or suggestions to corporate headquarters or, if required, create an actual floor plan and / or planogram modifications. In order to align labor more properly and decrease store-level delays, stores gain early visibility in coming merchandising modifications (Symphony Retail AI, 2018l).

Technology is involved in every aspect of the retail business, and category management is no exception. Technology's role in category management is to optimize categories at a shop/cluster level, by size, product mix, and inventory level. Newer technologies, such as cloud and AI, help in improving turn-around time by way of increasing dexterity and scalability.

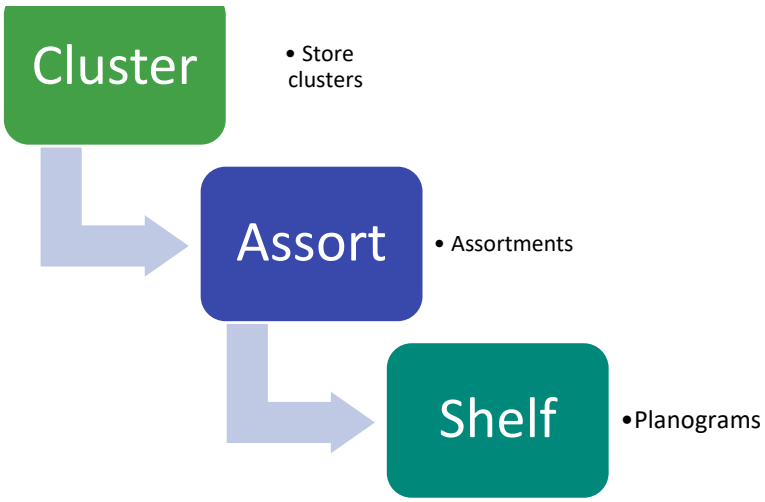
The bottom line of implementing technology is to allow greater visibility and comprehension of customer demand and the corresponding mapping of supply. Besides, suggestions on assortment, advertising, pricing, space, and promotions can be offered alongside different approaches for category management (EIQ Research Solutions, 2018).

2.4.1 Store Clustering

With specialized tools available, retailers can provide store clusters that align as tightly as possible with local consumers' demand for increased sales and waste reduction, while a mix of statistical modeling effectively incorporates customer behavior, customer segmentation, demand data, and important company drivers.

It also allows retailers to identify financial opportunities by cluster group to assess anticipated value on the basis of suggested clusters and enable demographic and loyalty date inclusion to drive more granular and appropriate shop clustering. Generating store clusters is mandatory for efficient assortment optimization, and Figure 7 explains the workflow, as well as the output of each step (Symphony Retail AI, 2018h).

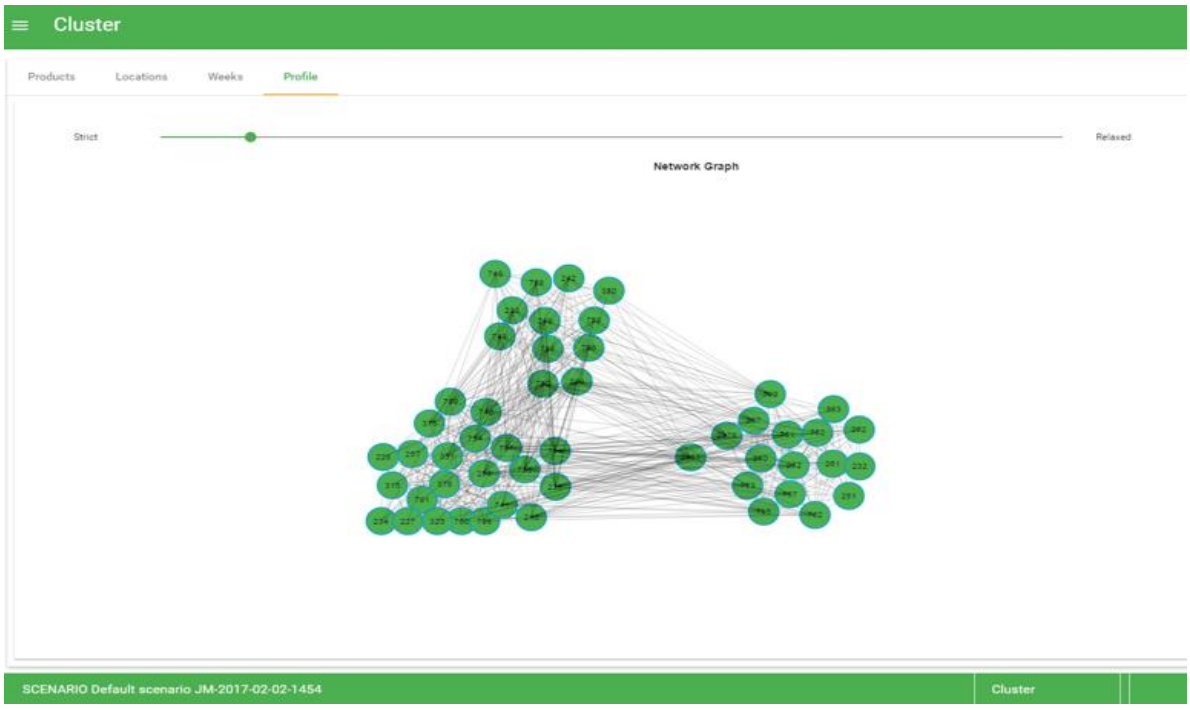
Figure 7: Steps in assortment optimization



Source: Symphony Retail AI (2018h).

Retailers can select any of the available KPIs and determine the weight for each KPI. This metric is then used by the tool to create groups of stores with similar patterns.

Figure 8: Screen displaying network graph for generated store clusters



Source: Symphony Retail AI (2018h).

After store clusters are generated, users can check the results. In Figure 8, we can see an example of stores in three different clusters and their correlation (Symphony Retail AI, 2018h).

2.4.2 Assortment Optimization

Tools for assortment optimization allow retailers to calculate optimized assortment based on a defined set of key performance indicators while leveraging up-to-date sales data, as well as other metrics like loyalty or demographics data. By infusing customer insight throughout the category planning process and incorporating macro and micro space planning into the assortment optimization method, retailers can interact and implement category strategy in shops more efficiently, leading in dramatically enhanced revenues, profit, and client satisfaction (Symphony Retail AI, 2018h).

The Assortment optimization application aids users in the overall performance of the assortment. The basic rationale underlying the 3-level assortment hierarchy default is as follows (Symphony Retail AI, 2018h):

- A core assortment is set at a banner level for those items which must/must not be carried in all stores;
- Cluster level assortments are created for local markets exhibiting similar product preferences. This includes the most common planogram layouts for each cluster.

Retailers need to satisfy the requirements of their most precious client sections to be competitive today and use client metrics and preferences to drive localized assortment and planograms to do so. To be able to achieve this, they are expecting the assortment optimization tool to (Symphony Retail AI, 2018h):

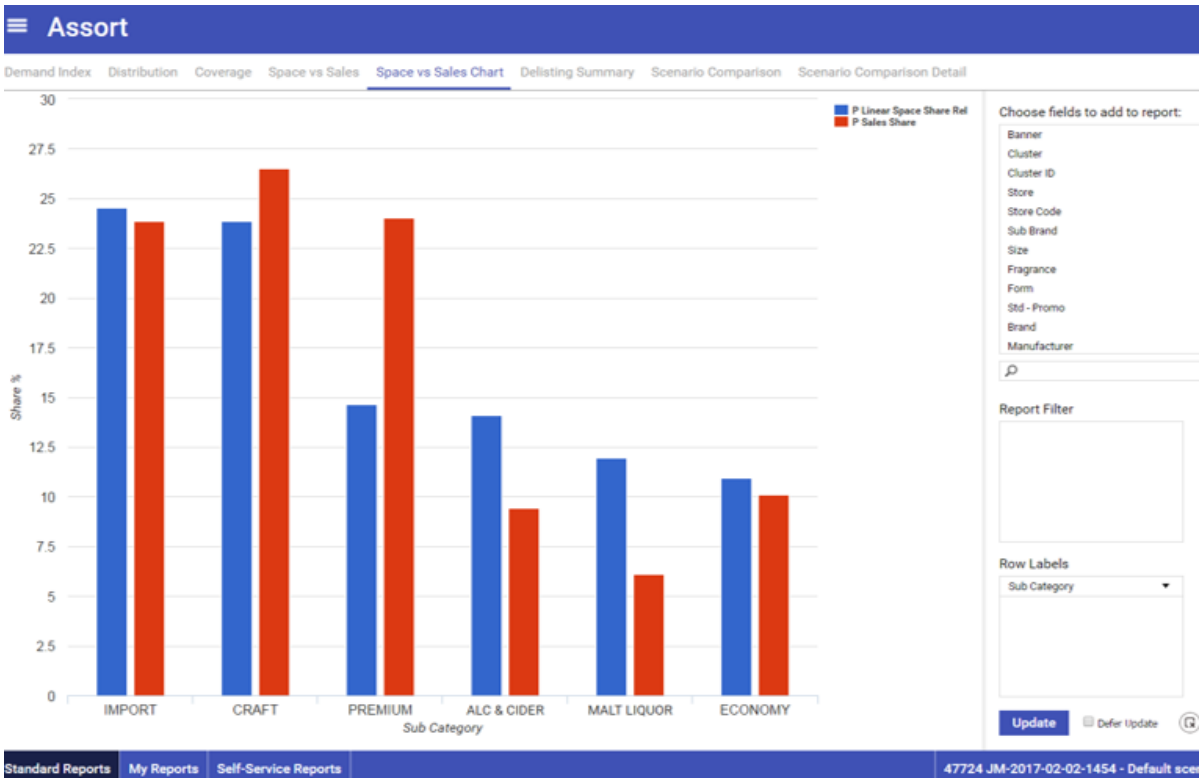
- Use customer segmentation to inform store clustering and localized assortment plans;
- Utilize customer metrics and preferences to drive localized assortments and planograms over the web;
- Identify cross-category dynamics that generate revenue opportunities;
- Generate optimized, relevant product assortments that are customer, space, and inventory aware;
- Access full insight to execution lifecycle visibility and management.

2.4.3 Shelf Planning

Accurate shelf space planning is critical to delivering customer-centric, space-conscious assortments.

Figure 9 shows an example of a beer assortment merchandised on a planogram using one of the cloud-based solutions. Localized, store-specific planograms boost customer satisfaction, sales, and accessibility of items.

Figure 9: Screen showing one of the most used reports in assortment optimization



Source: Symphony Retail AI (2018h).

The available tools make it easy for retailers and CPG suppliers to mix statistical modeling with customer behavior and main company drivers for shelf layouts to fulfill the needs of their clients. There are a lot of tools on hand, which support the process of micro merchandising, but recently, retailers started to implement cloud-based solutions, which empowers them to (Symphony Retail AI, 2018h):

– Promote cross-team collaboration through accessibility on any device for immediate visibility;
– Improve planogram to store compliance and headquarters (hereafter: HQ) to store communication;
– Deliver relevant merchandising through customer-centric planograms;
– Integrate with other applications to provide a smoother category management process.

After the optimized assortment is approved, the assortment changes are synchronized on the planogram. In Figure 10, we can see a planogram that had an item that was deleted from the optimized assortment and removed from the shelves (Symphony Retail AI, 2018h).

As the next step in the assortment optimization process, users have to merchandise planograms with items added to the planogram. New items added to the assortment are automatically available for selection.

Figure 10: Screen showing planogram with items automatically removed from shelves

Source: Symphony Retail AI (2018h).

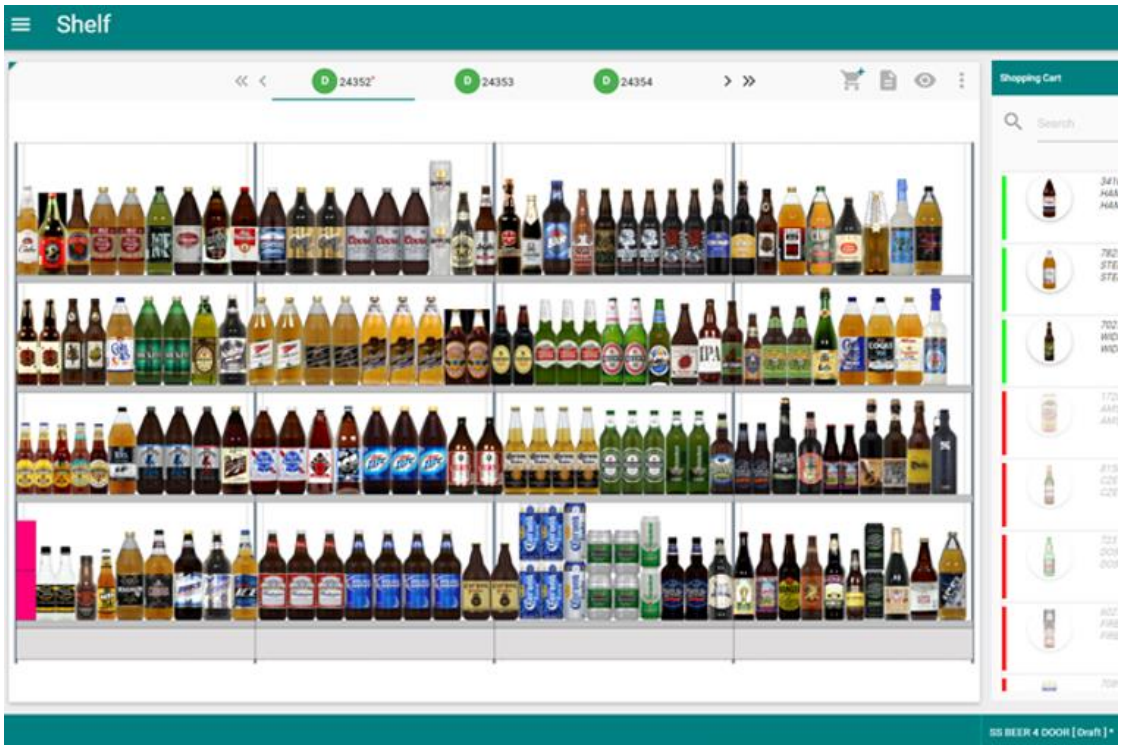
Before releasing a merchandised planogram to stores, users can analyze the planogram with the use of different charts. In addition, they can use highlighting tools, to analyze planograms, as shown in Figure 11 (Symphony Retail AI, 2018h):

Figure 11: Example of using highlight analysis on a planogram

Source: Symphony Retail AI (2018h).

After users are done with making changes to the planogram, they can release it to a relevant set of stores. Figure 12 shows an example of a merchandised planogram before being released to stores (Symphony Retail AI, 2018h).

Figure 12: Finished planogram



Source: Symphony Retail AI (2018h).

2.4.4 Planogram Automation

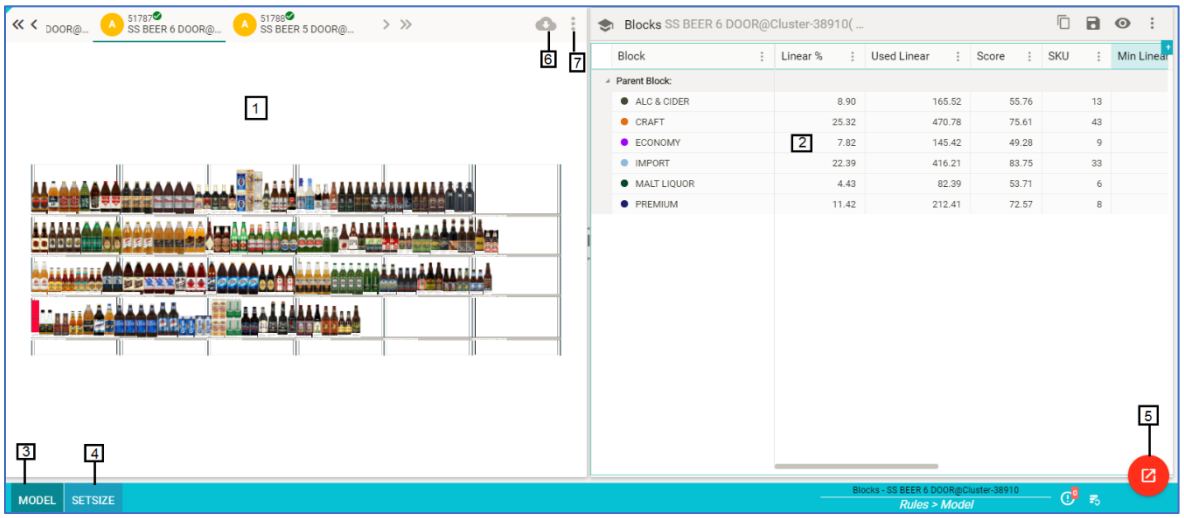
Tools for automating the creation of planograms are mostly used by retailers who are looking to create store-specific planograms based on dimensions of real equipment available in stores. They require good data quality and relevant inputs from end-users (rules used for automatically creating planograms) to be set up as well as created base (known as layout) planograms, which are used as a basis for store-specific planograms creation.

Tools for automating planogram creation enable users to (Symphony Retail AI, 2018h):

- Optimize product inventory while adhering to merchandising strategy and physical constraints;
- Drive efficiency for category planning teams by automating the process by which store-specific planograms are generated;
- Automate the production, management, and analysis of cluster and store-specific planograms for faster implementation of the strategy.

Users have to define rules based on which store-specific planograms are getting generated, as shown in Figure 13 (Symphony Retail AI, 2018h).

