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A Review of Artificial Intelligence used in Assortment Planning

A Suggested Approach Applied in the Fast Fashion Industry

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En Litteraturöversikt av Artificiell Intelligens i Sortimentplanering

Ett Föreslaget Tillvägagångsätt i Snabbmodebranschen

av

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EXAMENSARBETE TRITA-ITM-EX 2021:211
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KTH Industrial Engineering and Management

Master of Science Thesis TRITA-ITM-EX 2021:211

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Approved	Examiner	Supervisor
2021-06-04	Jannis Angelis	Luca Urciuoli
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Abstract

The short life cycles and highly variable demand in the fast fashion market causes various challenges in a retailer's supply chain management processes. The essential task at hand is to provide the right product, at the right time, and at the right place. Due to this inherent difficulty, the bullwhip effect is a major issue in the fashion supply chain. To enhance customer satisfaction and increase the alignment between the supply and marketplace demand, companies have been pushed towards exploiting big data, supply chain analytics and AI techniques for better business decision making. One such critical but intrinsically complex decision is the development of a future apparel assortment; in particular defining its optimal breadth and depth. This thesis investigates how such AI techniques can be applied to develop a new assortment aligned with the future customer demands- and choice behavior.

The research was conducted through firstly performing a qualitative case study at a fast fashion retailer. This explored the critical business decisions in the supply chain lacking AI support. The findings, revealing the assortment planning process as one such critical area, guided the second part of the thesis: a systematic literature review exploring the AI techniques used in this process in the retail - and fashion industry. An appropriate framework of planning a static apparel assortment in the fast fashion industry was developed and used as a guide throughout the study.

The thesis discovered that there exists significant research in the field of applying AI techniques to generate and integrate knowledge about consumer demand- and choice behavior in the planning process of a future assortment. The main components to consider in this procedure is a) fashion forecasting, b) forecasting midterm demand, and c) forecasting product selection, incorporating the effects of substitution and complementarity at all times. This is believed to increase the alignment between supply and the marketplace demand, consequently reducing the bullwhip effect. The critical area for future research is how the discovered models are to be integrated in one single model. Namely, simultaneously utilizing consumer choice behavior models and fashion forecasting to predict future demand of new items. Thus, the risk of suboptimization may be mitigated.

Key words: Fast fashion, supply chain management, category sales planning, assortment planning, artificial intelligence, supply chain analytics

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Godkänt	Examinator	Handledare
2021-06-04	Jannis Angelis	Luca Urciuoli
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Sammanfattning

Modeindustrins korta produktlivscykler och högt varierande efterfrågan efter rådande trender skapar stora utmaningar i försörjningskedjan hos företag i branschen. Det essentiella målet för företagen är att tillhandahålla rätt produkt, vid rätt tidpunkt och på rätt plats. De komplexa karaktärsdragen i modeindustrin, där bland den fluktuerande efterfrågan, har gjort bullwhip-effekten till en stor utmaning i branschen. För att öka kundnöjdhet och anpassningen mellan marknadens utbud och efterfrågan har företag drivits mot utnyttjandet av big data i avsikt att förbättra kritisk affärsbeslutsfattning genom användandet av analytics och AI. Ett kritiskt och komplext beslut är utvecklingen av ett nytt produktsortiment, där definieringen av sortimentets bredd och djup är särskilt viktigt. Denna uppsats undersöker hur AI-modeller kan tillämpas för att hjälpa företag inom modeindustrin i utvecklingen av nya sortiment anpassade efter kundens beräknade efterfrågan och val.

Detta arbete inleddes med utförandet av en kvalitativ fallstudie hos en stor aktör verksam inom modeindustrin. Detta gjordes för att identifiera kritiska affärsbeslut i företagets försörjningskedja som saknade AI-stöd. Resultatet påvisade att sortimentsplanering var ett sådant kritiskt beslutsområde. Följaktligen utfördes en systematisk litteraturstudie i andra delen av arbetet i syfte att undersöka AI-modeller som appliceras i sortimentsplanerings-processen i såväl detaljhandeln som modebranschen. För att konceptualisera processen av att planera ett statiskt produktsortiment utvecklades ett ramverk som användes som en guide under hela arbetet.

Studien visade att det finns betydande forskning inom tillämpningen av AI-modeller i syfte att planera ett optimalt sortiment efter konsumenternas efterfrågan. De huvudsakliga faktorerna att överväga innefattar prognostiseringen av efterfrågan, trender samt substitution- och komplementeffekter. Ett kritiskt område för framtida forskning är hur de upptäckta modellerna ska integreras i en enda modell som inkluderar dessa faktorer i ett tidigt såväl som sent skede av planeringen. Det som eftersträvas i en integrerad modell är att mildra risken av suboptimering som identifierats i nuvarande litteraturs angreppssätt.

Nyckelord: Snabbt mode, försörjningskedja, kategoristyrning, sortimentsplanering, artificiell intelligens, supply chain analytics

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1. Introduction

This chapter introduces the background to this thesis followed by the thesis' problematization, purpose and research questions. Additionally, delimitations in regards to the two research questions are presented. Lastely, this chapter present this thesis expected contributions to the case company and to the literature.

1.1 Background

The fashion and apparel industry is one of the oldest industries in the world and the textile and clothing industry is stated to be the world's second-biggest economic sector by The European Commission (Niu et al., 2017; European Commission, 2013). In recent years, the industry has developed rapidly with increasing competition and production volumes while experiencing a drastic shift towards online sales (Niu et al., 2017). This has also been spurred by the pandemic COVID-19 (BCG, 2020). Due to this dynamic, and complex, nature the fashion industry has continuously intrigued researchers in the area of operations and supply chain management (SCM) (Christopher et al., 2004). Part of the complexity stems from ever-changing fashion trends and a volatile market situation that obstructs supply chain coordination, making it especially prone to the bullwhip effect (Wang et al., 2012). In contrast to other industries, fashion trends affect the customer product preferences frequently and therefore cause big demand variation (Wang et al., 2012). Moreover products in fast fashion, the mass-producing business model replicating high-fashion designs, generate an increased complexity as numerous assortments go through the supply chain simultaneously to meet the even more rapid change of demand (Zhu et al., 2018). Fernie and Sparks (2018) have defined the fashion markets by defining following describing characteristics:

1. **Short life cycles** - This characteristic refers to the ephemerality of the fashion products; they are designed after current momentary trends. As a consequence, the sales period is as short as months or weeks depending on the season.
2. **High volatility** - Generated by the fluctuations in demand caused by various influences such as weather and social media
3. **Low predictability** - The difficulty in demand forecasting due to the volatility of demand.
4. **High impulse purchase** - Customer purchase decisions in the fashion markets are often made on the spot and not planned in advance. The product must thus encourage buying and therefore the authors state the crucial role of ”availability”, in particular to the products colors, sizes etc.

As the fashion markets are associated with rapid change it is crucial for organizations to be flexible and responsive in order to succeed (Christopher et al., 2004). A strategy that has been adopted in order to reduce lead time and enable fast delivery is Quick Response (QR) (Choi, 2013). Although there is interest in the area of SCM in fashion, Zhu et al. (2018) state that there is a lack of research done on the textile supply chain management due to its complexity. This has further resulted in ineffective implementation of the QR-strategy (Lee, 2003).

The fashion supply chain processes simultaneously aims to provide the right fashion design at the right time, at the fastest speed with the lowest possible cost and maximise profit (Hui and Choi, 2016). Thus, its success partly depends on the Fashion Supply Chain Management (FSCM) and the supply chain members' decision-making to be accurate, efficient and quick while being flexible and aligned with the remaining members. The FSCM decisions are however becoming global in nature due to the massive up-scaling of the retailers and the advancement of the brand's retail networks, thus increasing complexity (Brun and Castelli, 2008). Decisions range from design and pricing to inventory and delivery. The challenge of decision making in the fashion supply chain is a consequence of its complexity (Zhao et al., 2020). There is therefore an interest in looking at which decisions are causing fashion retailers to fail in meeting customer demands, as well as being agile and flexible, and how this decision making can be improved in order to increase the efficiency of the FSC and increase the alignment between the supply and marketplace demand.

Today's business environment has seen exponential growth and availability of data. Companies have consequently increased their efforts to exploit such data for improved competitive advantage via big data and advanced analytics (Chen et al., 2012). Big data involves the capability to process data characterized by velocity, variety, and volume. Advanced analytics refers to the process of transforming such data into the required basis to make the best decisions (Rose et al., 2017). Moreover, it transcends the traditional business intelligence of performance indicators and dashboards by incorporating, inter alia, algorithmic techniques from Artificial Intelligence (AI) (Rose et al., 2017). Big data in combination with advanced analytics enables improved decision-making and lowered costs, especially within supply chain management. This is referred to as Supply Chain Analytics (SCA) (Wang et al., 2016). Due to the demanding FSCM processes of, amongst others, forecasting, predicting and optimizing, the fashion industry has received increased attention from the SCA literature, and AI in particular, as problems on all analytical levels may be approached and improved with the utilization of AI (Wong et al., 2013).

Choosing what assortment to carry is a fundamental decision that has to be made by all retailers. The decision must be made early on in the supply chain as it affects production. However, understanding what to include in the assortment and how much without knowing what the customers want makes the choice reliant on data such as previous sales and trends. Historically, retailers have managed to base the assortment planning on previous years, feeling and observation from global fashion shows, but with today's rapid trend shifts this is not enough to remain competitive. The use of AI supported SCA to enhance the assortment planning process is today of high interest to retailers, as the included products in the assortment have a significant impact on sales and also gross margins. Consequently, this area has also been given high priority by consultants and software providers (Kök et al., 2014). Deciding what products to offer is not a new problem, and even though the academic field on assortment planning is not huge, it does provide suggestions on how to approach the problem. Kök et al. (2014) however, writes that there is no one ”best” solution that has emerged, and thus there is more to discover. Offering the customers what they want at the right timing is complex in the dynamic environment present in the fashion industry. However, if a retailer manages to improve its assortment planning there are several benefits including higher profit, decreased overproduction and higher customer satisfaction.

1.2 Problematization

The fast fashion industry is characterized by short life cycles, highly volatile and unpredictable customer demands (Wong et al., 2013). The supply chain processes are further long as there are many stakeholders and dependencies involved. These distinct features increase the complexity of decision making in the FSC. To cope with such disputes and increase supply chain efficiency, light has been shed on the value of SCA and the use of AI techniques that may generate valuable analytical insights and guidance in all levels of decisions (Wang et al., 2016). Moreover, several research contributions demonstrate the effectiveness of AI techniques for decision making in the fashion industry, as well as their superiority over classical approaches (Guo et al., 2011). Since the supply chain is one of the major factors affecting the companies' competitive advantage (Alicke and Iyer, 2013), it is undisputed that actors cannot afford to fall behind in such emerging technological areas. Hence, the adoption rate of AI supported SCA has lately increased significantly amongst actors.

Despite the fact that SCA and AI research in the fashion industry is gaining increased attention (Wong et al., 2013), it is reported that the fashion industry lacks such integration in its supply chain processes (Giri et al., 2019). To improve business profitability and remain competitive, fashion retailers must increase the alignment between the supply and marketplace demand. This may be achieved by using AI supported SCA in critical decision making, aiming to increasingly understand and satisfy future customer demands. However, the prevalent issue of industry practitioners lacking ability to 1) identify relevant AI models and gather suitable and high-quality data, and 2) a low acceptance, routinization and assimilation of BDA by organizations and supply chain partners remains an issue (Schoenherr and Speier-Pero, 2015; Fawcett and Waller, 2014; Dubey et al., 2016). Thus, there is a need to 1) identify the crucial decision making processes in the FSCM that are lacking, but would benefit, from AI supported SCA, 2) contribute to the industry practitioners by reporting the state-of-the art of proposed AI techniques targeting such supply chain processes, and 3) contribute to the academia by reporting the findings of the level of AI maturity in the industry, bridging the gap between the two practitioner groups.

Planning a future apparel assortment is one of the most complex decision making processes in the FSCM due to the 1) uncertain customer demand- and behaviour and fluctuating trends, and 2) the long supply processes requiring the planning to be initiated one year in advance of market release. Hence, the fashion retailer is in need of intelligent methods to understand and predict future customer demand- and behaviour to increase the alignment between the supply and the marketplace demand.

Utterly, the essential problem under investigation is two-fold, 1) identify to what extent AI supported SCA have been adopted to improve different levels of decision making in the FSCM processes, and 2) synthesize the body of knowledge within the literature of applied AI techniques and models in the planning process of a future assortment.

1.3 Purpose

The purpose of the thesis is 1) to improve the knowledge of the industrial level of implementation of AI supported SCA in the decision making in the FSCM processes prior to production, and 2) increase the understanding of how AI techniques may be applied in defining a future apparel assortment, particularly identifying the optimal breadth and depth of items that are aligned with future customer- demand and choice behavior.

The aim is to conduct a case study on a fast fashion retailer, using the Supply Chain Operations Reference (SCOR)-model to map the decision making, on all levels, in the FSCM processes. This allows for a structural identification and consequent identification of decisions lacking AI supported SCA. This consequently leads to the second aim of the thesis of conducting a systematic literature review to synthesize the body of knowledge within the discovered decision making of defining a future apparel assortment long in advance to its launch in the marketplace. This may bridge the gap between industry practitioners and academia by transferring knowledge to both groups, steering future choices of AI supported models in the industry as well as guiding future research targeting desired fields by all practitioners.

1.4 Research questions

RQ1: What supply chain management processes of a fast fashion retailer are lacking AI supported supply chain analytics in their decision making?

Based on the findings from RQ1 where assortment planning revealed to be an area lacking use of AI supported supply chain analytics:

RQ2: What AI techniques- and models are used to support the assortment planning process in the retail and fashion industry according to the literature?

1.5 Delimitations

Research question 1 - Case study

This study used one case company to empirically investigate the use of AI supported SCA solutions in its FSCM decision making. To further reinforce the findings, or to make them more general, it would be of interest to include several companies in the study. Moreover, the information gathered from the company was shared under a Non-Disclosure Agreement (NDA) between the case company and the authors of this study. Thus, the findings considered confidential to the company were excluded from the findings or made general in order to not disclose any sensitive information. Avoiding this when doing research from the inside of an organization is difficult and therefore the principle of maintaining confidentiality was considered a natural delimitation of this work.

Finally, the study's scope and consequently its length was formed after the time constraints set by the author's master thesis course. This further limited how much of the supply chain was covered in the investigation. Together with the case company, it was decided to focus on the first part of the supply chain: initiated at the stage of planning the production until the stage of the actual production, as the FSCM prior to production was believed to lack most AI support in its SCA. The narrowing of the scope allowed the authors to gain deeper insights into specific areas that were of interest to the case company; investigated in research question 2. All levels of decisions, operational, tactical and strategic were included in the scope as the pre-study showed that many techniques were applicable on all of these levels.

Research question 2 - Systematic Literature Review

Upon completing the assortment planning framework (figure 5), it was decided to exclude a) fashion forecasting, and b) forecasting short-term sales from the SLR. The case company had already initiated development of AI models targeting these areas, hence they were of less relevance in the literature investigation.

In order to get a deeper understanding of the concept of assortment planning, the search strings used in this study's literature review were broadened to include papers focused both on a general retail- and fashion supply chain. This was done in accordance with the case company as most solutions in general retailing are transferable and applicable in fashion retailing. However, if articles were too nished on specific goods or physical assortment planning issues, such as planning shelf-space for fresh produce like groceries, they were excluded. As an addition to the systematic literature review, the study used forward snowballing to allow for interesting findings outside of the papers resulting from the database searches. This allowed for more fashion specific papers to be included in the review. However, all cited articles in the papers yielded from the search were not investigated as this study was conducted under a given time constraint.

With respect to the suggested framework of the assortment planning process (figure 5), the review delimits its focus on forecasting mid term category demand- and product selection. Trend forecasting and forecasting short term sales of individual items were excluded. This was done in accordance with the case company since initial initiatives of developing AI solutions targeting those areas existed in-house. Moreover, the assortment planning delimits the focus on AI techniques facilitating the decisions surrounding the breadth and depth of the assortment, and not the development of specific design characteristics.

1.6 Expected contribution

The supply chain challenges that follow from the characteristics of the fashion industry are rather distinctive. This makes the fast fashion industry especially prone to benefit from AI supported SCA in critical business decision making in the FSCM. The literature is however stating that the usage of this within the industry is mostly confined to academic research, causing the AI penetration to be low at the industrial level (Giri et al., 2019). For the body of literature to be in line with how industry practice relates to or differs from academic research, there is a need for empirical investigations. Moreover, given the potential increase in business profitability and enhanced efficiency that can be realized by integrating AI supported SCA

Given the abductive nature of the study, the contribution will be formed from the continuous iteration between empirics and theory; i.e. investigating how the existing literature relates to the empirics and identify gaps in which the academia so far only consists of conceptual models and theory rather than industrial implementation. This process results in a proposed framework for targeting the assortment planning process in the fast fashion industry (see figure 5). By conducting a case study, the thesis intends to disentangle the FSCM processes that are lacking, but could benefit from, AI supported SCA. By exhausting the literature within the identified process of assortment planning, the study contributes by defining state-of-the-art knowledge and proposing how existing research may be implemented at the industrial level. The findings are believed to help fashion companies realize the role of AI supported SCA in the decision making processes of the FSCM, as well as guiding academia into future research areas

2. Method

This chapter presents the method used to successfully conduct this thesis by first introducing the research process, research design and the data collection. Following that, the quality of the studys' research design is discussed in regards to validity and reliability. The chapter ends with a reflection on the research ethics connected to the work.

2.1 Research process

The focus and research area of the thesis was established in accordance with the researchers' academic- and company supervisors. Consequently, the research was initiated by conducting a pre-study of the company, in which the problem formulation, purpose and research questions were formed. The pre-study furthermore facilitated the understanding of the business, mainly concerning the adoption, current state of knowledge and vision of further implementation of AI supported SCA. In parallel, an initial literature review was conducted to better understand the applicable areas for, and AI techniques used in, SCA in the decision-making processes in FSCM. Combining the insights from the pre-study and the initial literature review, our understanding of the company's needs became clear. This allowed the authors to comprehensively evaluate both the decision making processes within the company's FSCM and the different conceptual models, theories and previous studies in the literature that potentially could be applied to the company case. Upon completing the mapping of the decision making process, the scoping, limitations and search words of the systematic literature could be established. This initiated the second part of the study of performing the systematic literature review and compiling the findings. A holistic illustration of the research process is illustrated in figure 1.