Figure 13: Example of defined rules for store-specific planograms creation



Source: Symphony Retail AI (2018h).

After the rules are defined, automatic store-specific planograms generation can start. This process generates store-specific planograms, which exactly match the fixture size available in store, and contain store level relevant assortment based on rules set (Symphony Retail AI, 2018h).

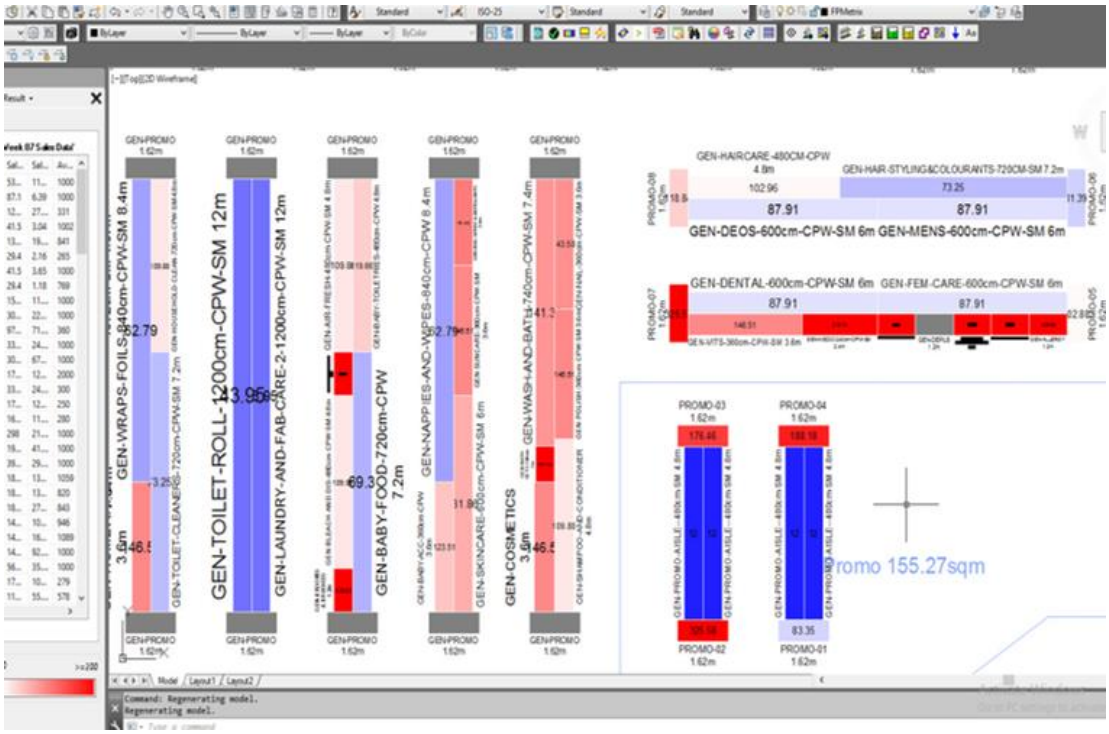
2.4.5 Floor-planning Tools

Customers want in-store experiences that warrant entering the shop. This implies that retailers need to handle their most precious assets effectively. Those who plan all store formats properly and offer the finest in-store experiences drive efficiency in high category performance. By evaluating efficiency down to individual categories and products on a store level, the correct macro space scheduling solution helps retailers manage their variable shop property. Retailers often have restricted insight into available in-store space, how much is assigned to which categories, location of category in the store, optimum adjacencies to other categories, and where a space change between them would boost the efficiency of floor space. And, in siloed schemes, data on the shop plan is often incomplete or semi-maintained. Advanced floor planning tools can connect to shelf planning and assortment optimization tools to generate a localized shopping experience for clients, resulting in more visits to the shop and enhanced customer loyalty. Figure 14 shows an example of a hotspot analysis performed on one of the floor layouts (Symphony Retail AI, 2018h).

2.4.6 Analysis Tools

Analysis tools provide visibility into the health of a category and insights into growth opportunities.

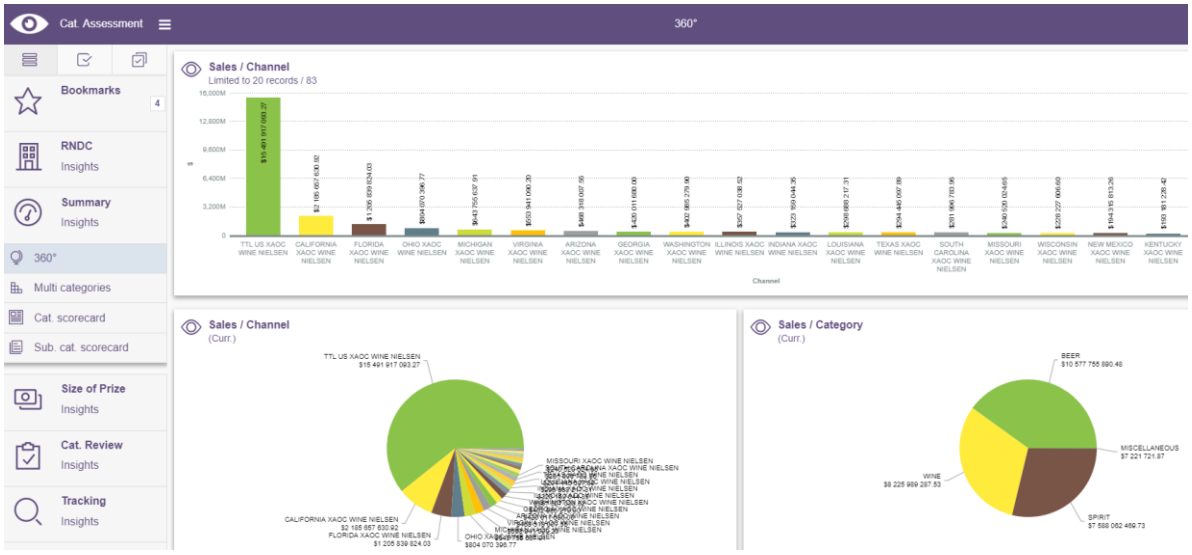
Figure 14: Screen from one of floor planning applications



Source: Symphony Retail AI (2018h).

With their use, retailers and CPG's are able to benchmark category performance in relation to the market and their competitors. It also allows us to view trends over multiple periods and identify category, brand, or product level opportunities and Adjust assortment, pricing, and rebalance distribution to drive category growth. In Figure 15, we can see a dashboard of one of the cloud-based analysis tools (Symphony Retail AI, 2019d).

Figure 15: Screen from one of the tools used for analysis



Source: Symphony Retail AI (2018h).

3 ASSORTMENT PLANNING IN SELECTED CASES

3.1 Methodology

Various methods were used to analyze the assortment planning processes in both selected cases. Additional to reviewing existing literature and internal materials available, unstructured interviews with representatives from both companies were conducted as part of the project implementation process for the assortment optimization software, which the authors of this thesis were actively involved in.

3.2 Norwegian Retailer

The first subject which will be analyzed in this thesis is a Norwegian retailer that operates a chain of grocery stores throughout Northern Europe.

Being a grocery retailer, the Norwegian company is particularly interested in keeping the leading role in the market, but also offering its customers the possibility to shop local and healthy products (Rema 1000, 2018).

In the following chapters, we will describe the Norwegian retailer in general, talk about the vision and the strategy of the company. Afterward, we will be focusing on analyzing and describing not only the assortment process used by the Norwegian retailer but also other processes that are currently in use.

The methodology for this analysis is a combination of reviewing existing literature and research in the field of category management, as well as trends and challenges in the branch. Data for the analysis was provided by one of the authors, who was involved in the design and implementation stages of the project of implementing the category management solution. During these phases, there were open discussions with the retailers' representatives to gather information on the current and desired processes.

3.2.1 Company Description

A part of Reitangruppen, the Norwegian retailer is a discount, small-format franchise retailer. The company manages a number of grocery stores, selling a variety of products, in addition to manufacturing and distributing their own brand of goods. Apart from Norway, they have stores in Sweden, Denmark, Latvia, and Lithuania (Rema 1000, 2016).

The Norwegian retailer is one of the country's biggest and best-performing brands, as well as being the leading grocery chain. Operating since 1979, the retailer offers customers throughout the country a fine selection of groceries with high quality but at low prices. The

retailer was the first in Norway to start operating in a franchise organized manner, running small-format stores (Rema 1000, 2016).

3.2.2 Strategy and Vision

The Norwegian Retailer currently implements the Red Ocean strategy. A Red Ocean strategy is a strategy that aims to fight and beat the competition. Companies that follow the Red Ocean strategy have their focus set on (Layton, 2009):

- being present and competing in an already existing market;
- beating the competition;
- the value/cost trade-off;
- exploiting existing demand;
- execution (better marketing, lower cost base, etc.).

Following the Red Ocean Strategy in the end forces organizations to follow one of two paths – differentiation or low cost. No matter which path organizations choose, all activities have to be aligned for correct implementation (Layton, 2009).

In the case of the Norwegian retailer, the main focus is set on beating the competition (Rema 1000, 2018). The Norwegian retail market has become really competitive in the last 10 years, with the likes of Coop, Joker, Kiwi, and Spar making big steps forward and increasing their market share. The Norwegian retailer is a discount/franchise retailer, meaning that one of their strategies is for the prices in their stores to be lower than the competition. In order to sustain that level, the Norwegian retailer has employees that visit the competition's stores in order to check the prices of the articles that they are offering. Afterward, they have to report back to their superiors and review the prices of the products. For the products that have a higher price, they lower it directly in the Master data management (hereafter: MDM) system. The price tags in the stores are directly connected to the MDM system, and prices are refreshed every 15 minutes. In some cases, the retail price of the product is lower than the product cost price, meaning that some articles will be sold not only without profit but at a loss.

The Norwegian client's corporate social responsibility is centered around making the store owners and their employees responsible for driving the sustainability agenda forward, making it a part of their everyday duties. Their vision is running a business where customers can buy not only affordable but also healthy products, produced with care for the environment, the people, and the animals. In order to fulfill their vision, in their opinion, it is a must to provide global and local management of the supply chain, as well as develop solutions to some of the key areas in sustainability (e.g., plastic waste, food waste, climate change …). Put bluntly, their vision is to put people, packaging, food waste and health as key figures in the business, because the common thing all these elements have is the possible

negative impact on society and the world, but at the same time, focusing on these issues can potentially influence in a positive way (Rema 1000, 2018).

3.2.3 Assortment Process Description

Like most retailers, the Norwegian retailer as well has built its category assortment based on the Russian doll effect and managed in the external system. There are three assortment sizes – small (size 1), medium (size 2), and large (size 3). Each larger assortment size includes items from the smaller assortment size, but also additional items available only in that assortment size. Following is an example.

A3 national assortment is composed of products from A1 assortment + products from A2 assortment + products from A3 assortment. Each store has assigned assortment based on store size – size one national assortment (A1) is linked to small size stores, size two national assortment (A2) is linked to medium-size stores, etc. In addition to multiple assortment sizes, there are different assortments based on supply availability. Some suppliers can supply items nationwide while others only for particular regions that are close by. Smallest suppliers can only supply enough items to supply a couple of stores. There are national, regional, and local assortments based on supply restrictions. National assortments A1, A2, and A3 are mandatory assortments and cannot be modified by stores. In addition to mandatory national assortment, stores can choose and add items to their store assortment from either:

- National Assortment of bigger size (add A3 item to store with A2 assortment);
- Optional national assortment list (assortment code B).

Stores also get a mandatory regional assortment assigned to them, which is also defined based on store size – R1, R2, R3. As in national assortment cases, regional assortments also hold an optional regional list – X assortment code. All items in regional assortments have limited availability to one or multiple regions and are not available nationwide. Small local suppliers get added to the local assortment list – L. These items are only available in certain stores and compose of the last layer of final store assortment.

Store assortment is thus composed of (see Figure 16):

- Mandatory national assortment based on store size;
- Mandatory regional assortment based on store size;
- Items added from optional national assortment (B);
- Items added from optional regional assortment (X);
- Local items.

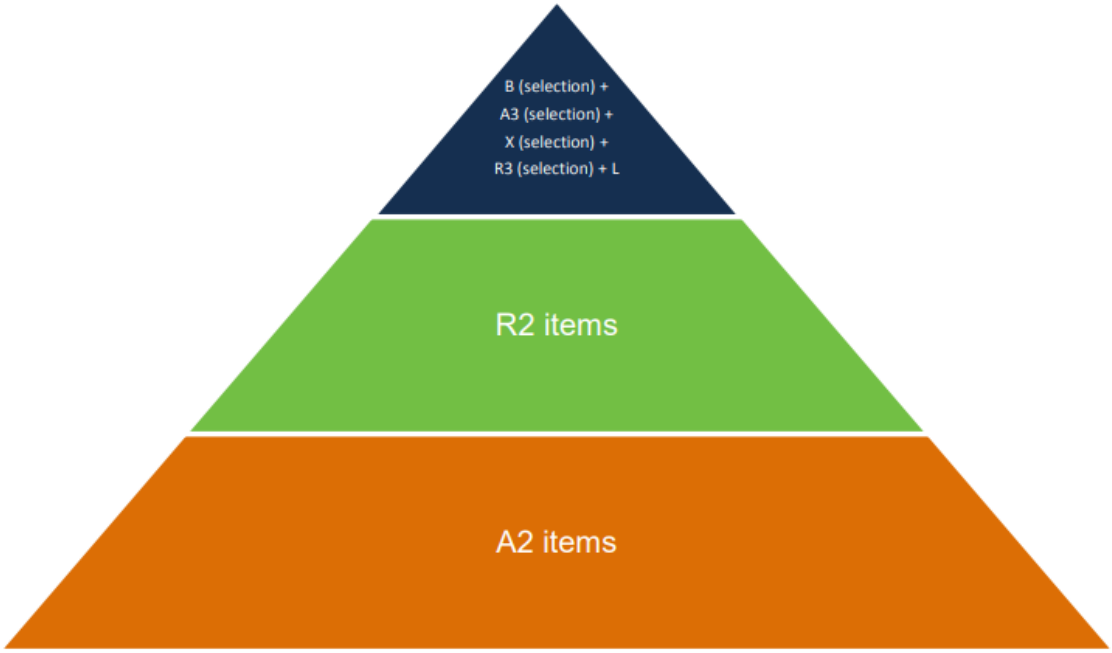
For example, a store of medium size from the Oslo region has the following items in the assortment of category Coffee:

- Mandatory national items from assortment list A2;
- Mandatory regional items from assortment list R2 Oslo;
- Items selected by store from assortment list B;
- Items selected by store from assortment list A3;
- Items selected by store from assortment list X;
- Items selected by store from assortment list R3;
- Local items defined and linked to store in the assortment list L.

Category reviews will be performed as required and not according to STAND011. STAND011 is a standard set by the Standardization Committee for the Norwegian Retail Industry (no. Standardiseringsutvalget for Norsk Dagligvarebransje), which states the responsibilities between suppliers and retailers during the implementation of new products to the Norwegian grocery market (Tradesolution EPD, 2018).

Category reviews would be evenly spread throughout the year to help manage the internal resource workload. A category will be reviewed at least once per year, with unplanned category reviews being initiated when required.

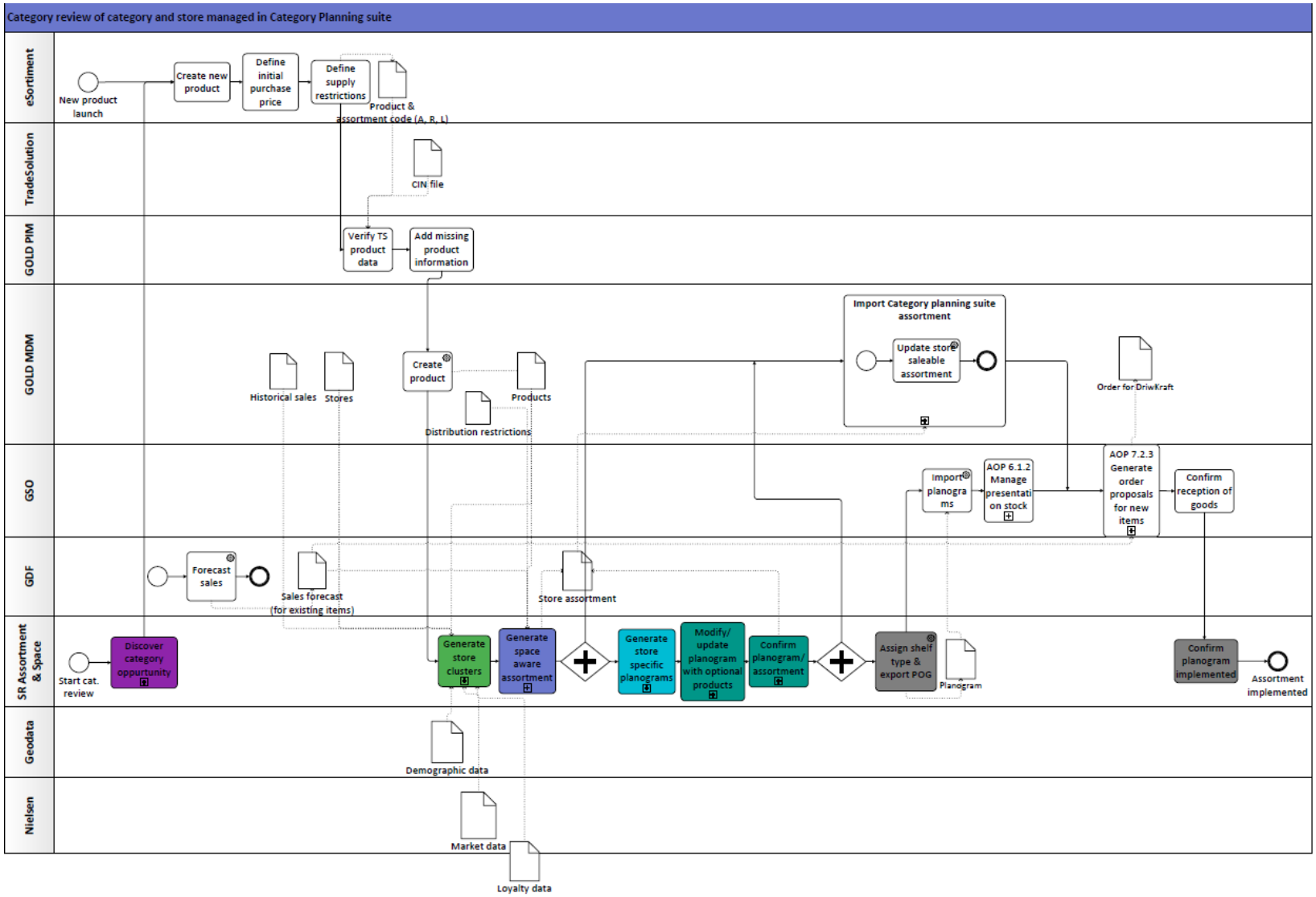
Figure 16: Medium size store assortment composition



Source: Smolej, Jončevski, & Wynn (2016).