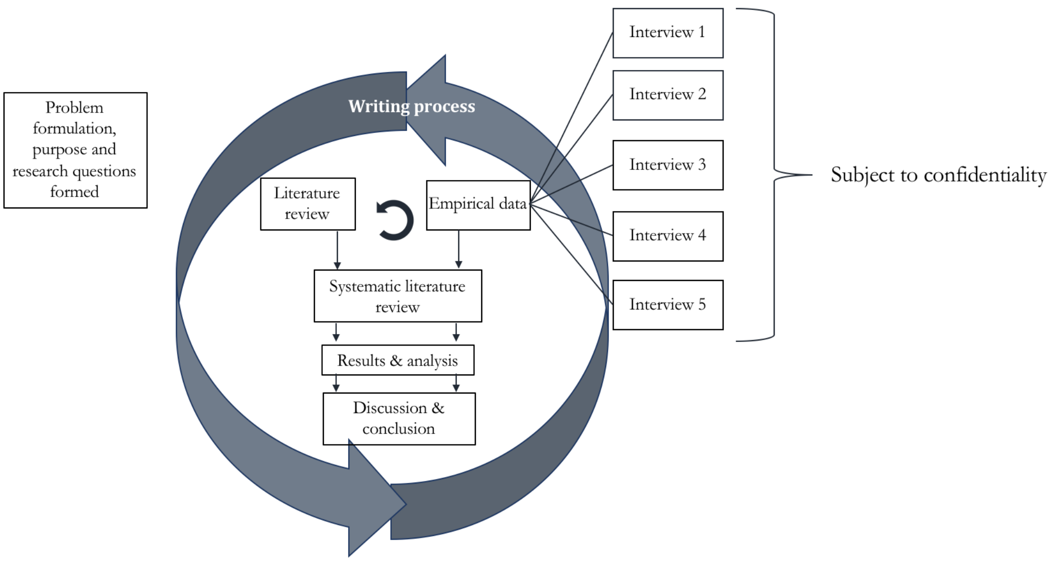

Figure 1. Research process

2.2 Research design

2.2.1 Case study

The purpose of this thesis was to investigate and map decision-making within FSCM and how AI supported SCA could be increasingly adopted to improve the alignment between the marketplace and the supply chain management in the fast fashion industry. To efficiently address the problem formulation and fulfill the purpose, an abductive research approach in the form of an exploratory case-study on an actor in the targeted industry was chosen. The case company is a global fast-fashion company that has experienced strong growth historically. During recent years, it has been challenging to adapt to the industry transformation with increased digital competition and adoption of more agile and flexible supply chains. To keep up with peers and tackle the industry transformation, the case company has lately heavily invested resources to enhance efficiency in the supply chain operations through, inter alia, increased implementation of AI supported SCA. Henceforth, the department working with AI in the supply chain has been selected as the unit of analysis for the case study.

The case study is an appropriate approach when one wants to study complex phenomena within its naturally occurring context, with the belief that the context will create a difference (Kaarbo and Beasley, 1999). The single case study design was thus chosen since the aim of unraveling the decision-making process within, and AI techniques conditioned on, the fast-fashion industry had an apparent influence from its context. The exploratory design is furthermore a relevant approach to use when there are no clear, or single sets, of outcomes (Yin, 2009). Issues related to "what is happening; to seek new insights" is hence efficiently approached adopting such a design (Robson, 2011). Oftentimes, the case study is found in a research context that lacks specific hypotheses and research questions (Streb, 2010). This setting further argued for the use of an abductive approach. At its core, this approach develops new concepts and theory rather than confirming existing ones, i.e. theory development rather than theory generation (Dubois and Gadde, 2002). Case studies in general involve difficulties associated with the interrelatedness of the various elements and their cause and effect. To overcome such oppositions, a flexible structure integrating an iterative approach is beneficial. In this study, such an approach was implemented by iterating from one type of research activity to another and moving between empirical observations and theory. This technique expanded the understanding of both empirical phenomena and theory and was considered necessary given the complexity of theory related to the research aim.

As a consequence of the choice of the abductive approach, the research is of a qualitative nature (Awuzie and McDermott, 2017). A combination of primary data , i.e. empirical data gathered through semi-structured interviews and an extensive systematic literature review including secondary data, i.e. peer-reviewed journals, articles and scientific reports was used. Thus, this study predominantly relies on the authors' qualitative interpretation in accordance with theory.

2.2.2 Systematic literature review

The second research question was examined with a qualitative research design through the method of a systematic literature review (SLR). The literature review process is a cornerstone of management research as it helps oversee the diverse knowledge for an academic field of interest (Tranfield et al., 2003). As the objective of this study was to conclude the existing knowledge in specifically chosen areas of the FSCM and with this add insight to the field, the SLR-method was considered a suitable method since it aims at reviewing and adding knowledge to an existing collection of literature (Tranfield et al., 2003). Management research has often been conducted with the use of traditional or ”narrative” literature reviews. However, these often lack the thoroughness required for a review to give a general unbiased understanding of the chosen field of study. Tranfield et al. (2003) evaluates the application of the systematic review methodology used in the medical sciences in management research with the aim to find an enhanced methodology that enables management knowledge to be evidence-informed. This was further concretized in a framework that this study used as guidance during the literature review. The case previously conducted case study helped give insights into the areas and decisions in the FSCM that were lacking but could benefit from the use of AI-supported SCA. If researchers in management can overcome the previous recurring problems of bias and use a thorough evidence-based approach as the one used in medical science, the legitimacy of the management research could be drastically improved. Furthermore, (Tranfield et al., 2003) states that if this is done, the SLR can provide practitioners, in this case companies in the fashion industry, “with a reliable basis to formulate decisions and take action”.

This study can further be categorized as a meta-synthesis following an inductive research approach. According to Dudovskiy (2018) a systematic literature review can be either categorized as meta-analysis or meta-synthesis where the latter is based on non-statistical techniques. The SLR in this study was conducted by evaluating and interpreting findings of different qualitative studies in contrast to a meta-analysis which is conducted by analyzing research on the same subject by the use of statistical procedures. Inductive reasoning is a general research approach built on theory. The goal is to observe certain occurrences to then find patterns and establish generalizations about the studied topic (Hyde, 2000). This approach is often used in qualitative research, and further when the phenomenon investigated is not yet clear to the researchers.

2.3 Data collection

2.3.1 Case study - interviews

The empirical data collection of this study was done by using semi-structured interviews. In qualitative data collection, the semi-structured methodology is the most frequently used interview technique (Dicicco-Bloom and Crabtree, 2006). To avoid adding to the lack of uniformity amongst the many semi-structured interviews in the literature, this study was inspired and guided by the framework for a qualitative semi-structured interview guide presented by Kallio et al. (2016). The author's research article aims at providing a framework and international advice for the creation of semi-structured interview guides. An interview guide lists the high-level topics and related questions to each topic that are planned to be covered during the interview (Bird, 2016). Semi-structured interview questions are based on previous knowledge and thus part of preparing the guide is gathering information about the research topic (Kallio et al., 2016). For the advantage of creating reciprocity between the person being interviewed and the person asking questions, semi-structured interviews were chosen for this study (Galletta, 2013). Further, the format allows for a setting where the participants' individual reasoning is expressed and the interviewer can ask new follow-up questions derived from the participant's response (Kallio et al., 2016). The interview guide contains the planned questions and is to be used during the data collection, but it is not meant to be followed strictly. Instead, by acting like a guide (Gill et al., 2008), it provides a structure for the interviewers to explore the research area by gathering similar types of data from each participant (Kallio et al., 2016).

The aim of the data collection was to gain a rich understanding of the important decisions in the fashion supply chain. Following steps in accordance with the framework presented by (Kallio et al., 2016) describes the method of this study's interview process.

1. Data collection through the use of semi-structured interviews in relation to the research questions was evaluated in order to identify prerequisites for its use. Turner (2010) states that there is a need for the researchers to have some prior knowledge of the topic when using semi-structured interviews, a criterion evaluated as fulfilled. It was further of interest to address issues that were meaningful to the specific participant. Allowing diverse perceptions and the focus to be on participant's specific thoughts is allowed in semi-structured interviews (Cridland et al., 2015), adding yet another prerequisite for its use.
2. The second phase consisted of retrieving and using previous knowledge. In order to later formulate insightful questions, information on the area was retrieved and mapped using the literature. This layed out a conceptual basis for the interviews and helped in understanding concepts and wording in the fashion supply chain and AI-area. Additionally, empirical knowledge can be used in this phase to give a deeper theoretical background (Krauss et al., 2009; Rabionet, 2014). In this case, people from the company helped at an early stage in giving background information to the areas that were to be investigated.
3. During the third phase, the preliminary interview guide was crafted by structuring previously gathered knowledge to a logical coherent form to act as a tool during the interviews. The guide is constituted by a list of questions (Whiting, 2008; Krauss et al., 2009). These questions then help in directing the conversation towards the right topic areas (Astedt-Kurki and Heikkinen, 1994; Krauss et al., 2009; Cridland et al., 2015). All questions aimed at being open-ended, well-formulated, not leading and single-faceted in order to generate vivid, spontaneous and in-depth responses. To encourage descriptive answers, questions were formulated using starting-words like *what*, *who*, *where*, *when* and *how* (Chenail 2014). As part of the aim with the interviews was to understand certain areas in the supply chain, some questions were formulated broadly (the main questions) to then be supported by several related questions (the follow-up questions) in order to use a "funneling"-technique towards certain related areas or to clarify the topic for the participant (Smith, 2008)

4. Through discussion and revising, the interview guide was assessed and altered. The interview phase itself later acted as a refinement of the questions as already answered questions could be eliminated or modified based on gained insights.

These steps finally resulted in a guide with a list of 15 questions that were used as support during the interviews. However, the discussion during the interviews evolved freely and was mostly driven by the use of a data table consisting of the supply chain and its different decisions. The table acted as a guide as the different parts of it were discussed together. With the help of the company supervisor, each part of the supply chain was mapped to a person considered a company expert in the area. This person was then booked for an interview that would be centered around this specific area, for example, Purchase. By jointly going through the different decisions and processes belonging to that area, the data table was altered both during and after the interview. Hence the participant could during the interview access the data table and be an active part of creating the content and alterations. The interview guide was still necessary as a way to gain a deeper understanding of questions that were not answered by going through the data table. Since certain questions are specific to the case company, the interview guide will not be shared in this study.

2.3.2 Systematic literature review

This section explains in detail how the systematic literature was performed. By a transparent and scientific process, i.e. a detailed approach that is replicable, the SLR differs from a traditional narrative review (Cook et al., 1997). The thoroughly described process, including used search words and databases as well as article selection criterias, aims at providing transparency and replicability to the study. The exhaustive literature searches that are a part of the SLR, further aims at minimizing bias. The following steps are inspired by the framework for conducting a systematic review by Tranfield et al. (2003) as well as the framework with the same purpose presented by Giri et al. (2019).

<u>Stage I: Planning the review</u>

Stated by Clarke and Oxman (2001) as a common part of the review planning, the initial step of this SLR included iterating definitions, clarifications and refinement. During this iterative process, the scope started out broad and then got re-defined according to relevance and size of the literature. The authors of this thesis aimed at keeping the research question rather open to not compromise the creativity during the literature review process, which can sometimes be the case according to Tranfield et al. (2003). Different search strings were tested to get an understanding of the research field and investigate key words of articles found relevant. A discussion with the thesis supervisor was also of help to finalize the planning and move on to the next step.

<u>Stage II: Performing the review</u>

The initial part of the research framework provided by Giri et al. (2019) is the article retrieval. In this step, the databases Scopus and Web of Science were used as they are well known and popular in academia. Further, the mix of Web of Science and Scopus was also chosen as Web of Science has articles of high quality but a somewhat lower coverage of publications while Scopus have a higher coverage of publications but in some cases questionable quality (Sjögårde, 2014).

The taxonomy and synonyms for the keywords were chosen in accordance with the thesis developed taxonomy of artificial intelligence in the fashion industry (See section "Proposed Artificial Intelligence taxonomy"). The search queries were designed to see how these methods and techniques were used in the fashion industry but also in other retail sectors in order to fully grasp their potential. Therefore the taxonomy for AI is fashion industry specific while the other part of the search query includes all retail sectors. The synonyms of the targeted search words for the assortment planning were chosen through discussion and inspiration of other articles in the field found during stage I. All articles on the subject within retail that applied the identified AI techniques were considered of interest as their approach could also be applicable within fashion retail. However, articles solely focused on the fashion retail industry were considered of highest relevance as they often took into consideration the unique characteristics of the fashion industry.

Artificial Intelligence	**Retail**	**Assortment planning**
Machine Learning	Fast moving consumer goods	Product assortment
Deep learning	Retail	Assortment
Data mining	Fast fashion	Assortment optimization
Artificial Intelligence	Fashion	Assortment planning
Neural network	Garment	Apparel planning
Expert System	Apparel	Assortment selection
Knowledge- based system	Cloth	Assortment problem
Intelligent System	Textile	Category sales planning
Evolutionary computation	fcmg	Category management
Fuzzy logic		

Table 1. Taxonomy used in search strings

Search string for Web of Science:

TS = ((artificial intelligence OR machine learning OR deep learning OR data mining OR intelligent system* OR knowledge-based systems* OR *expert system OR evolutionary computation OR *neural network OR fuzzy logic) AND (fmcg OR fast moving consumer goods OR retail* OR fast fashion OR fashion OR garment* OR apparel* OR cloth* OR textile*)) AND (AK=(product assortment* OR assortment* OR assortment optimization OR assortment planning OR apparel planning OR assortment selection OR assortment problem OR category management OR category sales planning))

Search string for Scopus:

TITLE-ABS-KEY(("artificial intelligence" OR "deep learning" OR "machine learning" OR "data mining" OR "intelligent system*" OR "knowledge-based systems*" OR "*expert system" OR "evolutionary computation" OR "*neural network" OR "fuzzy logic") AND (fmcg OR "fast moving consumer goods" OR retail* OR "fast fashion"

OR fashion OR garment* OR apparel* OR cloth* OR textile*)) AND KEY("product assortment*" OR assortment* OR "assortment optimization" OR "assortment planning" OR "apparel planning" OR "assortment selection" OR "assortment problem" OR "category management" OR "category sales planning")

TITLE-ABS-KEY/TS are short for Title, Abstract and Keyword and AND/OR are boolean operators that connect the different search words.

The search strings yielded 29 articles in total from both databases, 9 from Web of Science and 20 from Scopus. First, lists of all articles were exported and merged in order to remove duplicates. Then, as an initial screening, the abstract and the title of the articles were investigated in relation to the scope of this study and the inclusion/exclusion criteria. As the final number of articles after going through the screening process was considered a bit low and many articles referenced other interesting findings, it was decided to use *forward snowballing*. Forward snowballing refers to identifying new papers to include in a study by using articles cited in the identified articles from the literature search (Wohlin, 2014). The framework in figure 2 is a condensed version of the one presented by Wohlin (2014) and was used as guidance during the snowballing process.

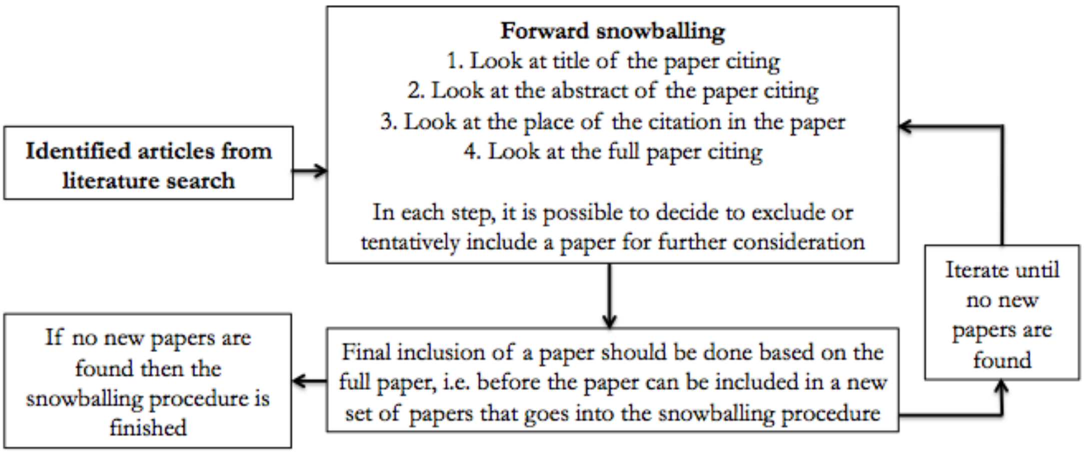

Figure 2. Framework for the process of snowballing

The use of snowballing allowed for deeper understanding of the topic and a better result as part of the aim was to understand the literature field on assortment planning, which was made possible by adding more articles. The second and last round of screening consisted of reading the full text of the articles and applying the inclusion/exclusion criteria again. From this, 29 articles remained and layed the base for the study aimed at answering RQ2.

Number	Criteria	Reason for Inclusion
1	No time constraint	To understand the development of the field
2	All journal articles indexed in Scopus and Web of Science databases	Since these are respected and popular databases in academia
3	All research that applied AI-techniques in retail	To really se examples of the use of AI in retail and not only theory or concepts
4	Focused on all level of decisions	To be in line with the scope

Table 2. Inclusion criteria in SLR

Number	Criteria	Reason for Inclusion
1	Non-English and non-Swedish articles	To avoid language barriers and misunderstandings
2	Articles with to much focus on a non-fashion retail area	As these could be difficult to apply in the complex and unique environment of the fashion industry
3	Articles with to little focus on actual model implementation	As the review aimed at investigating actual models and techniques
4	To advanced to comprehend given the background of this thesis' authors	To avoid any article too technically detailed and not also focused on the business side

Table 3. Exclusion criteria in SLR

<u>Stage III: Reporting and dissemination</u>

The final step of the SLR is the reporting and dissemination (Tranfield et al., 2003). As the objective of the review was to get an understanding of what different AI techniques were used in assortment planning according to the literature, all articles and their respective model of choice were gathered in a table. This provided a good mapping and overview of the different approaches taken in the literature. The table (table 7), and deeper insight are found in this study's Result and Discussion.

2.4 Quality of research design

Validity and reliability are the two most significant and fundamental aspects to assess in order to measure the quality of a study's research design (Mohajan, 2017). Yin (2009) suggests looking at four dimensions to assess a study's rigorousness and quality: internal validity, external validity, construct validity and reliability.