Figure 17 represents the general category review process that is currently used by the Norwegian retailer, while Table 1 depicts the Norwegian retailers' assortment steps.

Figure 17: High-level assortment process in the case of the Norwegian retailer



Source: Smolej, Jončevski, & Wynn (2016).

Table 1: Assortment process steps in the case of the Norwegian retailer

Step	Description
1	**<u>Discover new market opportunities (optional)</u>** Category manager reviews category performance against market performance and checks if there are any product opportunities on the market. If an interesting product, not present in MDM, is found in market data, the category manager contacts the supplier and investigates if it is possible to supply the product. If possible, the supplier enters product information into eSortiment as the next step. Products found in market data, which are not present in product master will be flagged as new product introduction (hereafter: NPI) products in Category Planning suite but will not be flagged as "Orderable" in order to exclude them from Assortment Optimization optimizer automatic selection.
2	**<u>Create new product (optional)</u>** The supplier creates a new product in eSortiment, which forms part of the product proposal list in the Category Planning suite. Product proposals will be flagged with "pre-launch" product status. Product proposals will be evaluated against each other and against current products based on estimated product performance and other factors. In addition to suppliers, category managers can add a product to smaller suppliers who do not have access to eSortiment. NOTE: – In the future, all suppliers will access eSortiment platform and add products; – The option to add a product in MDM will still exist though it will require more manual entry by MDM team; – Initially, it is not planned that the supplier will enter product proposals in eSortiment without the category manager's prior decision into which assortment code (distribution availability) should be placed. Only after the decision will be made to place the product in assortment, new product entity will be added to eSortiment by the supplier. This means that initially, supplier product proposals will always have assortment code before being integrated from MDM to Category Planning suite and phase-in decision will be made in eSortiment;

Table continues

Table 1: Assortment process steps in the case of the Norwegian retailer (cont.)

3	**Define initial purchase price (optional)** When a product is added by the supplier, initial purchasing conditions are entered – the purchase price is set by the supplier, and estimated volumes are entered. The purchase price can be changed later and is only set as initial reference for cost and profitability calculations. The purchase price can be negotiated during assortment planning in Assortment Optimization and updated in eSortiment.
4	**Define supply restrictions (optional)** Category manager assigns supply restrictions to each product using assortment codes: – A: product available nationwide; product will have no restrictions in Assort; – R: regionally available product; regions where the item could be supplied are selected; the product will be treated as forbidden in unselected regions in Assort; – L: locally available items; a store where item is available must be selected; the product will be treated as Mandatory for selected stores. If the item is seasonable, item assortment code M is used. M code means that item is available nationwide (same as code A) but is seasonal in nature. In addition, a season description can be assigned to the product. This will populate product attribute Season code in Category Planning suite and help distinguish seasonal products. If the product is a replacement for an existing product, a replacement link must be created in eSortiment (or MDM). This link will flow into the Category Planning suite and trigger historical sales performance inheritance from discontinued/replaced products. Replaced items will be flagged with "replaced" product status in the Category Planning suite. If the product is new to the market, volume estimation is inputted. If possible, the product is linked to existing referencing products, and a coefficient is defined. This will create a forecast reference link in MDM and will cause forecasted products to be populated in the Category Planning suite from referencing the product's forecast. The product must be confirmed by the category manager to initiate the transfer of data to MDM.

Table continues

Table 1: Assortment process steps in the case of the Norwegian retailer (cont.)

4	NOTE: – When category assortment is managed in the Category Planning suite, there will be no need to enter assortment size when entering assortment code. Only assortment code will be required to define distribution restrictions (e.g., Assortment code "A" for national products); – Until Category Planning suite is not managing category assortment for all stores in the same category, assortment size will remain mandatory input at this step, in order to support the assortment of stores managed in MDM; – Defining additional seasonality description, separate from MDM, will be possible in product attribute "Seasonality", which will be maintained in Category Planning suite; – For the period when the phase-out decision is executed in eSortiment, phased-out products will be marked with "Phased-out" status in the Category Planning suite (assortment code U).
5	**Verify TS product data (optional)** New product's data originating in eSortiment is enriched by TradeSolution data. Product dimensions are sourced, and attributes are populated. MDM team has the option to check and verify that data has no major visible errors.
6	**Add missing product information (optional)** MDM team has an option to fill any missing product attributes (article attributes), which are set as mandatory in MDM but are optional in TradeSolution and are missing from CIN file data. If any mandatory attribute values are missing, respective category managers will be notified by the MDM team. Category managers will provide values for missing mandatory attributes to the MDM team. Product attributes, which are maintained in the Category Planning suite, will not be entered at this point (e.g., category planning, flavor). After entering all required information, the product is validated with active status triggering data flow into MDM.

Table continues

Table 1: Assortment process steps in the case of the Norwegian retailer (cont.)

7	**Create product** New product proposals will be flagged as active in the Product information management (hereafter: PIM) system. Once validated in PIM, product data is transferred to MDM, where product and its sales and logistical variants are created using an automated process. Using an automated interface, the product information will flow from MDM to Category Planning suite, where a new entry in product master will be created. New products will be marked with "Pre-Launch" status. Dimension information in the Category Planning suite will be set by MDM during initial product creation. Users will be able to modify dimension information in the Category Planning suite though that information will not flow back to MDM or other systems.
8	**Generate store clusters** Product master, store master, historical sales, market data, and forecasted sales would be available to generate and analyze store clusters based on consumer behavior. This data will be loaded automatically using automated interfaces. Demographic and loyalty data might become available in the future and will be loaded manually by loading flat files though the Category Planning suite data load user interface. Consumer behavior store clusters can be further split based on regions, or groups of regions. This is done in order to enable Assortment Optimization to recommend regional items in the cluster part of the assortment. Splitting will be necessary only in certain cases: – When the category contains no regional product, no split is necessary; – When a category contains a moderate number of distinct regional assortments, some splitting is necessary; – When category contains near or as many distinct regional assortments as there are regions, clusters are split by region. Creating store clusters is an optional step, previously created store clusters can be loaded before generating new assortments.

Table continues

Table 1: Assortment process steps in the case of the Norwegian retailer (cont.)

9	**Generate space aware assortment** Once store clusters are generated or loaded, the category manager initiates category assortment review and evaluates new product proposals. At this step, the category manager can negotiate with the supplier and make changes (manual overrides) to assortment recommendation. Once they are satisfied with future store assortment, the scenario is approved.
10	**Create/update saleable assortment** Approval of assortment in Assortment Optimization can trigger the publishing of saleable assortment to MDM if the lead time of interface is configured to enable this. This assortment is stored in current saleable assortment tables in MDM. Category Planning suite saleable assortment is distinguished from MDM managed saleable assortment by being flagged as "externally managed". List of which category and store pair assortment will be maintained in MDM as externally managed assortment and will prevent updates of saleable assortment from other MDM internal processes. With the proposed time of assortment confirmation in Category Planning suite 8 weeks before go-live, increased interface lead time can increase the visibility of future assortment in MDM. Interface lead time for saleable assortment is set to 1 week before planogram planned go-live as default, to support established MDM process of generating store orderable and deliverable assortments one week in advance of planned start of sales of the product. NOTE: – the saleable assortment will be updated again after store reviews planograms in Shelf Planning and makes changes to optional assortment; – Minor changes to assortment are expected at that point though no new products will be phased-in, and no additional products will be phased-out at that point.

Table continues

Table 1: Assortment process steps in the case of the Norwegian retailer (cont.)

11	**Generate store-specific planograms** Once assortment is approved, the category manager creates model layout planograms and assigns blocking. The automatic process generates proposals for layout planograms. Layout planograms are created for each cluster assortment and shelf configuration and serve as templates for generating store-specific planograms. Merchandising support checks layout planograms and modifies blocking and rules if necessary. Shelf type is also updated on layout planograms. After layout planograms are deemed satisfactory, merchandising support adds prioritization of score and trigger process of generating store-specific planograms.
12	**Modify/update planogram with optional products** After store-specific planograms are created using Planogram Automation and approved (either automatically, by having a high score, or manually by Merchandising support), stores are notified of actionable planograms. Each store can check the actionable planogram and can make changes to optional products at this point. Stores are presented with a list of optional product which can be added to planogram to replace Planogram Automation placed optional products. The optional list is composed of products present in future assortments of other stores linked to the same distribution center (hereafter: DC). Mandatory products cannot be removed from the planogram by store users. Category Manager checks if product minimum distribution levels are reached after products are removed from planogram by store.
13	**Confirm planogram/assortment** Planogram is promoted by store or automatically a week before assortment is due to go live. This ensures guaranteed delivery of products on planograms. Planogram approval triggers two flows of data: – Updates of saleable assortment are sent to MDM; – planograms are sent to Automatic order processing (hereafter: AOP) once the release date is reached.

Table continues

Table 1: Assortment process steps in the case of the Norwegian retailer (cont.)

14	**Import planograms** The Category Planning suite sends approved planograms to the AOP planogram interface. Planogram data contains products, facings, capacity, and shelf type. Importation of planogram data triggers management of presentation stock.
15	**Manage presentation stock** Optional items will not be selected by franchisees in GOLD Store operation (hereafter: GSO) in the new process.
16	**Generate order proposals for new items** Based on assortment sent by Category Planning suite and replenishment parameters calculated from the planogram interface, order proposals are generated to replenish stores with products required to implement new assortment.
17	**Confirm reception of goods** Once the store receives products based on automatic order, it confirms reception and starts building the new shelf layout. Goods should arrive in the store in advance to facilitate shelf rearrangement on the date defined in the Category Planning suite as the date of assortment execution.
18	**Confirm planogram implemented** When the store implements a planogram, it has to confirm the implementation of the planogram in the Category Planning suite. The confirmation has no impact on store saleable and orderable assortments but will be used to help keep track of planogram implementation progress across stores.

Source: Smolej, Jončevski, & Wynn (2016).

Since the diagram shown in Figure 17 contains steps which are whole processes, following are more general explanations of those steps.

3.2.3.1 Generate Store Clusters

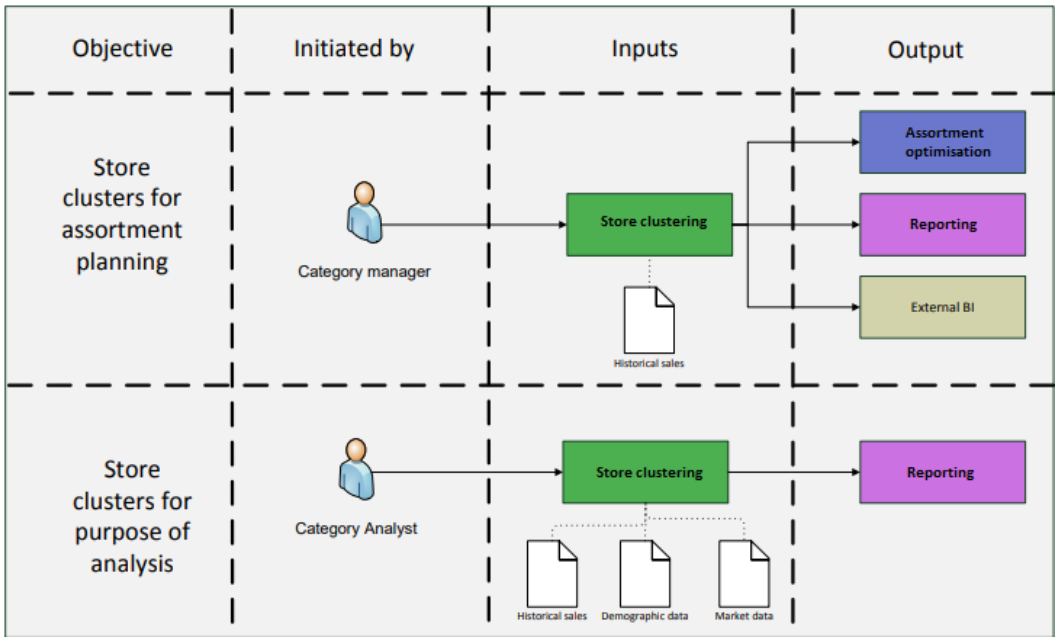
Store clustering can be defined as defining groups of stores based on consumer behavior or consumer segmentation. Store clusters can be created using the tool mentioned in section 2.4.1.

Clusters can be created manually based on store attributes (e.g., region) or calculated based on sales patterns, demographic indicators, and competitor stores in the area. A combination of two approaches can also be used to generate store clusters. Store clusters can be used to define cluster level assortments but can also be used for analysis purposes only. When created clusters for analysis purposes, clusters are not exported or used in other apps or systems. The advantage of creating store clusters based on consumer behavior is that a more consumer-driven assortment can be defined for that store cluster.

Two potential uses of clusters are:

- Store clustering for assortment planning: when generating clusters used in assortment planning, clusters will be generated based on past consumer behavior – historical sales. Stores will be automatically grouped together based on consumer shopping behavior;
- Store clustering for the purpose of analysis: when generating clusters used for analysis, clusters will be generated based on historical sales, demographic data, and market data. Stores will be automatically grouped together based on consumer shopping behavior.

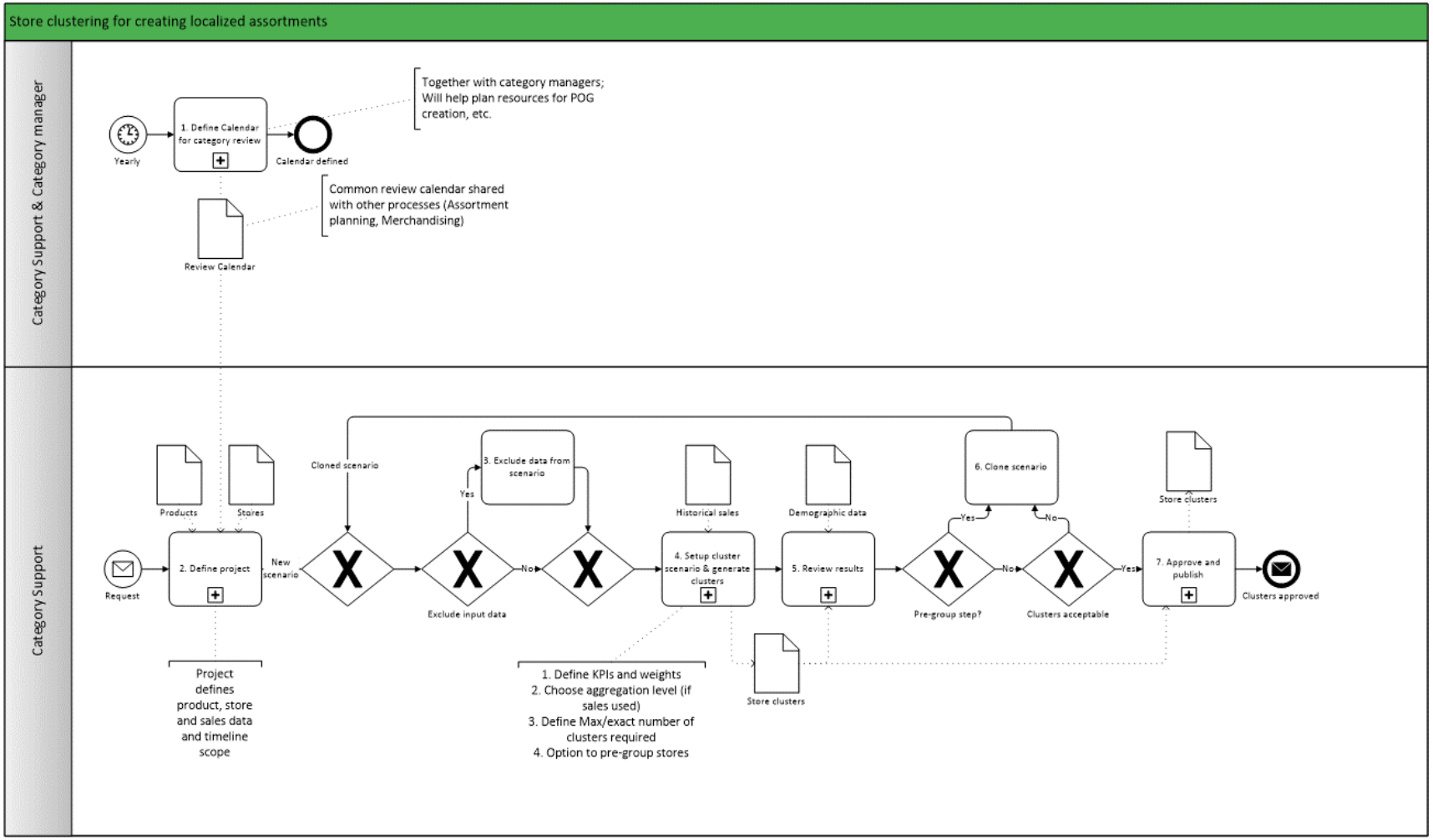
Figure 18: Different types of clustering



Source: Smolej, Jončevski, & Wynn (2016).