2.4.1 Validity

Validity refers to the accuracy of the study's findings (Altheide and Johnson, 1994). A study can be considered valid if the phenomena intended to be examined have been studied and the result is described truthfully (Collis and Hussey, 2013).

Internal validity

Internal validity refers to the causal connection between the study's research method and the author's conclusion (Yin, 2009). This is often referred to as the *credibility* of the study. By ensuring replicability, meaning that the study can be re-done and result in the same findings, a study can be assessed as having internal validity (Willis et al., 2007). To ensure this, the SLR in this study was done by following a predefined step-by-step framework presented by Tranfield et al. (2003) and Giri et al. (2019) that was thoroughly described in the method chapter. By clearly stating chosen data bases, search queries and criteria for inclusion/exclusion the study aims at increasing replicability. The case study was performed in a similar manner: by following a clearly stated framework by (Kallio et al., 2016). Although the results from the first research question can not be fully disclosed, it is believed that the method and research process allows for replicability.

External validity

The study's external validity, or *transferability*, refers to if the results can be generalized and thereby applicable to other areas or groups of interest (Gibbert et al., 2008). Due to the confidential nature of the case study performed in this research, part of the result can not be shared. However, it is believed that an equivalent study on a different fashion retailer would yield somewhat similar results as found in this study as the investigated case company is one of the biggest fashion retailers in the world. It is further the belief of the authors of this study that the result would mostly differ amongst younger fashion retailers that are "born" online. These are believed to have a higher degree of AI-use since their business model originated in a data-driven space (e-commerce).

Construct validity

Construct validity refers to if a study truly examines what is stated to be researched (Denzin and Lincoln, 2011). Hence, it indicates if the researchers have chosen a suitable method for studying the chosen question and thereby if the findings give an unbiased perception of reality. Mohajan (2017) writes that construct validity is especially important for empirical studies and hypothesis testing as the difficulty of bias often is present. As the first research question targeted a specific company, interviews were considered the optimal method as the people inside the organisation had the best knowledge on the matter. However, to enforce the result and make them more general, an even more suitable method would be to increase the number of studied companies. It is further considered that the methodologically and thoroughly performed SLR has led to the second research question to be constructively valid.

2.4.2 Reliability

The concept of reliability refers to the absence of differences in the study's results in case it was to be repeated by independent researchers. In essence, the same accuracy of the results should, regardless of the researcher, be generated (Collis and Hussey, 2013). It moreover implies that the findings must be derived from the empirics and not the researcher's intention to distort the result to comply with the researcher's own theories (Korstjens and Moser, 2018).

In the methodological approach of using semi-structured interviews, the reliability is decreased due to the lack of standardization. Not only does the unstructured method allow for the follow-up questions to vary distinctively depending on the interviewer; but also for the interviewee's subjective interpretation of the questions to impact the collected data (Collis and Hussey, 2013). To tackle the lack of standardization, an interview guide was used as a support during the interviews to decrease the risk of deviating too much from the main topics and to ensure that the results covered the focal topics of the study. Moreover, to cope with the subjectivity of the interviewees, triangulation of data, i.e. collecting the same information from several roles holding valuable insights, was done to increase the study's reliability. Nevertheless, an additional issue of the semi-structured approach is the difficulties of transcribing the collected data, increasing the complexity of its analysis. However, the interviews mainly consisted of mapping exercises of the decision making processes. Thus, the need for transcription and coding was not evident or crucial for the quality of analysis. To ensure that no information was lost, increasing the quality and reliability of the analysis, all interviews were instead recorded with the consent of the interviewees. This allowed the researchers to systematically guarantee that all valuable information had been captured and integrated.

Moreover, another problematic parameter impacting the reliability of the study was the issue of confidentiality; affecting the interviewee's willingness to engage in the planned topics. To overcome these challenges, the researchers clearly stated the purpose of the study and the adherence to the NDA in the introduction of each interview in order to establish the required trustworthiness among the participants.

In comparison to traditional literature reviews, the systematic approach of the SLR is deemed superior with regards to reliability. The main objectives of the SLR are to reduce researcher's bias, find as many primary studies relating to the research questions as possible as well as to increase repeatability, consistency and transparency (Ali and Usman, 2018). In this thesis, the reliability is ensured by providing a transparent guide of the undertaken procedure, including a disclosure of carefully selected inclusion- and exclusion criteria (see table 2 and 3). These enabled the authors to work in an objective and consistent manner in the screening process of the review. The repeatability aspect of the thesis is however challenged due to the utilization of forward snowballing. This somewhat obstructs other researchers to generate the exact same search result as the inclusion criteria for such papers were based on the knowledge and bias of the authors. However, forward snowballing is a recognized method that aims to improve the result of the SLR by utilizing referenced articles in the resulting papers of the main SLR. Hence, the risk of excessive bias and non-repeatability is limited since all included research is reliably processed using the same criteria.

2.5 Research ethics

The initial part of the study, carried out at the case company, required both authors to sign and respect a NDA throughout its course in the research process. This was demanded in order to have it authorized and validated. No sensitive company-specific data provided to the researchers, nor the name of the company, could be disclosed in the study. Thus, all numbers and specific information relatable to the company were concealed. Moreover, in accordance with Colis and Hussey (2014), all interviewees were informed about the confidentiality aspect to encourage more open responses. The informants involved were furthermore informed about the objective and aim of the research as well as their potential contribution to such in case of participation. It was lastly clarified that the joint contribution and compilation of all interviewees would be disclosed on a high-level in the research's final format to ensure the disclosed data could be related to an arbitrary actor in the industry.

Concerning the systematic literature review, the report holds full objectivity. The authors were impartial in relation to the collected data, derived analysis and results emerging during the study. The collaboration between the researchers was of respectable quality and both participated equally in all parts of the preparation as well as the conduction and compilation of the study.

3. Theoretical Framework

This chapter presents related theory to the thesis' questions and results. First a section on supply chain management and the SCOR model are presented, providing background to the first research question. Following that, a section on big data and supply chain analytics give insights to the use of AI in the supply chain as well as this thesis' proposed taxonomy of AI. The section ends by presenting a framework for the assortment planning process of a fashion retailer. This framework actsas a guide for the thesis' systematic literature review.

3.1 Supply chain management and the SCOR-model

The supply chain is referred to as the physical structure of suppliers, warehouses, customers and transportation where goods flow from the origin of raw material to the end-customer. SCM is furthermore defined to be the processes of controlling the flow of material and information between the supply chain domains. The main processes of FSCM in the initial part of the supply chain are illustrated in figure 3.

Figure 3. Main processes of FSCM

According to Choi (2014), the FSCM is coupled with forward and backward flows of products, information and funds in which the decision-making is driven by the consumer demand in the clothing market. The main goal of FSCM thus consists of the supply chain members working in coordination to deliver the right product at the right place at the right time (Čiarnienė and Vienažindienė, 2014). The aforementioned characteristics of the fast-fashion industry however result in high complexity and numerous challenges in the decision-making in the FSCM (Şen, 2008). The main objective for supply chain executives is thus to acquire meaningful information allowing them to increase the quality of estimation, predictions and uncoverings of unseen patterns to improve SCM decision-making (Lamba and Singh, 2017). SCA is altering the way SCM processes this data; resulting in better decision-making and increased competitiveness (Chavez et al., 2017).

The SCM decisions can further be broken down into three levels: the strategic, the tactical and the operational level (Ivanov, 2010). The strategic level concerns the long-term decisions that tend to be unstructured, having to consider multiple factors, uncertainty and change (Alexander et al., 2014). In contrast to the unstructured strategic decisions, tactical and operational levels are more definable, stable and structured; hence amenable to programming (Alexander et al., 2014). The main objective of such decisions is to perform the detailed work to meet the strategic goals.

3.1.1 SCOR model

In process oriented supply chain models, the SCOR model is considered to be the standard and used in reference in the SCM field by academics (Ntabe et al., 2015). The Supply Chain Council has developed the framework as a reference model for design and improvements of supply chains; determining, unifying and accomplishing supply chain processes (APICS, 2021). The SCOR model is furthermore defined as "a management tool used to address, improve, and communicate Supply Chain Management decisions within a company and with suppliers and customers of a company (Sme, 2004). Using building blocks of the supply chain, the model helps to structurally describe the various decisions involved in SCM. The SCOR model furthermore supports well-planned and accurate decision-making; contributing directly to the bottom line performance by lowering sourcing, transportation, storage, stockout and disposal costs (Souza, 2014).

The SCOR methodology assumes that all processes in the supply chain can be subdivided into one of five general subtypes; plan, source, make, deliver and return, see figure 4. While each interaction of two execution processes (source-make-deliver-return) is a "link" in the supply chain, planning sits on top of these processes and manages them (Huan et al., 2004) Due to the hierarchical position of the planning domain, it is critical for the performance of the whole supply chain. The main FSCM processes of the initial part of the chain, covering the "Source" and "Make" block of the SCOR model, consists of planning the production, planning the assortment, developing the products, quantifying the production volumes, purchasing the material and producing the end products, see figure 4.

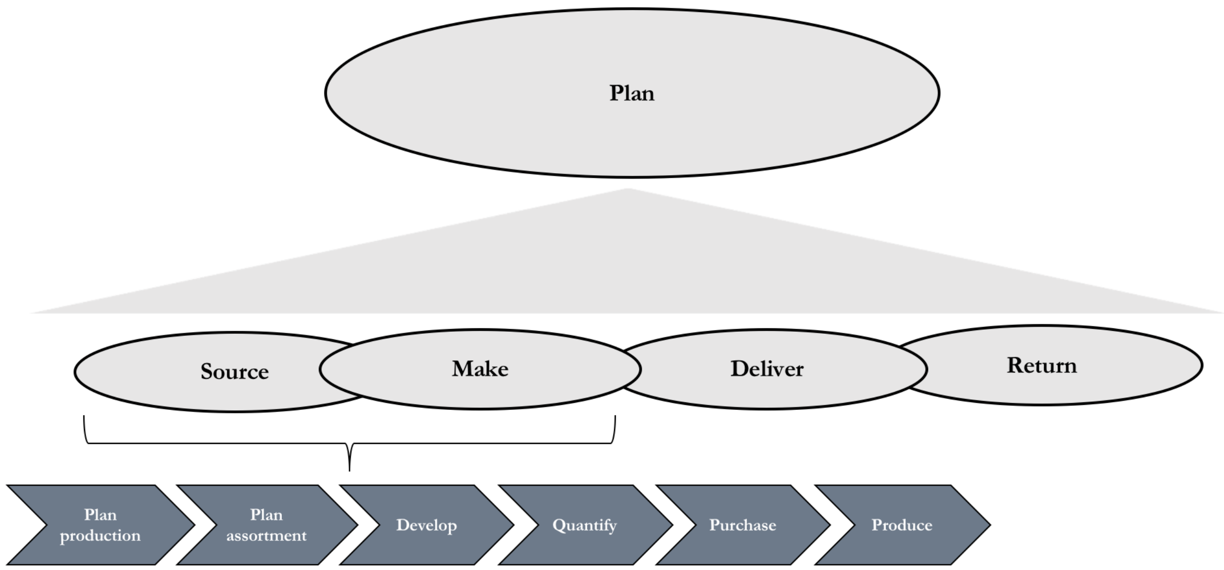

Figure 4. Combined SCOR model and FSCM processes (Sme 2004)

The SCOR model is a suitable framework for classifying the applications of SCA in SCM; setting the focus on the SCM processes and the various decisions at the different levels (Souza, 2014). As proposed by Chehbi-Gamoura et al. (2020), possible examples of uses of analytics in this field are presented in table 4.

SCOR main process	
Plan	Balances the demand and supply to meet the sourcing, manufacturing and supplying requirements. Example: examining the volumes of synchronous input data instantly to adjust and predict the schedules; where this has often been performed monthly and/or annually (Weng and Lin 2014).
Source	Includes the procurement activities to acquire goods/services aligning planned and actual demand. Example: analytics can be used in supplier selection and assessment (C.-H. Wang 2015).
Make	Is related to the transformation of products and services to meet planned and actual orders Example: manufacturing in plants can be improved by using analytics in smart manufacturing. (Davis et al., 2012).

Table 4. The three processes of SCOR (APICS, 2021)with examples of SCA

Moreover, focusing on examples of decisions within the SCOR processes, table 4 presents examples of integral decisions at the three levels in the FSC, applicable to SCA (Choi, 2016; Guo and Wong, 2013; Wong et al., 2013).

SCOR domain	Source	Make
Strategic	- Strategic sourcing - Supply chain mapping - Intelligent supplier selection - Price negotiation - Quality control	- Plant location selection - Product line mix at plants - Fashion design
Tactical	- Tactical sourcing - Supply chain contracts - Intelligent fabric selection	- Product line rationalization - Category management - Assortment planning incl. new product introduction - Sewing assembly line balancing - Sales and operations planning
Operational	- Materials requirement planning and inventory replenishment orders	- Workforce scheduling - Production scheduling - Marker making
Plan	Demand forecasting (long term, mid term and short term)	

Table 5. SCOR domains and examples of decisions atthe three levels in the fashion industry

At the operational level, SCA supports managers in crunching vast amounts of data from short-term demand planning, procurement, production, inventory and logistics (G. Wang et al., 2016). At the tactical level, managers handle decisions including inventory management of raw material and finished products (Lin and Wang, 2011). Moreover, tactical decisions include a new product introduction into an assortment category based on its expected sales and its effect on sales overall (Fildes et al., 2019).

Consequently, operational and tactical decision levels are in essence dependent upon the strategic objectives defined by the organization's top-level management. Such decisions include, inter alia, product design and development as well as strategic sourcing (Wang et al., 2016). Due to the lower accuracy of information details in strategic planning, top-level managers aim to translate complexity and uncertainty of the external environment into more comprehensible concepts for lower management levels (Wang et al., 2016). The traditional decision-making processes are however limited since strategic decisions have been grounded in historical data and in the decision maker's experiences. For a long time, these unstructured decisions have thus relied on more general management models to aid decision-making rather than quantitative and predictive methods (French et al., 2009). Naturally, the risk of inaccurate decisions is increased on such an intuitive basis (Arya et al., 2017). Recent developments however suggest greater degrees of ability in working with unstructured contexts using big data and SCA (Alexander et al., 2014).

In addition, the SCOR "Plan" block includes all levels of decisions as it focuses on computing demand forecasting at all time frames; long, mid and short term. Using predictive analytics, sophisticated demand forecasting has great potential in supporting such decisions to increasingly align the marketplace demand with the supply chain activities.

3.2 Big Data, Supply Chain Analytics and Artificial Intelligence

Big Data Analytics and Supply Chain Analytics

Big data is used to describe the data, which compared to traditional data, consists of large growing sets in various structures with complex properties that require advanced algorithms and robust technology to be analyzed (Oussous, 2018). When defining big data most researchers use the three dimensions of *volume*, *velocity,* and *variety* (the 3Vs) (Laney, 2001, Furht and Villanuster, 2016; Lee, 2017; Oussous, 2018). *Volume* refers to all data generated and/or collected by the person or business handling it. This data is generated and managed at an increased speed, referring to the second dimension of *velocity*. The third dimension of big data, *variety*, refers to the diversity of data types generated such as images, text, clickstreams, etc. (Lee, 2017). Conclusively, big data is a large amount of complex data sets in heterogeneous structures increasing in size by the minute through endless flows such as social media and the internet of things. The massive growth of big data has led to the development of big data analytics (BDA). BDA entails the use of advanced analytical tools to extract information from large data sets and thereby gain valuable insights unattainable by traditional analytical methods (Tsai et al., 2016). This in turn enables decision making to be data-driven. As an addition to the 3Vs (Nguyen et al., 2018) points out several scholars emphasize to include *veracity* and *value* in order to fully comprehend the rigorousness of BDA. These dimensions refer to the actual data analysis which is critical in order for the collection, storage, and management of data to create value. Big Data can fundamentally enhance businesses' performance by enabling improved decision making (McAfee et al., 2012). This is made possible by the fact that big data analytics allows for measuring and analyzing the data which translates into a greater understanding of the supply chain. Consequently, the application of Big Data Analytics (BDA) in SCM is getting increased attention from both academics and practitioners (Nguyen et al., 2018), hence the field supply chain analytics. The adoption of advanced technologies in supply chains, such as RFID, Internet of Things and different types of sensors have equipped businesses with the data and the tools to coordinate different parts of the chain. Adding the use of BDA on top of this has empirically proven to improve supply chain agility, increase customer satisfaction and reduce operational costs (Sheffi and Goentzel, 2015; Subramanian and Ramanathan, 2012). BDA can be used across the entire supply chain, for example, to detect frauds, optimize production or decide cost-reduction by the use of real-time data to sense demand (Nguyen et al., 2018). These advantages have led to the expectancy of high adoption of BDA in SCM, however, in 2016 Wang et al. stated that only 17% of enterprises had put BDA in to practice the supply chain functions. Even if this number is expected to be higher today, there seems to be a lack of understanding on how to effectively implement BDA in SCM (Schoenherr and Speier-Pero, 2015). Other reasons for the low adoption of BDA to improve supply chain performance include the difficulty in recognizing the proper data to use (Schoenherr et al., 2015) and a low acceptance and integration of BDA amongst the organization and its supply chain partners (Gunasekaran et al., 2017).

It has previously been stated that big data often is defined by attributes such as volume, velocity, variety, value and veracity. However when discussing BDA, it is also common to use the taxonomy of data analytics under three main levels: *descriptive*, *predictive* and *prescriptive* (Nguyen et al., 2018). Descriptive analytics is done during a set time period or when desired (Wang et al., 2016) and is the simplest form of BDA (Nguyen et al., 2018). It aims at identifying problems and opportunities by describing what happened in the past (Wang et al., 2016; Nguyen et al., 2018). Predictive analytics instead aims at predicting future events (Nguyen et al., 2018) through the use of programming and advanced algorithms that processes the data in order to find predictive patterns and reasoning for why these patterns might occur in the future (Wang et al., 2016). Prescriptive analytics aims at determining and assessing complex decisions through decision making mechanisms and tools (Rehman et al., 2016). It can be used in for example multi-criteria decision-making and optimization (Wang et al., 2016). These three categories of BDA have all been incorporated in SCM and have come to revolutionize business' supply chains (Nguyen et al., 2018).