Table 2 shows a detailed description of the cluster generation process in the case of the Norwegian retailer, while the detailed diagram for cluster generating is shown in Figure 19.

Figure 19: Detailed process for store clustering in the case of the Norwegian Retailer



Source: Smolej, Jončevski, & Wynn (2016).

Table 2: Detailed process steps for store clustering in the case of the Norwegian retailer

Step	Description
1	**Define calendar for category review (optional)** Category reviews will be performed as required and not according to STAND011. If required, category reviews can be planned in advance and enable spreading the workload throughout the year to help manage internal resource workload. A category will be reviewed at least once per year. Unplanned category reviews are initiated when required. The calendar review date serves as a reference for managing internal resources.
2	**Define project** Based on the category review calendar or category manager's request or based on STAND011, Category Support creates a reset project. Reset project defines scope: – Which products to use; – Which stores to use; – Which sales to use (forecasted/historical); – Who are persons responsible for specific tasks; – When each task should be completed; – When planograms (and assortment) should be implemented.
3	**Explore (optional step)** Users can explore data to test different KPIs and weights before generating end clusters.
4	**Exclude data from scenario (optional step)** If required, Category Support can exclude data from scenario:

Table continues

Table 2: Detailed process steps for store clustering in the case of the Norwegian retailer (cont.)

4	Products; – Stores; – Week of sales. If product/store or sales week skews results of clustering because of abnormalities, it can be excluded from the data set used for generating store clusters. NOTE: excluding stores will cause them not to be included in store clusters
5	**<u>Setup cluster scenario</u>** A compound performance indicator (hereafter: CPI) composition is defined at this step. Different KPIs are weighted for the composition of the final CPI. Only historical sales performance will be used as KPIs: – Store margin; – Value chain margin; – Sales volume; – Sales value; – Unit sales; – Rate of sale. Aggregation level of sales is selected. – E.g., category, sub-category, brand, supplier. The maximum number of clusters is decided at this step. – Instead of the maximum number of clusters, the exact number can be selected. If required, stores can be pre-grouped at this step. – Pre-grouping needs to be done in advance in a different scenario. After setup is complete, the generation of clusters is initiated by Category Support.

Table continues

Table 2: Detailed process steps for store clustering in the case of the Norwegian retailer (cont.)

6	**Review results** Category Support reviews generated store clusters. Review of clusters will be done based on the following data: – Historical sales performance; – Demographic data (when available). Generated clusters can be compared with clusters generated in previous scenarios (but part of the same project) if any exist. The category manager will review generated clusters to provide feedback. In addition to reviewing clusters based on consumer behavior, a report on distinct regional assortments in the category is reviewed. Based on the number of distinct regional assortments in the category, the following actions are possible: – There are no regional assortments in a category, and clusters are not split; – There are near, or as many distinct regional assortments are there are regions; cluster scenario is cloned, and cluster split by regions; – There are a couple of distinct regional assortments in a category, and the cluster scenario is cloned, clusters are split based on region and merged back into distinct groups.
7	**Clone scenario (optional)** If generated clusters are not acceptable, Category Support will clone the scenario and execute steps 3-5 again. Can also be performed: – to create new clusters on the same data set (based on a different set of KPIs); – compare results from previous scenarios. The scenario is also cloned if initial store clusters were generated as pre-grouping steps. The cloning step is also used when the regional split of clusters is required.

Table continues

Table 2: Detailed process steps for store clustering in the case of the Norwegian retailer (cont.)

8	**Approve and publish** Clusters are approved by the category managers. After approval, clusters are published to Assortment Optimization as input for assortment planning/optimization using the same project. Assortment clusters will be published and visible on Category Planning suite platform apps (generate an analysis of cluster performance).

Source: Smolej, Jončevski, & Wynn (2016).

3.2.3.2 Generate Space-aware Assortment

Assortment planning and management could be of different magnitudes:

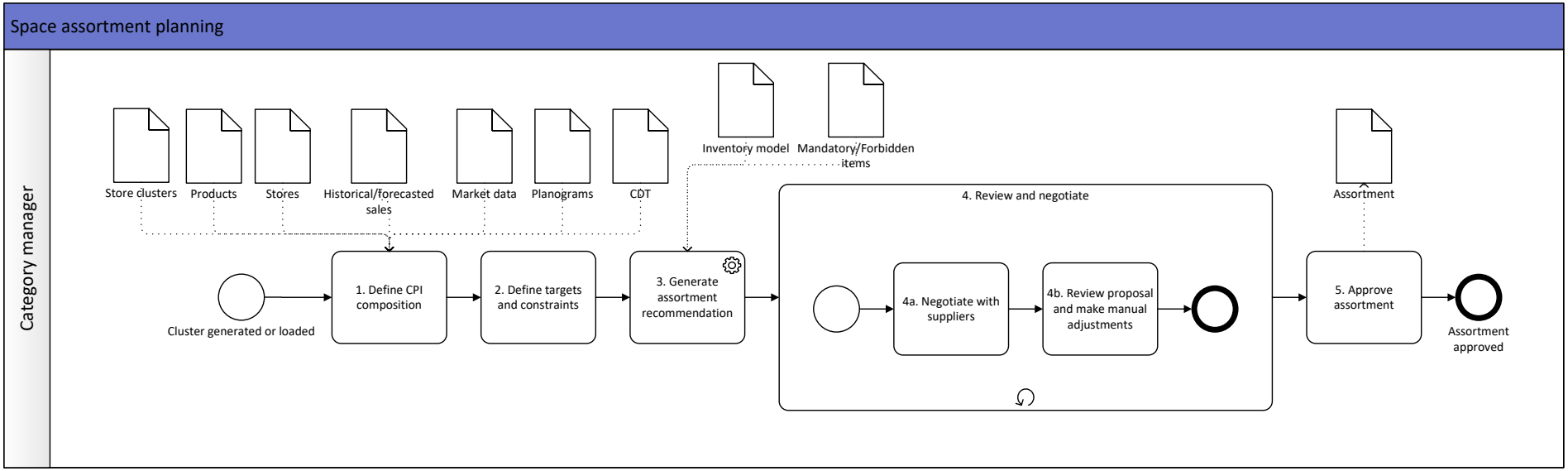
- minor changes to an assortment (e.g., product replacements);
- full assortment evaluation and optimization

When doing minor changes for the assortment, there is no need for category managers to be involved, because most of the time, these minor changes include simple product replacements and/or seasonal products. This means that the defined assortment is fine as it is, but that it just needs a bit more tuning.

Full assortment review is usually done because assortment is underperforming. In this case, category managers start by creating different CPIs in order to evaluate the categories. Based on budget objectives, they then set the sales growth target for the category they are responsible for. The next step is to set the space constraints and the variety of protection restrictions, which should reflect the consumer behavior in the specific cluster. Both targets and especially constraints are set on national and cluster (consumer behavior + region + size) level. As a result of all these steps, an assortment recommendation is being generated, and if it does not meet the constraints and targets, it gets optimized in multiple iterations.

Figure 20 shows the detailed space assortment planning process, while Table 3 outlines the specific steps.

Figure 20: Assortment optimization process in the case of the Norwegian retailer



Source: Smolej, Jončevski, & Wynn (2016).

Table 3: Generating space-aware assortment steps in the case of the Norwegian retailer

Step	Description
1	**Define CPI composition** CPI template selected during project creation is pre-applied to the scenario. Category managers can modify different KPIs composing CPI. CPI composition can be defined differently for each customer decision tree (hereafter: CDT) branch. KPIs and default weight that will be available and used in Assortment Optimization is defined in KPIs and measures.
2	**Define targets and constraints** The category manager sets sales growth targets for different branches of CDT based on category objectives and stock-keeping unit (hereafter: SKU) restrictions. Space constraints (Linear Space Max., Linear Space Share.) and variety protection restrictions (SKUs Min., SKUs Max, Coverage Max) are set. Constraints and restrictions on cluster level should reflect the consumer behavior in that cluster. Both targets and especially constraints are set on both banner (national) and cluster (consumer behavior + region + size) level. Example: Banner level space constraint is set to 80% of available linear space in smallest store space available. Cluster level space constraint is set to fill the remaining space up to 100% of space available. CDT trees need to be defined in advanced and selected during project creation.
3	**Generate assortment recommendation** The category manager initiates assortment recommendation, first on banner level, and later on cluster level.

Table continues

Table 3: Generating space-aware assortment steps in the case of the Norwegian retailer (cont.)

3	Distribution restrictions from MDM - Must stocks (mandatory items per store) and must not stock (forbidden items per store) are taken into account at this step. In addition to mandatory/forbidden products, the optimizer uses a product sales estimate and inventory model to calculate the correct number of facings and capacity to have sufficient stock in the store matching minimum set days of supply (hereafter: DOS). In addition to DOS, the min/max number of facings can be set in the inventory model to further manage recommended facings and capacity. Store local exceptions (assortment code L – mandatory local items) are taken into account and added to respective store assortments at this step. If the recommendation is not sufficient, constraints and targets can be changed, and optimizer activated again. Some Inventory model values will originate from MDM. Inventor model values not derived from MDM will be managed directly in the Category Planning suite platform.
4a	**Review and negotiate – negotiate with suppliers** After Assortment Optimization generates assortment recommendations (banner, cluster, or/and store level), the category manager reviews the assortment. Based on products that are proposed to be added into assortment, negotiations with the supplier are initiated. Negotiations with the supplier will not be executed and managed in the Category Planning suite system but in external systems/tools.
4b	**Review and negotiate – review proposal and make manual adjustments** If negotiations with the supplier are not successful or category manager is not pleased with the recommendation, he can override automatically proposed assortment and manually add/remove products from assortments. Category managers can, at any time, see assortment visualized on the shelf to help them review and make decisions on assortment.

Table continues

Table 3: Generating space-aware assortment steps in the case of the Norwegian retailer (cont.)

4b	Step 4a and 4b are iterative and can be repeated multiple times before a satisfactory result is achieved.
5	**Approve assortment** Once the category manager is satisfied with assortment and concludes supplier negotiation, they approve the final assortment. The approved assortment is published to Planogram Automation, which uses it as an assortment rule to generate model layout planograms. Part or cluster level assortment will become optional in Shelf Planning by applying business rules. Approval of assortment triggers the flow of saleable assortment from the Category Planning suite to MDM.

Source: Smolej, Jončevski, & Wynn (2016).

3.2.3.3 Generate Store-specific Planograms

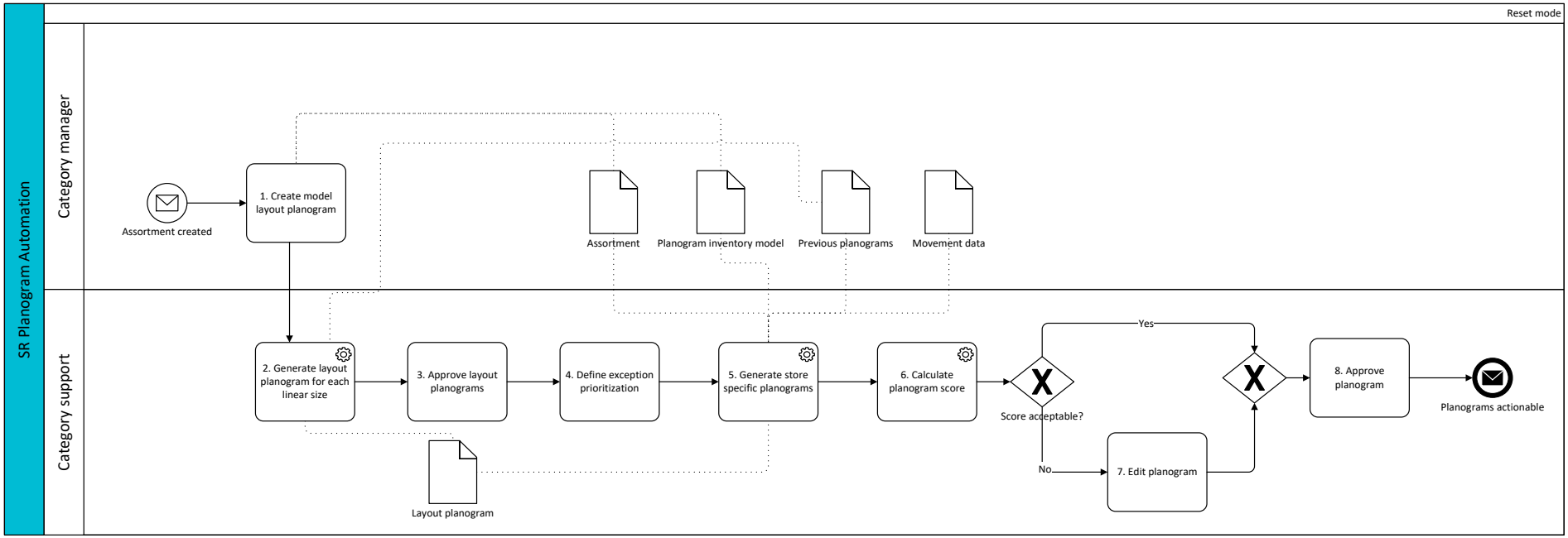
A store-specific planogram is the representation of each store's specific assortment. As a whole, it paints a picture of where a product needs to be placed, at what orientation, with what capacity, etc.

In order for a store-specific planogram to be created, category managers need to define rules, according to which the planogram can be then created. The category managers are making sure that the rules they are putting in place are reflective of their analysis and vision for the category. The rules may include things such as:

- Pallets will be used and are used; lower shelf holds pallet; best sellers normally go on lower shelf as pallets;
- Supplier A has to have 30% of available space on the planogram;
- Products from category A should appear on the left-hand side of the fixture.

Merchandisers then, in an iterative process, create the store-specific planograms using the tool mentioned in section 2.4.4. Figure 21 shows the high-level diagram of the store-specific planogram generation process, while Table 4 outlines the steps in said process.

Figure 21: Store-specific planogram generation



Source: Smolej, Jončevski, & Wynn (2016).

Table 4: Process steps for store-specific planograms generation in the case of the Norwegian retailer

Step	Description
1	**<u>Create model layout planogram</u>** After assortment is defined in Assortment Optimization, the category manager creates model layout planograms in Shelf Planning Light. Model layout planograms are created for each cluster based on the biggest cluster assortment (based on the number of SKU in cluster-size combination). Model layout planograms are not created for each distinct shelf configuration in the cluster (number of shelves and height of shelves). The difference in the number of bays does not require a new model layout planogram – this aspect of adjustment is covered during layout planogram creation. Model layout planograms are created from the selection of currently active planograms – the biggest size planogram is selected from one store in each cluster. Planogram Automation automatically places blocks on the initial version of model layout planograms. Automatic block placement can be driven by CDT defined in the project. The category manager rearranges each block by either dragging and dropping, or by rearranging products in each block. Category managers can delete existing block definitions and create new blocks based on either product attributes, performance measures, or CPI scores. Blocks can be placed inside blocks – this enables multiple levels of rules on product placement on planograms. Block definitions also indicate where local exception items should be placed on final store-specific planograms and how products on planograms should be rearranged when Planogram Automation is creating store-specific planograms. Category manager assigns size/shape rules to each block (mandatory % of shelf space, straight edge or rugged, must cover whole bay, etc.). Compliance with these rules will enable a higher presentation score of store-specific planograms. Category manager can ensure presentation rules (sequence of products, adjacent products) by either manually placing products in the right order or by assigning presentation rules to each block. Once the category manager is satisfied with model layout planograms, the work is handed over to category support staff. This is done by triggering the generation of layout planograms.

Table continues

Table 4: Detailed process steps for store-specific planograms generation in the case of the Norwegian retailer (cont.)

2	**Generate layout planogram for each linear size** Based on model layout planograms, Planogram Automation creates layout planograms for each linear size of planograms and shelf configuration existing in each cluster. All blocking and rules associated with blocks are transferred from the parent model layout planogram to layout planograms. If the layout planogram has less linear space than the model layout planogram, products are removed in accordance with assortment for such linear space. If assortment is still too big, products are removed based on the lowest CPI score in each block.
3	**Edit & Approve layout planograms** Category manager reviews automatically generated layout planograms. If corrections are required, blocks are rearranged/redrawn for a specific layout planogram. Block size and presentation rules can be modified at this step.
4	**Define exception prioritization** Category manager can apply scoring priority (weight) and drive through this what action Planogram Automation engine needs to take if it runs out of space when creating store-specific planograms. More priority can be assigned to either assortment (presentation score), financial (number of facings), or logistical (do not replace with smaller packaging). The category manager can select multiple layout planograms to assign the same prioritization to multiple layout planograms.
5	**Generate store-specific planograms** Automatic approval and rejection score are defined for the project. Category support queues generation of store-specific planograms based on stores linked to each layout planogram. The generation of planograms is triggered and executed on the server. For each store, local products are added (or removed), and products rearranged based on blocking rules. Facings, packaging, and consequently, capacities of shelves are adjusted based on store-specific product performance. Users are notified when store-specific planograms are created.

Table continues

Table 4: Detailed process steps for store-specific planograms generation in the case of the Norwegian retailer (cont.)

6	**Calculate planogram score** Based on the configured weight of each score, the planogram performance index is calculated. The planogram performance index is combined from three different planogram scores: – Financial score; – Logistical score; – Presentation score. Planogram is automatically approved if it achieves approval score defined in the previous step.
7	**Edit planogram (optional)** Planograms that do not achieve an acceptable score are reviewed by category support. If requiring editing, they are manually modified in Shelf Planning.
8	**Approve planograms** Once all planograms are considered satisfactory, category support approves planograms and places them into actionable status.

Source: Smolej, Jončevski, & Wynn (2016).

3.2.3.4 Modify/update Planograms

Process wise, modifying/updating planograms is considered to be a separate process, but it is almost exclusively done as an extension step to the previous process. The reason why it is represented as a separate process is that this is done by actual store owners.

When the merchandising team creates the planogram, store owners have a limited time to make the changes they feel are needed for the planogram. Changes include:

– Stores will only be able to add products from their DC. The number of these items is to be limited to what can physically fit on shelves;

- Mandatory products can be moved around the planogram, but their facings cannot be decreased, and those products cannot be moved;
- Stores can remove optional products or reduce/increase their facings;
- Optional products will be defined as the bottom x% of a sub-category's cumulative CPI score;
- This x% can be configured per category;
- If the 'worst' product in a subcategory contributes more than x% of the CPI for that subcategory, then all products in that subcategory are mandatory.

Store users have the option of changing optional part of assortment in Shelf Planning. This action is allowed after store-specific planograms are approved by Category support and is planned to commence no later than two weeks before planned planogram go-live. Store users are able to add optional items from the cart and remove the optional parts of the assortment already placed on the planogram.

Store modifications are advised to be completed before one week of the deadline to guarantee delivery of all products on the final planogram. Best performing and items manually added by category support/category managers will be locked for changes by applying merchandising lock BR. Once satisfied with changes, store users promote the planogram to Pending/Live. Once complete, the planograms will reflect the actual merchandising in the store.

3.2.4 Benefits of the Current Assortment Process

This section lists some benefits of the current assortment process in the case of the Norwegian retailer.

One of the benefits of the assortment process is that the output is the so-called space aware assortment. This means that the assortment for each store is built based on the actual shelf space in the stores, which allows for the optimized assortment to fit on the shelves without issues. In addition, space aware assortment aids the planogram implementation process in the store, because there is no need for adjustments in terms of space.

The Norwegian retailer's assortment process also uses store-specific planograms. Store-specific planograms are planograms tailored to the specifics of each store (e.g., logistics). As an extension to this process, store-specific planograms are then sent to an external system, which triggers an order to be automatically placed and processed, in order for the goods to arrive in the store before the planogram needs to be implemented.

The Norwegian retailer is also using its own forecasting solution, which was embedded in the general assortment process. This feature allows for forecasted sales to be used in order to build the assortment based on performance from previous periods, potential in a certain region, etc.

3.3 Dutch retailer

The second subject, which will be analyzed in this thesis is a Dutch retailer that operates a chain of specialty stores throughout Europe. Being a non-food retailer, the Dutch company is particularly interested in keeping the margin level and ensuring that high-selling products are always in stock. Their product pallet is pretty diverse, ranging from housewares to toys and garden products (Blokker Holding, 2013). In the following chapters, we will describe Dutch retailer in general, before focusing on assortment process analysis and description, before comparing its assortment optimization process to the Norwegian retailer.

The sources utilized for analysis will be a combination of reviewing existing literature and researches on the topic of category management, trends related to this branch and challenges encountered by retailers, open discussion with representatives of retailer, to acquire knowledge on current and desired processes related to assortment, which was done as part of implementation project for category management tools with the retailer and finally comparing both assortments processes to point out the differences between them and potentially discover opportunities.

3.3.1 Company Description

The Dutch company is in the household goods, living, and toys retail business, which operates a chain of specialty stores throughout Europe. Originally a family business in the Netherlands, retailer currently operates over 10 retail formats in eight nations with around 2,200 shops and around 21,000 staff. As a non-food distributor, the retailer is especially interested in margin protection and in ensuring that common products are on stock. Because sometimes they are linked to a film release or fashion trend, many retailer lines have a particular selling chance window. Their product pallet is pretty diverse, ranging from housewares to toys and garden products. Their slogan is: ‘everything for in and around the house’ (Symphony Retail AI, 2019b).

Since November, this Dutch retailer has been on sale and has been making losses since 2014. There are 474 shops in the Netherlands, plus 77 franchise shops, and 128 in Belgium and Luxembourg. The retailer posted a loss of €344m in 2017, almost double the year-earlier loss. Total sales over the year fell by some €400m to €1.6bn, due to both divestments and ‘weak sales results, the company said last year (Dutch News, 2019).

3.3.2 Strategy and Vision

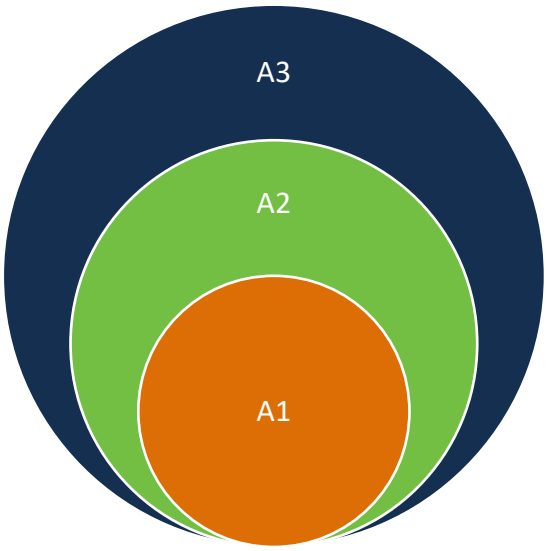
In 2017, Blokker Holding began a major overhaul of its stores because both sales and profits had been under pressure for years. Part of the reorganization involved the related banners, which were also part of the holding (Dutch News, 2019).

On April 1st, 2019, the company was sold to a domestic retail entrepreneur and investor. This is the consequence of a sales process in which a fresh owner has been searched for these retail chains who want to construct the future of these businesses together with the staff. The shop formulas retain their prominent place in the retail scene in the Netherlands and Belgium with this planned purchase and enter the next stage in their wealthy history (Blokker Holding, 2019).

3.3.3 Assortment Process Description

Category assortment for Dutch client is built using the Russian doll effect. There are 3 assortment sizes – small (size 1), medium (size 2), and large (size 3). Each bigger size includes items from the smaller assortment and additional items available only in that assortment size. The assortment is defined on a product level, with DOS of 7 days – since most of the stores receive deliveries once a week. An example is shown in Figure 22 (high-level assortment):

Figure 22: Example of Russian doll effect when building assortment



Source: Jarc (2017).

A3 assortment is composed of products from A1 assortment + products from A2 assortment + products from A3 assortment. Each store has assigned assortment based on store size – size 1 assortment (A1) is linked to small size stores, size 2 national assortment (A2) is linked to medium-size stores, etc.

Store assortment is thus composed of:

- Assortment based on store size;
- Items added by from the franchisee (items existing in Dutch retailer's MDM system);
- Local items.

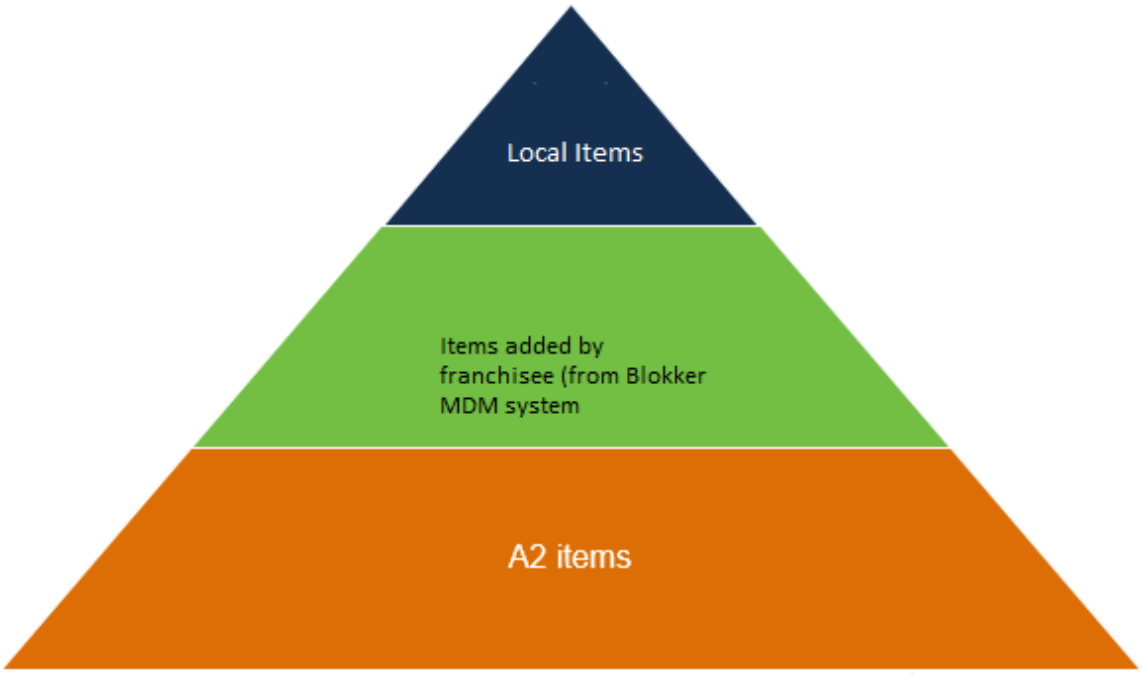
An example is shown in Figure 23 (store assortment). A store of medium size has the following items in the assortment of category Coffee:

- Items from assortment list A2;
- Items selected by store (from existing items in Dutch retailer's MDM);
- Local items defined by the store.

Category reviews are prioritized based on:

- importance of the category in regard to the whole strategy of the company;
- peak selling periods (Christmas, Mother's Day);
- workload across the weeks.

Figure 23: Example of Russian doll effect when building assortment

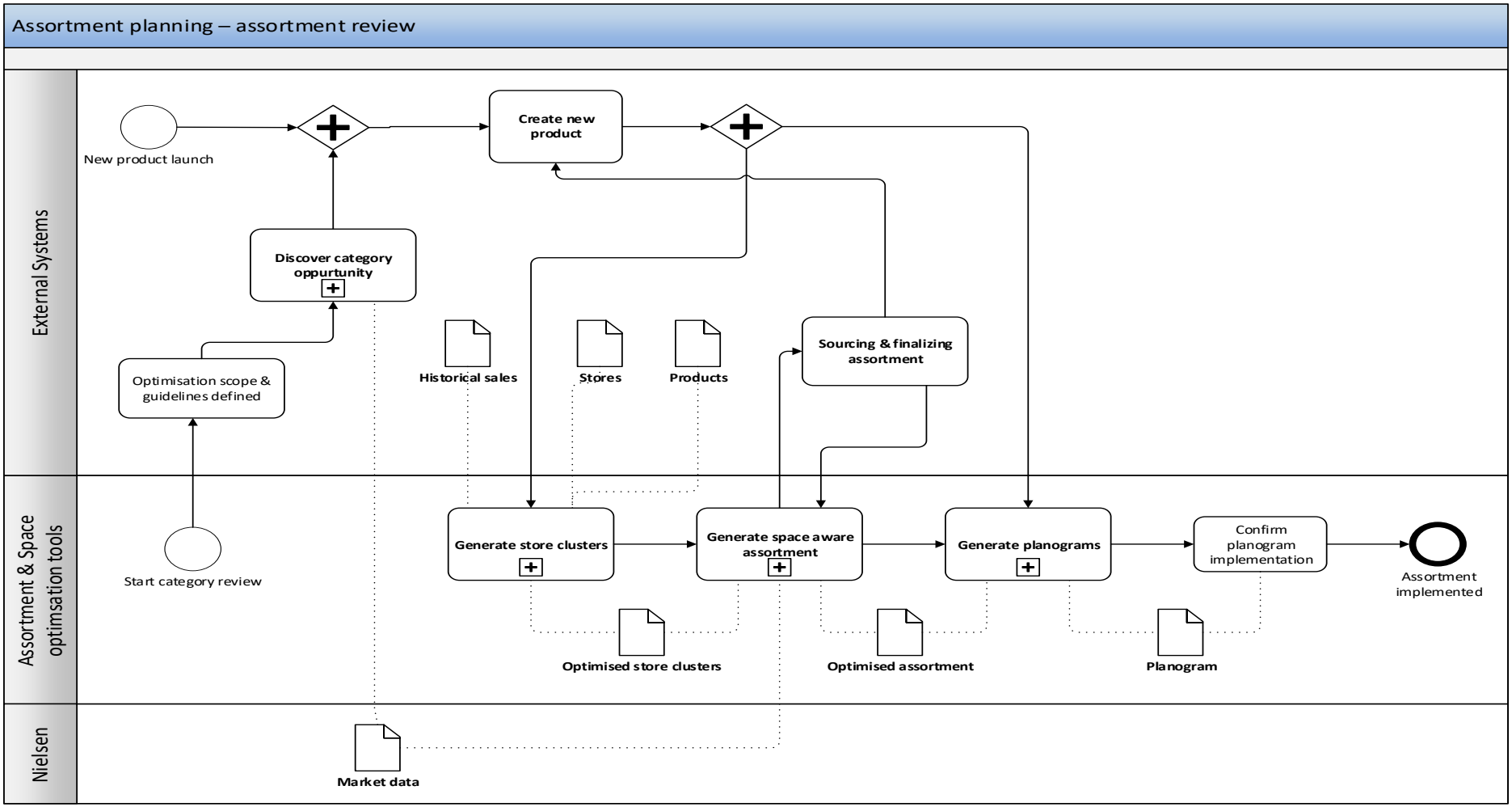


Source: Jarc (2017).

Assortment optimization is usually done 2 times per year, but this depends on the season and product group. For example, Garden and Christmas assortment is optimized once per year, and other categories are optimized more than 2 per year. Assortment optimizations can also be run on an ad-hoc basis – for example, if revenue, margin a.o. changes in certain direction – usually discovered after regular evaluation process (4, 12 weeks after assortment has been optimized).

The diagram shown in Figure 24 represents the general high-level category review process currently used by the Dutch retailer, while the details of each step are defined in Table 5.

Figure 24: High-level assortment process in the case of the Dutch retailer



Source: Jarc (2017).

Table 5: High-level assortment process steps in the case of the Dutch retailer

Step	Description
1	**<u>Optimization scope & guidelines defined</u>** The below decisions are extrapolated based on company strategy and serve as a basis for assortment optimization: – Determine Category Role (destination, occasional, routine, convenience); – Determine CPI. Most commonly used are: Sales (volume and amount), Margin, Rate of Sales (unit and value). – Create CDT; – Define assortment selection/protection rules; – Determine shelf presentation rules. Targets and objectives are set as the output of discussion between Category Manager director, Category Manager and director of Marketing&Formula. Based on guidelines set, relevant category managers prepare/define: – Prepare Category Plan; – Define targets per segment.
2	**<u>Discover new market opportunities</u>** The category manager reviews business performance in the category and checks whether product possibilities are available on the market. If the market data contain an exciting item that is not present in an external scheme, the Category Manager shall contact the provider and examine whether the item may be supplied. This is the phase in which a clear schedule is discussed for the entire assortment optimization. – Current assortment performance analysis is performed; – Online potential, high sellers from close markets (e.g., Belgium); – Supplier bonus analysis. Additionally, potential inclusions into assortment are assessed based on: – Market trends; – Competitor assortment.

Table continues

Table 5: High-level assortment process steps in the case of the Dutch retailer (cont.)

2	Based on the analysis performed, the high-potential items are identified.
3	**Create new product (optional)** A new product is defined in an external system by defining all of the relevant product characteristics and master data. Product proposals will be assessed on the basis of projected product results and other variables against each other and with present products (in the following steps of assortment optimization).
4	**Calculate store clusters** The generation and analysis of shop clusters based on consumer behavior will include a product master, a store master, historical sales, and market data. Currently, the Dutch retailer is clustering their stores only based on store size (product attribute). There is currently no approval process for created clusters in place, nor any reports are delivered as an output. No additional tools used in the current process (Access …), and there is no calendar created for store clustering. The process described above has been implemented and executed at Blokker for many years and is normally undertaken every 5 years (sometimes more frequently).
5	**Generate space aware assortment** Upon generation or loading of store clusters, category managers initiate a review of category sorties and evaluate fresh product proposals. In this step, the current assortment is identified for analysis; the ranking of products based on CPI is the basis for the category optimization. Current assortment and identified high-potential products are getting ranked using a unified CPI metric.

Table continues

Table 5: High-level assortment process steps in the case of the Dutch retailer (cont.)