Artificial Intelligence in the fashion industry

AI is a technique that has proven to be valuable across many application fields, from general purpose areas such as decision making to specific tasks such as robot control (Guo and Wong, 2013). Problems on all analytical levels, descriptive, predictive and prescriptive, can thus be approached with the use of AI (Giri et al., 2019). Researchers and participants in the fashion industry have paid increased attention to AI techniques over the last decades. Particularly, it has been suggested to improve decision making in the FSC operations, as proposed in table 5. Hence, AI techniques play an integral role within SCA in the fashion industry. Below section aims to define and classify the AI techniques used in the decision making processes in the FSC operations.

Proposed Artificial Intelligence taxonomy

The proposed taxonomy of AI in this paper is based on the research of applied AI techniques in the FSC, as found in the contributing papers of Guo and Wong (2013) and Giri et al. (2019).

It is a daunting task to define AI. No precise definition exists as researchers from different fields use the term differently, incorporating varied interpretations of AI (Guo and Wong, 2013). Hence, AI is an umbrella term that captures many different models, techniques and methods. At its core, AI techniques have the ability to 1) artificially simulate the human brain, 2) act intelligently as a human, 3) actively learn and adapt as a human, 4) process symbols and languages and 5) perform intelligent actions (Guo and Wong, 2013). In this study, AI is referred to as a technique that uses human reasoning as a guide to provide better services. In essence, being any kind of learning system. This learning involves computer programs (systems) that simulate intelligent processes including reasoning, associative memory and understanding symbolic information in a context.

In the context of learning, the term "Machine Learning" becomes relevant. AI experienced a new boom in 2010 due to the explosion of machine learning algorithms. This was a consequence of the increased access to massive volumes of data, i.e. big data, and the discovery of highly efficient computers to calculate learning algorithms (Pereira and Borysov, 2019). Utterly, machine learning learns from old data to predict future outcomes. While the techniques and algorithms of machine learning are considered novel, the basic concepts that such algorithms exploit for learning are based on relatively old theorems, like Bayesian inference (18th century) or formal neurons (1943). The objective of machine learning is in this context not to acquire already formalized knowledge but to understand the data structure and integrate such into models, in particular automating tasks. Despite the machine learning's ability to construct models in a fairly autonomous way, human intervention is still of essence when choosing training data, identifying possible biases or distinguishing the applicability and reliability of the machine's discoveries.

Moreover, according to Guo and Wong (2013), AI techniques may roughly be divided into two categories: symbolic AI and computational intelligence. The former category involves the explicit embedding of human knowledge and behaviour rules into computer programs and focuses on developing knowledge based systems. Both Giri et al. (2019) and Guo and Wong (2013) have found such "Expert Systems", or "Intelligent Systems" (Giri et al., 2019), common in the fashion industry. The fundamental idea behind expert systems is that expertise, that being the vast body of task-specific knowledge, is transferred from a human to a computer (Guo and Wong, 2013). The rule-based expert system employs a set of IF-THEN rules to represent such information to build the system's knowledge base. To sophisticate the accumulation of knowledge, "Data mining" has been another powerful technique to unearth previously unknown information and patterns from large data sets. While data mining and machine learning are considered to be separate concepts, they may at times overlap. Machine learning may for example use data mining to find patterns and make better predictions.

Consequently, with the advent of machine learning, incorporating human knowledge by coding by hand has been replaced by letting computers discover such rules utilizing correlation and classification on the basis of a massive amount of data, i.e. big data. Historically, "hard computing techniques" following binary logic, i.e. learning based on boolean values have dominated. Since knowledge oftentimes is not binary, such learning may be inadequate at times. Hence, computational intelligence has transpired; often referred to as "soft computing techniques". Such representation of knowledge is much closer to the way the human brain works as it aggregates data to partial truths. In the decision-making problems in the fashion industry, those primarily include 1) "Evolutionary Computations", 2) "Artificial Neural Networks"(ANNs) , 3) "Deep Learning", and 4) "Fuzzy Logic" (Giri et al., 2019; Guo and Wong, 2013).

Evolutionary computations is defined as an umbrella term including techniques inspired by optimum-seeking mechanisms, iteratively improving the performance of solutions until an optimal solution is obtained. Common algorithms include genetic algorithms and harmony search.

ANNs are built of a number of interconnected neurons, or nodes, analogous to the neurons in the human brain (Guo and Wong, 2013). It is an adaptive system that discovers associations between inputs and associated outputs, iteratively updating the network settings of the data patterns from the training samples. The most common type of ANNs is the feedforward network. What distinguishes such from other networks is that the connections travel in a single directed path rather than in a loop, moving forward on a layer-by-layer basis. Deep learning is part of machine learning methods based on ANNs but are much larger networks with additional layers, being applicable and successful in case large sets of data exist.

Fuzzy logic is referred to the set of concepts and methods for treating imprecise information, and is often referred to as "reasoning with uncertainty." This is beneficial in case the data is incompletely defined in contrast to crisp data, commonly occurring in human reasoning and communication (Guo and Wong, 2013).

3.3 The assortment planning process

This section presents a proposed taxonomy and framework of the assortment planning process within the FSCM. This mainly comprises the findings of Hübner (2017), Kang (1999) and (Kök et al., 2009).

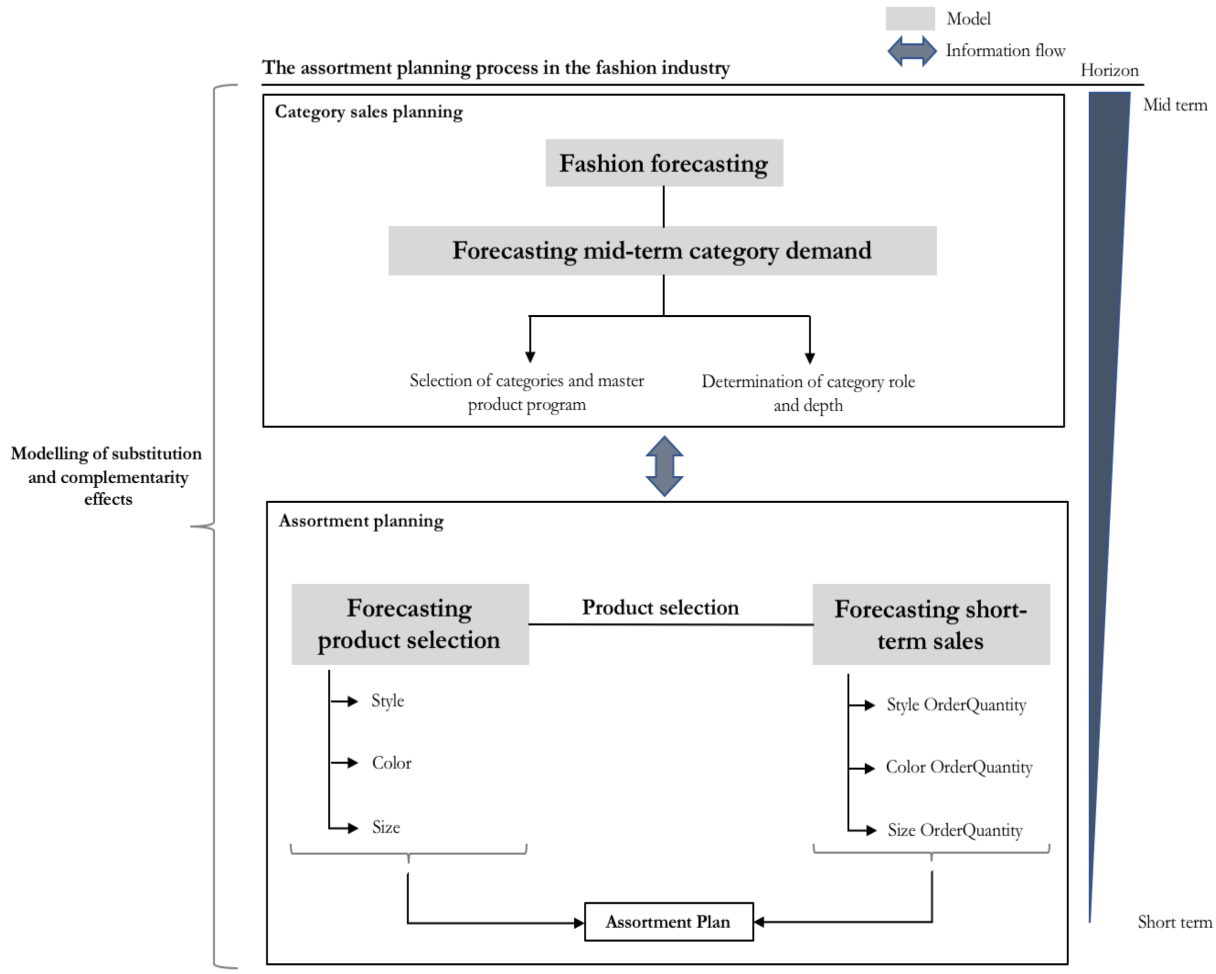

Figure 5. Framework for the assortment planning process in the fast fashion industry

One of the major critical business decisions in the fashion industry prior to production is the planning of items to include in a future assortment. This process includes supply chain operations at all levels of decisions. The aim of the assortment planning process of a retailer is to decide on the optimal product lines, i.e. compilations of products to include in the assortment (Kök et al., 2009). Successful assortment planning includes a balance among 1) the number of categories (breadth), 2) the number of items, or stock-keeping units (SKUs), in each category (depth) and the amount of inventory to allocate to each SKU (Mantrala et al., 2009). Moreover, the ultimate goal of the assortment planning process is to maximize the sales or gross margin by offering the most appropriate merchandise that enables consumers to find and buy what they want. As the products the retailer chooses to carry has a substantial impact on the company's profit, the assortment planning process has become a crucial area to prioritize for both retailers, consultants and software providers (Kök et al., 2015). Furthermore, the timing of the release of an item is not linked to when the item is designed or produced in the fast fashion industry. There is often a long production lead time and relatively short selling season, making it impractical and costly to modify the assortment and reorder products during the season (Caro et al., 2014). Hence, under the static assortment planning. i.e. an assortment that is not revised during the selling season, there is a need to use sophisticated methods to detect and predict customer demand and purchasing behaviour long in advance (Caro et al., 2014).