5	The assortment is calculated for every cluster of stores separately. In this step, the optimized assortment is calculated (considering CPI ranking, targets set, and product dimensions) and reviewed. Assortments that fit the actual shelf in stores are created – this is called "space aware" assortments. Calculate optimized assortment: – Set targets (sales, number of SKU's per supplier …) for proposed assortment; – Review expected performance vs. Target performance; – Check inventory. Analysts can alter the performance (sales) of an article to protect the product from being dropped from the proposed assortment. Adjust the targeted performance of existing products (optional). Adjust protection rules (optional) Products that are performing well on the market (with other retailers) can be included in the proposed assortment. Include market products into proposed assortment based on Assort recommendations. If any changes to optimized assortment are needed after step "sourcing & finalizing assortment", category managers can manually adjust the automatically calculated proposal, calculate alternative scenarios (what-if) or add completely new products to the assortment. After completely new products are added to the assortment, basic product data needs to be gathered and inputted into the system.
6	**Sourcing** This is the phase in which the category manager should determine the source of supply for new items. This can be done by buying directly from a supplier from the rack or by developing products. The latter can be done in different forms. Category management is in the lead for the search.

Table continues

Table 5: High-level assortment process steps in the case of the Dutch retailer (cont.)

6	When constructing the timeline, so-called "lead times" for products need to be considered. The lead times, in general, are set as follows: – Private label development, 47 weeks; – Long lead times in the Far East, 37 weeks; – Shorter lead times in Europe, 26 weeks. This is the phase in which the new product range is physically put together. This can be done in a sketch on a shelf plan, but certainly for more complex shelves plans, it is wise to build this physically. This determines what fits and what the assortment and price structure will look like. At this point, other teams are invited to check on visual merchandising / visual design here so that they can already think along with you how the idea of the category manager can be optimally put on the shelf. For newly introduced items (new introductions), the supply chain coordinator checks the progress and feasibility of the transport process. For items removed from assortment, Category Managers must present a reduction plan for delisted items (discount offers, "last chance" points,) In case Category Manager decides a completely new item (not in optimized assortment) will be added to the assortment, it needs to get added by using the MDM external system.
	<u>Generate planograms</u> In the case of a new product launch, the next step of the process, after "create new product" is generating planograms. This is because, in case of minor changes to the assortment (1 to 1 change), there is no need to reassess the whole assortment and optimize it. The whole purpose of such minor changes is to refresh existing assortment with a few items that changed packages or if some items suddenly become unorderable from the supplier. In case the "Generate planograms" step is triggered by a category review process (following "Sourcing & finalizing assortment", the optimized assortment is automatically synchronized on planograms by deleting items that were removed from the assortment and adding items (not directly on shelves) that were added to the optimized assortment.

Table continues

Table 5: High-level assortment process steps in the case of the Dutch retailer (cont.)

7	Users (space team) are merchandising new planograms by adding new items on relevant positions within a new planogram. Further visual optimizations are done to planogram – where on a planogram item is placed, what are neighboring items, … After planograms are released to stores (start and end date of the planogram is defined), a pdf version of planograms and selected report is created and shared with stores. The following reports are created in this step: - Planogram assortment (list of items that are placed on planograms); - Plus/min per planogram (what items are newly included in the planogram and which ones are deleted from planogram); - Visualization of planogram. In case new items are introduced in the proposed assortment (manually added from category managers) – they need to be populated with relevant data Basic reporting on finalized planograms is done – highlighting, performance reporting, checking DOS. This is done with shelf planning tools.
8	**<u>Confirm planogram implementation</u>** When a planogram is implemented by the store, the planogram must be confirmed as implemented (by sharing confirmation in Category planning tools). Confirmation will be used to help keep track of the progress of planogram implementation across stores.

Source: Jarc (2017).

The diagram of the assortment process (see Figure 25) shows high-level processes included in the Dutch retailer's assortment optimization process that also include some important subprocesses, which are described in the following chapters.

3.3.3.1 Generate Store Clusters

The clustering of stores is a process of identifying store groups, which relies upon analyzing both consumer segmentation or behavior. Store clusters can be created using the application mentioned in section 2.4.1.

Store clusters can be created manually, with the creation being based on store attributes (e.g., geographical region) or calculated dynamically using different data sets like historical sale patterns, different demographic indicators as well or competing local stores. The generation of shop clusters can also be combined with two methods. The benefit of developing customer-driven clusters is that they can have a more consumer-driven range. Two potential uses of clusters are (Jarc, 2017):

- clustering for the purpose of assortment definition: cluster generation is based on previous customer conduct (e.g., historical sales) in the creation of clusters used in assortment definition;
- clustering for analytical purposes: when generating clusters that are used for evaluation purposes, clusters are produced based on historical sales, population data, and market statistics. Store clusters will automatically group together, depending on customer buying behaving. Stores are grouped automatically based on consumer behavior.

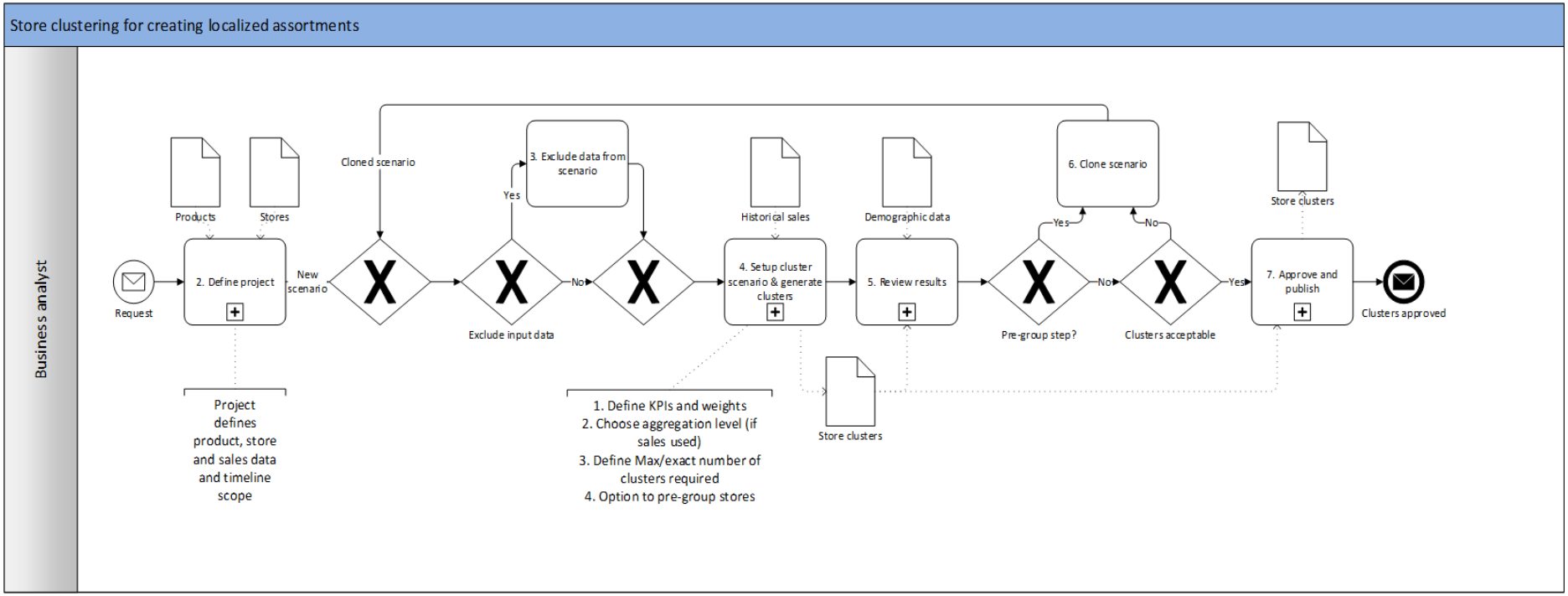
The diagram in Figure 25 represents the detailed cluster process used in the case of the Dutch client (Jarc, 2017), while Table 6 contains details of each step of the process.

Table 6: Detailed process steps for store clustering in the case of the Dutch retailer

Step	Description
1	**Define project** Based on the category manager's request, the Business Analyst initiates a process for store cluster generation. The scope needs to be defined: – Which products to use; – Which stores to use; – Which sales to use (forecasted/historical); – Who are persons responsible for specific tasks; – When each task should be completed; – When planograms (and assortment) should be implemented.
2	**Explore (optional step)** Users can explore data to test different KPIs and weights before generating end clusters.

Table continues

Figure 25: Detailed process for store clustering in the case of the Dutch retailer



Source: Jarc (2017).

Table 6: Detailed process steps for store clustering in the case of the Dutch retailer (cont.)

3	**Exclude data from scenario (optional step)** If required, Category Support can exclude data from scenario: – Products; – Stores; – Week of sales. If product/store or sales week skews results of clustering because of abnormalities, it can be excluded from the data set used for generating store clusters. Excluding stores will cause them not to be included in store clusters
4	**Setup cluster scenario** CPI composition is defined at this step. Different KPIs are weighted for the composition of the final CPI. The following metrics are most commonly used as KPIs: – Sales value; – Unit sales; – Unit Rate of sale; – Value Rate of sale; – Margin. Aggregation level of sales is selected. – E.g., category, sub-category, brand, supplier. The maximum number of clusters is decided at this step. – Instead of the maximum number of clusters, the exact number can be selected. If required, stores can be pre-grouped at this step. Pre-grouping needs to be done in advance in a different scenario.

Table continues

Table 6: Detailed process steps for store clustering in the case of the Dutch retailer (cont.)

5	**Review results** Business Analyst reviews generated store clusters. Review of clusters will be done based on the following data: – Historical sales performance; – Demographic data (when available). Generated clusters can be compared with clusters generated in previous scenarios if any exist.
6	**Clone scenario (optional)** If the generated clusters are not acceptable, the Business Analyst will clone the scenario and execute steps 3-5 again. Can also be performed: – to create new clusters on the same data set (based on a different set of KPIs); – compare results from previous scenarios. The scenario is also cloned if initial store clusters were generated as a pre-grouping step.
7	**Approve and publish** Clusters are approved by Business Analyst. After approval, clusters are published to the Assort optimization module as input for assortment planning/optimization using the same scope (as defined in step 1).

Source: Jarc (2017).

The above process describes the store clusters generation process, which is in use with Dutch retailer.

3.3.3.2 Generate Space-aware Assortment

There are 2 different processes which exist in assortment management (Jarc, 2017):

- Minor (or 1 for 1 product replacements) changes to assortment;
- Full category review (includes evaluation and optimization of full assortment).

In the event of minor modification of the range, category managers do not need to be engaged because these minor modifications most often include easy product and/or seasonal product substitutes. That implies the specified range is okay but requires only a little more adjustment.

Usually, the entire assortment is checked because it does not work or because a full category review is due based on the category review calendar. In this situation, the category managers begin by generating various CPIs to assess the categories. They set the sales development goal for the category for which they bear responsibility, based on the budget goals. The next step is to establish the limitation of space and variation security, which should represent the customer conduct of the cluster. Both targets and especially constraints are set on cluster (only size in the case of the Dutch retailer) level. All these steps lead to an assortment of recommendations that are optimized in various iterations, by running through multiple iterations of optimization of assortment.

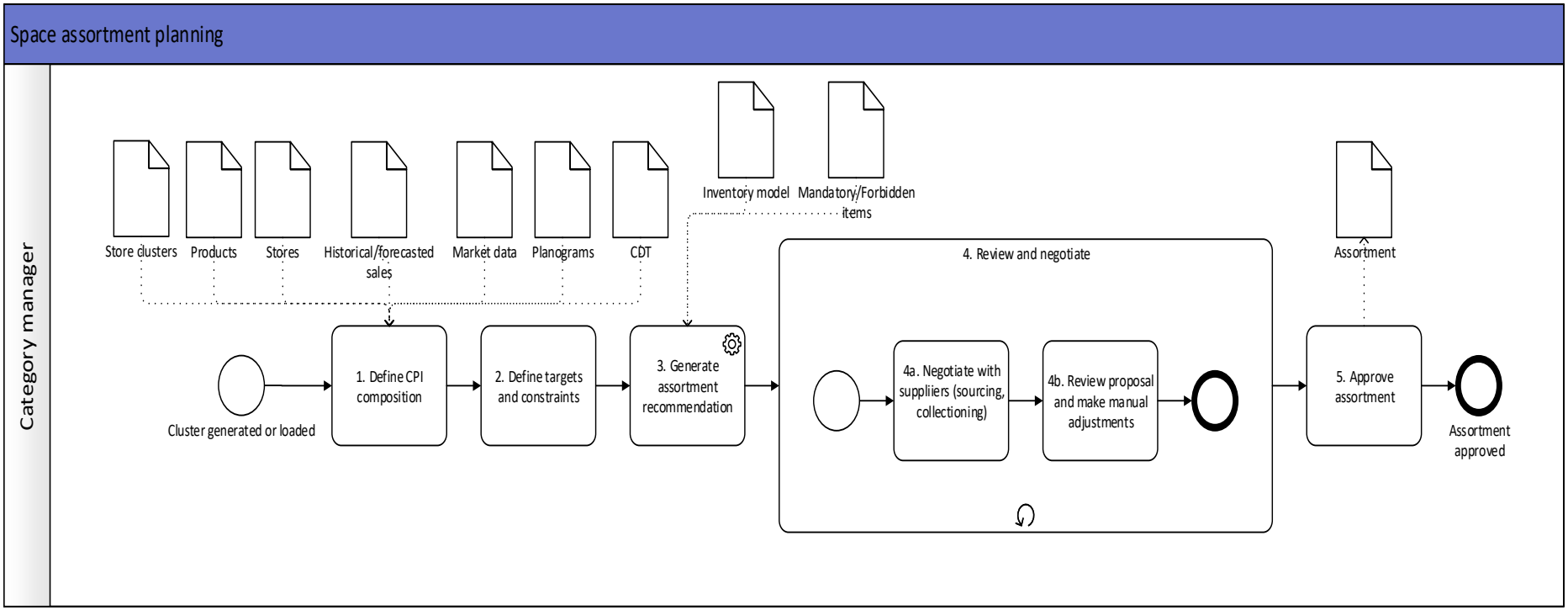
Figure 26 represents the detailed Assort to-be process used in the Dutch retailers' assortment process, while a detailed description of the steps is available in Table 7.

Table 7: Detailed process steps for assortment optimization in Dutch retailer

Step	Description
1	**Define CPI composition** The assortment manager determines the weight of different KPIs composing a CPI. CPI composition can be defined differently for each CDT branch. KPIs and default weight that will be available and used in assortment optimization is defined in KPIs and measures.
2	**Define targets and constraints** Business analysts set sales growth targets for different branches of CDT based on category objectives.

Table continues

Figure 26: Assortment optimization process in the case of the Dutch retailer



Source: Jarc (2017).

Table 7: Detailed process steps for assortment optimization in Dutch retailer (cont.)

2	Space constraints (Linear Space Max., Linear Space Share.) and variety protection restrictions (SKUs Min., SKUs Max, Coverage Max) are set. Constraints and restrictions on a cluster level should reflect the consumer behavior in that cluster. CDT trees need to be defined in advanced and selected during project creation.
3	**Generate assortment recommendation** In addition to mandatory/forbidden products, the optimizer uses a product sales estimate and inventory model to calculate the correct number of facings and capacity to have sufficient stock in the store matching minimum set DOS. In addition to DOS, the min/max number of facings can be set in the inventory model to further manage recommended facings and capacity. If the recommendation is not sufficient, constraints and targets can be changed, and optimizer activated again.
4a	**Review and negotiate – negotiate with suppliers (sourcing, collectioning...)** After the Assortment optimization application generates assortment recommendations (banner, cluster level), the category manager reviews the assortment. Based on products that are proposed to be added into assortment, negotiations with the supplier are initiated.
4b	**Review and negotiate – review proposal and make manual adjustments** If negotiations with the supplier are not successful or business analysts are not pleased with the recommendation, they can override the automatically proposed assortment and manually add/remove products from the assortments. The business analysts can, at any time, see the assortment visualized on the shelf to help them review and make decisions on alter the assortment. Step 4a and 4b are iterative and can be repeated multiple times before a satisfactory result is achieved.

Table continues

Table 7: Detailed process steps for assortment optimization in Dutch retailer (cont.)

5	**Approve assortment** Once the category manager is satisfied with the assortment and concludes the supplier negotiations, he approves the final assortment. The approved assortment is published to planogram generation (merchandising) software.

Source: Jarc (2017).

3.3.4 Benefits of the Current Assortment Process

Below are some of the benefits of the current Dutch retailer's assortment process.

The benefit of the current process is that the output is a space aware assortment, which means, that optimized assortment fits the shelves in stores, and it helps with the implementation of planograms in stores. The current process is also utilizing tools that automatically populate newly proposed items on planograms and deletes items, which were not included in the assortment from the planograms.

Base planograms (which define current assortment) are automatically included in the assortment optimization process, which eliminates potential human error in this step of the process.

4 ASSORTMENT PROCESS EVALUATION AND COMPARISON

In this chapter, we will be analyzing the compliance of assortment processes used by both retailers against their company strategy. To be able to create an assortment process that reflects the company strategy, the category role must be defined first.

Roles in the category are micro strategies that retailers use to create shopper-friendly experiences in their shops. They also assist drive sales development in the category by defining how the category meets the requirements of individual shoppers. The function of the category defines the retailer's significance in the category itself. They identify the role that the retailer wishes to play in each shop in the category. Category roles can be used to boost shopper traffic, support shopping needs, feature unique occasions, or create shopper-friendly target categories (Category Management Solutions, 2019).

Roles in categories assist retailers in implementing policies aimed at meeting the requirements of customers. For instance, a retailer might want to be known as it's market's best shop for promoting health-focused articles that meet the shopper's requirements. The retailer would store a broad range of natural and organic products across the main categories in this instance. Their choice would assist distinguish them from their competition in their market. Roles in a single category can and often can differ within distinct categories. A retailer may want to be the low-price leader in one segment to attract shoppers to their shop while stocking a broad range of premium products to distinguish them from their rivals. On premium specialty products like organic and plant-based products, etc., they could then gain a greater margin (Category Management Solutions, 2019).

Different category roles (Symphony Retail AI, 2019c):

- Destination (The reason shoppers go to a store)
    - Will consistently deliver superior value to the target shopper;
    - share growth will be the retailer's focus;
    - The retailer will promote this category heavily;
    - Used a traffic builder.
- Convenience (Not normally part of the main shop cart)
    - Reinforces image of the retailer as one-stop-shop;
    - Delivers good everyday value to target shopper;
    - Profit is the retailer's focus.
- Routine (Shoppers prefer to buy goods here)
    - Helps build retailer image;
    - Delivers consistent value for target shopper;
    - Profit is the retailers' key focus.
- Seasonal/Occasional
    - Goods bought infrequently or at particular times of year – e.g., Christmas.

4.1 Compliance of the Dutch Retailer's Assortment Processes With Company Strategy

Once a traditional purchasing organization, the Dutch retailer was organized to buy products that rotate very rapidly very cheaply and to sell those at low rates but in large quantities. This business model does not work anymore. You can't merely beat the unlimited product ranges at amazing rates you can find online. Thanks to a customized product range, the customer needs to be catered (Rompaey, 2019).

Nevertheless, the Dutch retailer still has a market, but it will have to alter radically. How? Stores have to become points of service and instances of the display. Dutch retailer will have to innovate again and become a friend and confidant of the consumer, but that will involve an enormous turnaround (Rompaey, 2019).

The issue is whether the Dutch retailer can do that because, in such a big business, it is not simple to reverse course. It is no longer the biggest company that wins, but the one with the fastest velocity. Is there a future in this leaner corporate framework? According to Jorg Snoeck from RetailDetail, "Any shop chain born in an internet-free globe that has not drastically changed its structure will inevitably face this reality" (Rompaey, 2019).

4.2 Compliance of the Norwegian Retailer's Assortment Processes With Company Strategy

The Norwegian retailer was founded in the late 1970s with a purpose to carry only the most essential 1,000 products in its assortment. For a while, that business vision and strategy was working for them.

With harsh competition entering the Norwegian market, the company needed to adapt, because carrying only a thousand articles in the assortment all of a sudden wasn't enough. Over the years, with people becoming more health-conscious, practicing sustainability and care for the environment in every possible area, the Norwegian retailer shaped its strategy and vision according to the people's views on life.

This eco-awareness is especially accentuated in Norway, with people leading lives where the focus is on consuming healthier food, taking care of the environment, and being sustainable wherever possible.

When building assortments, The Norwegian retailer has rules in place, with which they make sure that every store carries (Rema 1000, 2018):

- 200 organic products;
- 85 wholegrain products;
- 60 allergy-friendly products;
- 80 sugar-free products;
- 60 lactose and gluten-free products;
- 450 keyhole labeled products.

Vision for the future is for these numbers to continue to rise, given the path that our world is on. This would mean that the company will remain on the sustainability road and to continue to provide healthy options to its customers (Rema 1000, 2018).

If we compare the vision of the Norwegian retailer with the challenges that modern retailers face today (see section 1.2), we can conclude that the company is directly addressing two of the challenges, with partial extension to one more.

The fact that the Norwegian retailer is pushing the sustainability agenda in every aspect of its business lets us know that the environmental awareness (see section 1.2.3) challenge is

directly addressed. This extends to the conscious consumer (see section 1.2.2) because the Norwegian population has a high percentage of awareness, in the sense that people want to know what they consume and where does that product come from.

The challenge that is partially addressed is consumer habits and preferences (see section 1.2.5). Like we said before, the Norwegian retailer has rules about adding healthy products to each store's assortment. All of these products carry the Keyhole nutrition label, which certifies that the product has met certain requirements for salt, sugar, fat, and fiber content. The aim is to make it easier for consumers to find and choose healthier foods (Nordic co-operation, 2010).

4.3 Comparison of Assortment Processes

In this section, we will be sharing the results of the assortment process comparison between the two chosen retailers. Due to a few fundamental differences between the retailers, we cannot expect the assortment processes to match by default.

One of those fundamental differences is the branch that both retailers operate in. The Norwegian retailer operates in the grocery branch, while the Dutch retailer represents the home improvements branch, with both of them having their own operating principles. This means that their assortment processes differ, as well. While a typical grocery retailer is focused on FMCG, where volume is much higher, the Dutch retailer must be focused on maintaining its margin.

The next fundamental difference is the type of retailer. While both retailers consider themselves franchise retailers, the Norwegian retailer allows for much more decision-making power (when it comes to assortment) its store owners (franchises). The Dutch retailer offers assortment related decision making to franchisees only in some very limited cases (local products), while the Norwegian retailer gives its franchises the power to alter (but not radically change) the final assortment according to their needs.

The third fundamental difference is the logistics system. The fact that the retailers are representatives of different branches greatly affects their assortment and their logistic processes, as well. Seeing as the Dutch retailer's products don't have an expiration date, while products in the Norwegian retailer pallet do, being part of the FMCG group of articles. This also means that assortment cycles and delivery dates with Norwegian retailer are much lower than with the Dutch retailers. The Dutch retailers' supply chain is organized based on push-based principles as a result of the branch (long delivery dates from Asian manufacturers, demand dependent on launch of television series …) and logistics factor (no expiration dates …), while Norwegian retailer's supply chain is pull-based (demand-driven, short delivery dates).

Due to geographical conditions of the country operated in, branch, and the fact that franchisees have much more decision-making power when it comes to the assortment (local products), the Norwegian retailer's logistics system is much more developed than the Dutch retailers'. Norway is a country with a much more diverse terrain than the Netherlands, with high terrain in general and numerous land features caused by glaciers and topography. Although most of its population is concentrated in the southern part of the country, there are multiple bigger cities in the central and northern parts of it as well. All of these calls for a developed and much more complex logistic system that utilizes road, rail, water, and sky transportation.

The Norwegian retailer is using tools that allow for the creation of store-specific planograms (based on store-specific calculated assortment), while the Dutch retailer does not use these tools. This means that Dutch retailer does not have assortment tailored to the demand of local customers, which can have an impact on sales, but in a negative way.

Generally, both retailers are following the best practice approach, which was described in previous chapters in this thesis, but there is still plenty of room for improvement, especially by including tools to plan floor plans and add different data sets into their assortment decision processes like demographics, loyalty, or transferable demand data. Both retailers would benefit from the inclusion of AI in its assortment process, which would help with predicting the most optimal future assortment by recognizing trends from supplied sales data and optimize their category review calendars by monitoring number and performance of new market data items.

4.3.1 Similarities

Despite the different branches of retail that both companies operate in, there are a few similarities in their assortment optimization process.

Both retailers are performing category analysis of the current assortment, prior to using assortment tools to calculate the optimized assortment. This step could be skipped, as those steps are also done within the tools themselves and therefore make any analysis prior to using the tool, redundant. By eliminating this step, both retailers would benefit from greater efficiency of its assortment processes and cost-saving from better utilization of human resources.

Both the Norwegian and the Dutch retailers cluster their stores based on historical sales data, and they do that before defining the assortment. This enables them to define the assortment more precisely and on a more granular level.

Similarities do not end there, as both retailers are calculating any opportunities based on market data (products to include in assortment) prior to using the tools to calculate the optimized assortment. This step could be skipped, as those steps are also done within the

tools themselves and therefore make any analysis of market data prior to using the tool, redundant. By eliminating this step, both retailers would benefit from greater efficiency of its assortment processes and cost-saving from better utilization of human resources.

Decisions of what to sell in stores are one of the most important decisions that every retailer has to take. This might be the reason why both retailers are executing separate analysis steps (evaluating current assortment, as well as calculating opportunities based on market data) outside the system – to check the results of the optimized assortment done by specialized tools and therefore gaining trust in its output.

Another similarity is generating space aware assortments, which (as described in previous chapters) brings benefits in the subsequent steps of the process, for example, merchandising planograms, where assortment fits the shelf space available, as well as implementing such planograms in stores later in the process, lower stock quantities, … The above statement might be resulting from the fact that both retailers are using the same tools to generate store clusters and optimized assortment.

Both retailers track implementation of planograms in the stores by using collaboration platforms between stores and headquarters users, which help to provide feedback on the actual implementation in the stores as well as clarifying any questions that the stores might have on the topic of planograms.

None of the retailers use demographics or loyalty data in their assortment decision processes. By adding these two data sets into their assortment processes, they would be able to generate even more personalized assortments, which would better suit their customers and therefore drive greater sales.

4.3.2 Differences

This section contains the differences in the assortment processes of the Dutch and the Norwegian retailer.

When it comes to creating products, the Norwegian retailer grants access to the MDM to its suppliers, so that they themselves can create new products. This is done because suppliers have a complete set of information for each product and to ensure data will be complete. In the case of the Dutch retailers, employees are the ones responsible for creating new products in the MDM system.

The next difference is sales forecasting. The Norwegian retailer uses a sales forecasting solution, which predicts future sales for products, which can alleviate long term assortment planning. This solution leverages complex forecasting algorithms in order to calculate future sales. The Dutch retailer does not use solutions for forecasting sales.

One of the best-practice approaches mentioned in section 2.1 is exactly sales forecasting, which means that the Norwegian retailer can fully take advantage of all the benefits that come from forecasting sales when defining assortment. Using transferable demand data can bring even more benefits, but that is not the case with both retailers.

The Norwegian retailer uses distribution restriction data hailing from the complex logistics process. Distribution restriction data is put in place as a business rule and prevents users from accidentally adding a product when defining an assortment. The Dutch retailer does not use distribution restriction data, and errors can happen while defining assortment.

One of the benefits of using distribution restriction is forcing local assortment to stores, which is also one of the best-practice approaches mentioned in section 2.1. The Norwegian retailer does this on a shop level and not on a cluster level, which means that it is more granular and comprehensive.

One of the key differences between the two retailers is store-specific planograms. The Norwegian retailer creates store-specific planograms using the tool mentioned in 2.4.4, which can and brings numerous advantages in the assortment definition process. The Dutch retailer does not create store-specific planograms.

The automatic order processing for stores can be thought of as an extension to the previous point. The Norwegian retailer uses this feature automatic order processing for stores, which is based on the assortment defined by the store-specific planogram. The Dutch retailer has a process where orders for stores are created manually.

The Norwegian retailer allows franchise store-owners to alter the assortment on the planogram before it goes live and is implemented in the store. The Dutch retailer allows its franchises to alter the assortment in limited and pre-approved cases.

4.4 Options for Improvement

4.4.1 Norwegian retailer

Following are some observations that can lead to an improvement in the Norwegian client's assortment process.

The Norwegian client is currently clustering stores based only on historical sales data. Clustering stores based only on sales data can have its advantages, but at the same time, dividing stores by only using one data-set omits a lot of things. Given that the tools support a more granular clustering approach using other types of data, the Norwegian client can benefit from this approach. Besides sales data, clustering can be done based on:

- Demographics data;

- Loyalty data;
- Market data;
- Geographical data.

Using at least one of these datasets can add more depth to the assortment, since the way it is done now, the generated assortment has no other impact on the store assortment, besides adding good-performing items to it. Consumer behavior is not targeted as it could be by using, e.g., loyalty data, and the assortment is not tailored based on localized consumer needs and preferences.

Another change in the process that can be done by the Norwegian retailer is the use of Floor Planning tools (see section 2.4.5). As of now, they are not using it but could benefit greatly from it. A Floor Planning solution incorporates many business functions that follow distinct and separate user processes, like:

- New Store/Store Refurbishment: the starting point for this process is that a new store has been decided by the business and the endpoint is having a fully merchandised and optimized store that the franchisee can access and implement;
- Category Space Change: the third function is to allow to make a change in category space across the estate in order to react to changes in the market (e.g., declining sales). There needs to be a process in place that enables the head office to identify categories that need their space change, recommend how space should be changed in a store to accommodate the change in circumstances for the category and manage the roll-out of this change in stores. The start point of this process is the Category Manager analyzing the macro performance of an exceptional category, and the endpoint is the changes being implemented in stores;
- Store Space Change: the purpose of this process is to ensure that the information held centrally about a store reflects the reality of what is happening in the store.

4.4.2 Dutch retailer

After performing an analysis of the process, the improvements listed below have been identified as potential betterments for the Dutch clients' high-level assortment process.

The Dutch retailer is creating the same store cluster for all categories, and it is based on store size. This means that the assortment process is based on store clusters that don't specifically represent the buying patterns of the local shoppers. For example, small stores in suburban areas will have the same space allocated and the same assortment available for the gardening category as stores located in the center of a big city.

The retailer is not using advanced tools to help with store-specific planogram creation, but instead is creating the same planograms for a cluster of stores. While this means that with

relatively low effort, relevant planograms are created, those planograms are not completely suited for the local customers.

Even though the Dutch retailer is using tools, which create space-aware assortment, they are still physically creating planograms to determine if the assortment will fit on shelves. This step could be skipped.

The retailer does not have any specialized Floor Planning solutions included in its assortment process. By implementing such tools in assortment process, they could maximize revenue per square meter by analyzing which categories are outperforming others and allocating more space in stores to those categories.

A few steps in the Dutch retailer's process were identified as duplicates and could be skipped:

- The following step is duplicated in the process (»Internal Assortment analysis« = »Rank Assortment«) - » Internal Assortment analysis« could be skipped;
- The following step is duplicated in the process (»External identification of opportunities« = »Market data inclusion«) – »External identification of opportunities« step could be skipped;
- The following step is duplicated in the process (»Select new high-potential products« = »Calculate&Review«) - »Select new high-potential products« could be skipped;
- In the Collectioning phase, amongst other activities, the shelf with products is physically built to check if the proposed products fit on the planogram. This could be skipped, as the proposed assortment is space aware, because the tools offer these capabilities.

An additional issue with the process execution itself is that while one way of working has been created, it is not being followed by all people in the same way.

The Dutch retailer is not using demographics or loyalty data in its assortment optimization process, which would allow for even more personalized assortment for its Clients. Their data sets are not easy to obtain because of associated costs.

CONCLUSION

The aim of the thesis was to assess the methods of assortment optimization used by separate retailers from different nations by comparing both assortment processes to point out the differences between them and potentially discover opportunities. To achieve this, we unified the notations of the processes and compared the processes, describing benefits, options for improvement as well as similarities and options for improvement of the processes. By doing this, we gained a deeper knowledge and understanding of the assortment processes, which will help us with future implementations of assortment optimization modules, while the thesis will also be used for internal training purposes on this subject.

A good category scheduling process must be supported by a single platform that acts as a critical repository for all data (transaction, efficiency, loyalty, space, fixtures, client preference, etc.) that can inform category planning and implementation activities. This provides both internally (inter-departmental and store) and externally (suppliers, field teams) an opportunity for efficient cooperation. Because of the amount of information accessible to a retailer, they should use a collaborative model to improve the chance to create a cohesive attitude to client demand and product preferences while managing inventory levels and profitability efficiently. Solutions should be cloud-based so that everyone can access appropriate data anytime, anywhere, and on any smart device via role-based security through a browser.

Retailers around the world have come to know that shoppers are no longer as passive as they once were assumed to be – they don't just want fair-priced goods; they want solutions to their lifestyle needs. It is no longer a question of what distributors and their partners want to sell, but what, where, and how shoppers want to purchase. This means that successful retailers should not be interested in selling shelf space to the highest bidder but should merchandise shelves with both localized and relevant assortment.

Historically, there has been a firm reliance on POS and syndicated data sources to optimize the assortment process. This sort of information has limitations as it does not always take into account demographic changes, preferences, sales and social trends, and other factors that can provide a comprehensive perspective of shopper conduct.

AI allows distributors to gather understanding from shoppers automatically and predictively. This enables them to evaluate and predict the consumers‘ future conduct based on previous purchasing habits and responses to future market trends. This enhances many characteristics, including the ability to create trend-right, real-time shopper-focused assortments to meet best and anticipate the customers‘ near-term and future needs across all categories.

With the performed analysis, we discovered that while detail level processes or assortment optimization are very similar between the two retailers, the high-level assortment processes differ primarily in terms of time elapsed from start to end of assortment optimization cycle (due to lead times in sourcing the products).

In general, both retailers follow the best practice strategy outlined in earlier sections of this thesis, but there is still plenty of space for improvement, notably by including instruments to plan floor plans, and by adding various information sets to their assortment decision processes, such as demographics, loyalty, and transferable demand information. Both distributors would profit from the incorporation of AI in their assortment system, which by tracking the amount and efficiency of fresh market data products, would assist in predicting the best future assortment by acknowledging trends from provided sales information and optimizing their category review calendars.

The thesis will help build the internal business understanding of various assortment procedures, which may vary from nation to nation and from branch to branch. This topic has been chosen as we want to deepen our current knowledge on the different assortment procedures in use that will assist with our understanding of procedures with other retailers that we will find in our job within our business and hopefully and maybe help wider interested audiences.

The fact that analyzed retailers operate in different branches and countries did have an influence on the results of the performed analysis, as the shopper behavior, supply chain, and other factors of assortment analysis differ between analyzed subjects. Additionally, due to the fact that one of the selected retailers has an existing MDM system implemented by the same software provided as the assortment optimization modules meant that we had access to a greater level of detail when it came to information not directly related to the assortment optimization modules. Working with data that are not generally accessible, meant that we were not able to include all the details into the thesis, which had an impact on the end result. Taking this into account, coupled with the fact, that assortment optimization processes are entering an exhilarating phase, which will be assisted by outputs of AI calculations and machine learning, it would be interesting to perform an analysis of two retailers assortment process output from same branches and countries, where one of the analyzed subjects will be using AI to support assortment optimization process, and the other one using existing data sets from today.

REFERENCE LIST

1. Arh, G. (2006, June 18). Odgovor na zahteve kupca: Upravljanje blagovnih skupin se vse bolj uveljavlja. *Finance*. Retrieved June 15, 2019, from https://www.finance.si/155921/Odgovor-na-zahteve-kupca-Upravljanje-blagovnih-skupin-se-vse-bolj-uveljavlja?cctest&

2. Arh, G. & Češnovar, N. (2006, June 19). Idealna prodajna polica: Primera iz slovenske prakse: Mercator in Unilever. *Finance*. Retrieved June 15, 2019, from https://www.finance.si/155922

3. Avberšek, A. (2017, October 20). *Upravljanje blagovnih skupin se začne in konča pri zadovoljnem kupcu*. Retrieved July 02, 2019, from https://www.dmslo.si/zapis/upravljanje-blagovnih-skupin-se-zacne-in-konca-pri-zadovoljnemu-kupcu

4. Baird, N. & Rowen, S. (2012, January 26). eCommerce 2012: Back To The Future. *RSR Research*. Retrieved June 25, 2019, from https://www.rsrresearch.com/research/ecommerce-2012-back-to-the-future

5. Bandyopadhyay, S., Rominger, A. & Basaviah, S. (2009). Developing a Framework to Improve Retail Category Management Through Category Captain Arrangements. *Journal of Retailing and Consumer Services, Forthcoming, 16*(4), 315 - 319.

6. Basuroy, S., Mantrala, M. K. & Walters, R. G. (2001, October). The Impact of Category Management on Retailer Prices and Performance: Theory and Evidence. *Journal of Marketing, 65*(4), 16–32.

7. Bergsma, E. (2012a). Analyzing your first planogram – A step-by-step guide. *Schappen Plannen*. Retrieved July 28, 2019, from http://schappenplannen.nl/Documents/White_Paper_-_Analyzing_your_first_planogram.pdf

8. Bergsma, E. (2012b). Planogram Data Requirements How much data is really needed. *Planograms*. Retrieved July 28, 2019, from http://www.planograms.eu/Documents/White_Paper_-_Planogram_Data_Requirements.pdf

9. Blattberg, R. & Fox, E. (1995). *Category Management: The Category Plan.* Evanston: Northwestern University.

10. Blokker Holding. (2013, August 29). *Dutch client description*. Retrieved July 23, 2019, from https://blokkerholding.nl/

11. Blokker Holding. (2019, June 24). *Management buys Blokker*. Retrieved July 28, 2019, from https://nieuws.blokkerholding.nl/management-koopt-blokker-en-big-bazar/

12. Bristol, M. (2018a, July 9). *AI-Enabled Personalized Marketing Will Drive FMCG Forward*. Retrieved July 11, 2019, from https://www.theshelbyreport.com/2018/07/09/column-ai-enabled-personalized-marketing/

13. Bristol, M. (2018b, June 7). *How to Create an Effective Personalized Marketing Strategy*. Retrieved July 11, 2019, from https://www.mytotalretail.com/article/how-to-create-an-effective-personalized-marketing-strategy/

14. Butcher, J. (2019, January 16). *Grocery retail – what are the key trends for 2019?* Retrieved July 12, 2019, from https://www.kamcity.com/kamlibrary/industry-issues/grocery-retail-what-are-the-key-trends-for-2019/

15. Category Management Association. (2014). *The Theory and Practice of Optimizing Assortment and Space.* Retrieved July 26, 2019, from https://consumergoods.com/secure-file/6292

16. Category Management Association. (2016). *What is CatMan 2.0?* Retrieved July 15, 2019, from https://www.catman.global/overview

17. Category Management Solutions. (2019, August 6). *The 6 most important brand roles in retail*. Retrieved August 20, 2019, from https://categorymanagementsolutions.com/6-important-brand-roles-retail/

18. Citeman. (2010, March 11). *Category Assessment*. Retrieved July 12, 2019, from https://www.citeman.com/9165-category-assessment.html

19. Dewsnap, B. & Hart, C. (2004, July). Category Management: A new approach for fashion marketing? *European Journal of Marketing, 38*(7), 809–834.

20. Dupre, K. & Gruen, T. W. (2004). The use of category management practices to obtain a sustainable competitive advantage in the fast-moving-consumer-goods industry. *Journal of Business & Industrial Marketing, 19*(7), 444–459.

21. Dutch News. (2019, April 1). *Blokker family agree to sell Blokker stores in a management buy-out.* Retrieved August 1, 2019, from https://www.dutchnews.nl/news/2019/04/blokker-family-agree-to-sell-blokker-stores-in-a-management-buy-out/

22. ECR Europe. (1996). *European value chain analysis study: final report.* Brussels: ECR Europe.

23. EIQ Research Solutions. (2018, March 29). *Competing in the age of Amazon.* Retrieved July 24, 2019, from https://progressivegrocer.com/competing-age-amazon-profitable-category-diversification-expansion-leveraging-customer-insight

24. eTail. (2019, August 19). *Five key challenges facing retailers today - and how to solve them.* Retrieved August 23, 2019, from https://etaileast.wbresearch.com/five-key-challenges-for-retailers-how-to-solve-them-ty-u

25. Fahimi, S. (2018, August 27). *How Deep Learning Supports Growth-Driven Forecasting*. Retrieved August 2, 2019, from https://consumergoods.com/how-deep-learning-supports-growth-driven-forecasting

26. Hong, S., Misra, K. & Vilcassim, N. J. (2013). The Perils of Category Management: The Effect of Product Assortment on Multicategory Purchase Incidence. *Journal of Marketing, 80*(5), 34–52.

27. Hübner, A. H. & Kuhn, H. (2010, January 11). Retail Shelf Space Management Model with Space-Elastic Demand and Consumer-Driven Substitution Effects. *SSRN Electronic Journal, 20*(3), 1–19.

28. Jarc, U. (2017, December 19). Dutch client design document. Unpublished internal document. Ljubljana: Symphony Retail AI.

29. Karolefski, J. & Heller, A. (2006). *Consumer-centric category management: How to increase profits by managing categories based on consumer needs.* Hoboken: John Wiley & Sons.

30. Kilcourse, B. (2016). *RSR: Making category management relevant in the age of the informed consumer.* Retrieved July 29, 2019, from https://www.symphonyretailai.com/knowledge-hub/rsr-making-category-management-relevant-age-informed-consumer/

31. Kilcourse, B. (2018). *Why FMCG retailers are on the cusp of big supply chain changes.* Retrieved July 30, 2019, from https://offers.symphonyretailai.com/rsr-research-why-fmcg-retailers-are-on-the-cusp-of-big-supply-chain-changes.

32. Kramar, A. (2008). *Upravljanje z blagovnimi skupinami: primer blagovne skupine vode brez okusov* (master thesis). Ljubljana: Ekonomska fakulteta.

33. Kuijpers, D., Simmons, V. & Wamelen, J. v. (2019). *Reviving grocery retail: six imperatives.* Retrieved August 20, 2019, from https://www.mckinsey.com/industries/retail/our-insights/reviving-grocery-retail-six-imperatives

34. Kurtulus, M. & Toktay, L. B. (2007a, January 11). Category Captainship: Outsourcing Retail Category Management. *SSRN Electronic Journal, 14*(5), 1–47.

35. Kurtulus, M. & Toktay, L. B. (2007b, January 11). Category Captainship: Who wins, who loses? *SSRN Electronic Journal*, *14*(6), 1–8.

36. Kurtulus, M. & Toktay, L. B. (2008, July 1). The Impact of Limited Retail Shelf Space on Category Management. *SSRN Electronic Journal*, *15*(6), 1–38.

37. Layton, S. (2009, April 21). *Red Ocean vs. Blue Ocean*. Retrieved August 14, 2019, from http://www.corporatestrategy.com/red-ocean-vs-blue-ocean/

38. Lindblom, A. & Olkkonen, R. (2006). Category management tactics: an analysis of manufacturers control. *International Journal of Retail & Distribution Management, 34*(6), 482–496.

39. McDonald, P. (2018, August 8). *3 Ways Wholesale Distributors Can Improve Planning.* Retrieved July 25, 2019, from https://www.supplychainbrain.com/blogs/1-think-tank/post/28593-three-ways-wholesale-distributors-can-improve-planning

40. Michaud, T. (2018, September 26). *AI no longer in infancy; set for retail growth spurt*. Retrieved June 16, 2019, from https://www.symphonyretailai.com/knowledge-hub/ai-no-longer-in-infancy-set-for-retail-growth-spurt/

41. Nordic co-operation. (2010). *The Keyhole: Healthy choices made easy*. Retrieved August 2, 2019, from http://norden.diva-portal.org/smash/get/diva2:700822/FULLTEXT01.pdf

42. Oracle Retail. (2009a, August). *Lifecycle Space Planning: Aligning Your Store-Specific Space Execution with Overall Corporate Growth.* Retrieved July 26, 2019, from https://www.semanticscholar.org/paper/Lifecycle-Space-Planning-%3A-Aligning-Your-Space-with/d614a3b780332

43. Oracle Retail. (2009b, August). *Retail Lifecycle Space Planning.* Retrieved July 25, 2019, from https://www.semanticscholar.org/paper/Lifecycle-Space-Planning-%3A-Aligning-Your-Space-with/d614a3b780332c36b27be0dc8cdd5c04bab0d8a1

44. Preuss, U. (2012). Changing the game. Unpublished internal document. Cologne: Symphony Retail AI.

45. Promo Marketing. (2019, January 2). *The changing face of retail: the key trends and challenges facing retailers.* Retrieved August 2, 2019, from https://www.promomarketing.info/changing-face-retail-key-trends-challenges-facing-retailers/

46. Rebernik, B. (2014). Category management introduction. Unpublished internal document. Ljubljana: Symphony Retail AI.

47. Rema 1000. (2016, August 15). *Norwegian client description*. Retrieved June 11, 2019, from https://www.rema.no/om-rema-1000/

48. Rema 1000. (2018). *Corporate Social Responsibility.* Retrieved July 15, 2019, from https://rema1000.dk/wp-content/uploads/2019/05/REMA-1000-2018-CSR-report-english-komprimeret.pdf

49. Rigby, D. K. (2012, May 11). *The Future of Shopping.* Retrieved August 3, 2019, from https://hbr.org/2011/12/the-future-of-shopping

50. Robinson, M. (2018a, January). BattleCard SR Assortment Optimization. Unpublished internal document. London: Symphony Retail AI.

51. Robinson, M. (2018b, November 2). *Get ahead of the competition: Transform retail category management with AI.* Retrieved July 30, 2019, from

https://www.symphonyretailai.com/knowledge-hub/3-ways-artificial-intelligence-can-transform-retail-category-management-strateg

52. Robinson, M. (2018c, April 3). *Optimizing Category Management Through a Customer-Centric Approach*. Retrieved July 30, 2019, from https://www.mytotalretail.com/article/optimizing-category-management-through-a-customer-centric-approach/

53. Robinson, M. (2018d, June 20). *Supercharging Your Customer-Centric Category Planning with AI*. Retrieved July 30, 2019, from https://risnews.com/supercharge-your-customer-centric-category-planning-artificial-intelligence

54. Robinson, M. (2019, May 20). *16 critical characteristics of successful assortment optimization.* Retrieved July 30, 2019, from https://www.symphonyretailai.com/knowledge-hub/16-critical-characteristics-of-successful-assortment-optimization/

55. Rompaey, S. V. (2019, August 6). *Analysis: Is Blokker enough for Blokker?* Retrieved August 22, 2019, from https://www.retaildetail.eu/en/news/algemeen/analysis-blokker-enough-blokker

56. Rosenblum, P. & Kilcourse, B. (2018). *How high volume retailers are responding to the innovation imperative*. Retrieved July 29, 2019, from https://www.symphonyretailai.com/knowledge-hub/viewpoint-how-fmcg-retailers-are-responding-to-the-innovation-imperative/

57. Rosenblum, P. & Rowen, S. (2011, August). *Twenty-first Century Merchandising Takes Hold: Benchmark 2011.* Retrieved July 29, 2019, from https://www.rsrresearch.com/research/twenty-first-century-merchandising-takes-hold-benchmark-2011

58. Sadar, T. (2010). *Upravljanje z blagovnimi skupinami v podjetju Mercator: primer blagovne skupine trajno mleko* (master thesis). Ljubljana: Ekonomska fakulteta.

59. Scheibenreif, D. (2012, April 24). *Assortment and Space Optimization Capabilities for Consumer Goods Manufacturing.* Stamford: Gartner.

60. Smolej, P., Jončevski, I. & Wynn, M. (2016, November 1). Norwegian client design document. Unpublished internal document. Ljubljana: Symphony Retail AI.

61. Spector, R. (2005). *Category Killers: The Retail Revolution and Its Impact on Consumer Culture.* Boston: Harvard Business School Press. Retrieved from https://www.thefreelibrary.com/Category+Killers%3a+The+Retail+Revolution+and+Its+Impact+on+Consumer...-a0135655183

62. Starec, N. (2013). *Prenova poslovnega procesa managementa planogramov v trgovskem podjetju* (master thesis). Ljubljana: Ekonomska fakulteta.

63. Symphony Retail AI. (2018a, March). Category Planning Buyers Guide. Unpublished internal document. London: Symphony Retail AI.

64. Symphony Retail AI. (2018b, April). Category Planning General Grocery. Unpublished internal document. London: Symphony Retail AI.

65. Symphony Retail AI. (2018c, May). Competing in the Age of Continuous Retail Disruption. Unpublished internal document. London: Symphony Retail AI.

66. Symphony Retail AI. (2018d, May). *Competing With Amazon in Grocery Just Got a »Whole« Lot Tougher*. Retrieved July 6, 2019, from https://www.symphonyretailai.com/knowledge-hub/competing-with-amazon-in-grocery-just-got-a-whole-lot-tougher/

67. Symphony Retail AI. (2018e, March). Customer-Centric Category Management. Unpublished internal document. Ljubljana: Symphony Retail AI.

68. Symphony Retail AI. (2018f, March). Embracing Customer Centricity. Unpublished internal document. Atlanta: Symphony Retail AI.

69. Symphony Retail AI. (2018g, May). *How AI will Transform Promotion Management.* Retrieved August 10, 2019, from https://www.symphonyretailai.com/how-ai-will-transform-promotion-management/

70. Symphony Retail AI. (2018h, March). Internal Symphony RetailAI documentation. Unpublished internal document. Boston: Symphony Retail AI.

71. Symphony Retail AI. (2018i, April). Key business challenges for growth-focused retail. Unpublished internal document. London: Symphony Retail AI.

72. Symphony Retail AI. (2018j, May). Opportunities in Retail. Unpublished internal document. Atlanta: Symphony Retail AI.

73. Symphony Retail AI. (2018k, March). Profitable Category Diversification & Expansion Leveraging Customer Insight. Unpublished internal document. Paris: Symphony Retail AI.

74. Symphony Retail AI. (2018l, March). Retail Merchandiser – AI-Enabled Retail. Unpublished internal document. Paris: Symphony Retail AI.

75. Symphony Retail AI. (2018m, March). Retail Technology Innovation Index Derivative Report. Unpublished internal document. Atlanta: Symphony Retail AI.

76. Symphony Retail AI. (2018n, March). SR Allocation - Sales Kit. Unpublished internal document. Paris: Symphony Retail AI.

77. Symphony Retail AI. (2018o, May). SR Assortment and Space. Unpublished internal document. Bangalore: Symphony Retail AI.

78. Symphony Retail AI. (2018p, May). Top 5 Retail Business Disruptors. Unpublished internal document. Atlanta: Symphony Retail AI.

79. Symphony Retail AI. (2019a). 5 Retail Grocery Trends Shaping Today's Marketplace. Unpublished internal document. Atlanta: Symphony Retail AI.

80. Symphony Retail AI. (2019b, June 24). *Blokker Holding improves Customer-Relevant Assortments and Store Layouts*. Retrieved August 12, 2019, from https://www.symphonyretailai.com/blokker-holding-selects-symphony-gold-to-support-customer-relevant-assortments-and-store-layouts/

81. Symphony Retail AI. (2019c). Intro into Category Management. Unpublished internal document. Ljubljana: Symphony Retail AI.

82. Symphony Retail AI. (2019d, June). Solution & Product Naming Guide. Unpublished internal document. Bangalore: Symphony Retail AI.

83. Symphony Retail AI, EIQ Research Solutions. (2018, November 14). *AI brings precision to grocery assortment optimization*. Retrieved July 26, 2019, from https://progressivegrocer.com/ai-brings-precision-grocery-assortment-optimization

84. Tradesolution EPD. (2018). *A quick guide to EPD API*. Retrieved July 20, 2019, from https://tradesolution.no/wp-content/uploads/Quick-Guide-to-EPD-API-2018.pdf