The assortment planning process of a retailer can be divided into four main parts (Hübner 2017):

1. *Category sales planning*
2. *Assortment planning*
3. *Shelf-space planning*
4. *In-store replenishment planning*

These steps are not done in isolation, rather a share of information between each step is required in order for the process to be smooth. Further, they must also align with the organisation's planning horizon as well as the organizational hierarchies and responsibilities (Hübner, 2017). The time horizon indicates how far in advance the activity is done in relation to when the actual assortment is finished and available to the consumers. It also correlates to the level of decision. The mid-term decisions are most often strategic or tactical, while the short-term decisions, such as alterations to the assortment while in store, are operational and connected to how the products are marketed. However, a retailer can take into consideration substitution and complementarity both mid-term and short-term depending on how the assortment is planned. This paper focuses on the two first steps in the assortment process, namely category sales planning and assortment planning.

3.3.1 Category Sales planning

The term category sales planning includes forecasting of midterm category demand, selecting categories and defining their role and depth (Hübner et al., 2013). This is both a strategic and tactical process, treating product categories as business units and customizing them to satisfy customer demands (Gnau et al., 1992; Hübner and Kuhn, 2012). It is an integral activity for each retailer since inaccurate demand planning on this level negatively affects stores' behaviour- and performance. Poor category demand planning also has a negative ripple effect on the other parts of the assortment planning process, thus becoming the cornerstone of effective assortment planning. In the fashion industry in particular, this activity should be initiated with a fashion forecast. Fashion forecasting is difficult as trends change rapidly (Shi et al., 2021). Many retailers do this based on feeling amongst the designers, or manually by searching through design collections shown across the world (Shi et al., 2021). Today however, retailers are starting to realize the benefits of using AI for trend detection and prediction, for example by using image and computer vision to detect attributes in images and other media (Shi et al., 2021).

Category sales forecasting

The volatile customer demands, tremendous product varieties and short product life cycles cause production planning activities to be a complex decision process in the FSCM, impacting all members of the chain (Wong and Guo, 2010; Xiao and Yang, 2008). Without sales forecasting, operations only respond retroactively; resulting in poor production planning (Fildes and Hastings, 1994).

Multidimensional hierarchies

The demand forecasting may be characterized on three dimensions: the product aggregation level, the position in the supply chain and the time granularity, see figure 6 (Fildes et al., 2019).

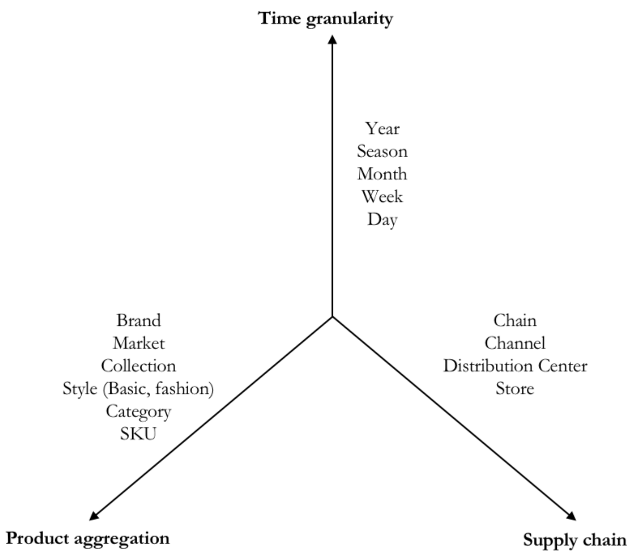

Figure 6. Multidimensional hierarchies in fashion sales forecasting

The previous body of literature of fashion sales forecasting has dominantly set the focus on forecasting sales volumes and profiles of individual SKUs, usually only involving short-term forecasting (Wong and Guo, 2010). Due to the short life cycles and frequent introduction of new products, this is not enough in the FSC. In various tactical decisions across the supply chain, initial forecasts on a higher product aggregate level, such as *category* and *style*, are required. Prior to initiating a new assortment, a fashion retailer is in need of holistic guidelines concerning the overall category demand. In the tactical promotional assortment plan being planned across the chain, forecasts should hence be done on a *chain* or *market* level (Fildes et al., 2019). The higher the level of decision, the lengthier the time granularity. For category sales planning, the time horizon should thus be set at *season* or *year*. Such forecasts may help the fashion retailer to properly set the annual sourcing budget and plan the production (Thomassey, 2010). Moreover, in the case of a fashion retailer having outsourced production to countries far away from the marketplace, early-stage category sales forecasting becomes increasingly important since the business needs to 1) ensure production capacity in time and 2) allow for longer lead times (Thomassey, 2010).

Consequently, having forecasted category demand, managers and designers may receive guidelines that help determine the number of different categories, i.e. the assortment breadth, and styles to include in each fashion category, i.e. the assortment depth. There is however a need to complement category forecasts with SKU-level forecasting. This is because the category demand will be affected by the chosen SKUs in the product mix due to the effects of substitution and complementarity.

Furthermore, to accurately design and develop an efficient sales forecasting system, Armstrong (2001) argues it is critical to know the product, the sales features and the deployment of the forecasts. Due to the special characteristics of the fashion industry, this becomes increasingly important. When designing a fashion sales forecasting system, important characteristics to consider are a) the exogenous factors, b) the seasonality, and c) life cycle (trend) of products (Thomassey, 2014; Armando and Craparotta, 2019; Kaya et al., 2014).

Exogenous factors

The fashion market is strongly affected by several factors. Such factors - exogenous factors - are most often not controlled and at times unknown. Some positively affect the purchase decisions while others impact the traffic to the store or marketplace (Little, 1998). A suggested, non exhaustive list of such factors has been developed by Little (1998), see figure 7.

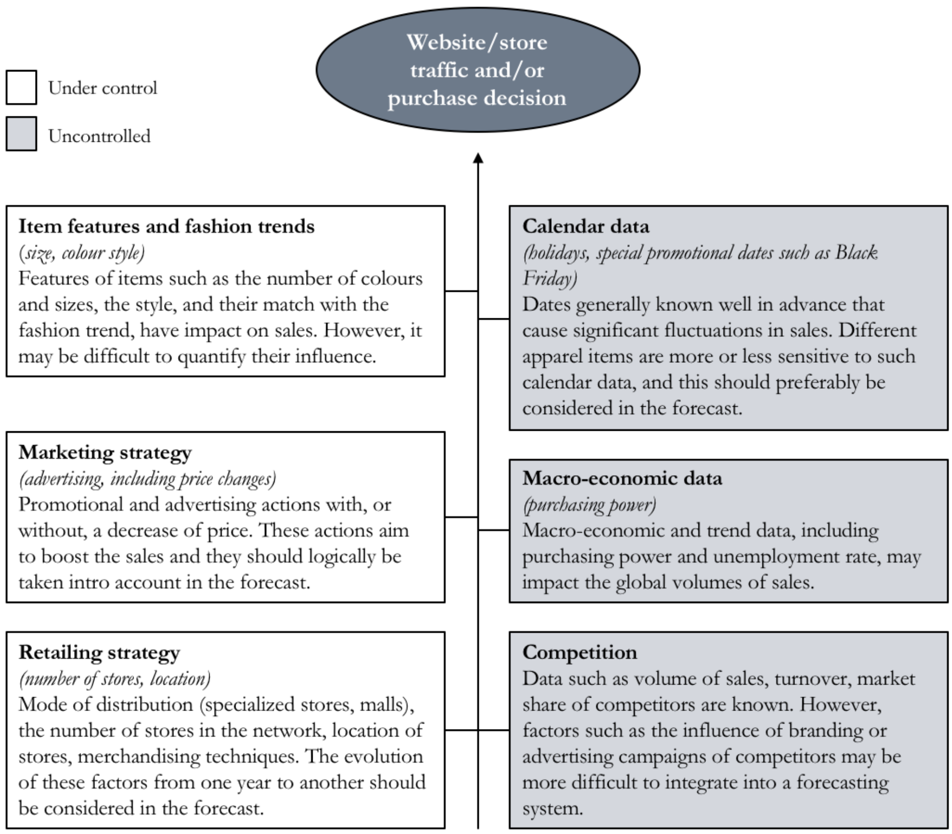

Figure 7. Exogenous variables in the fashion industry (Little, 1998)

These different variables should be categorized according to their impact on sales. Some variables may generate temporal fluctuations without having a significant impact on the overall sales volume, such as Holidays, whereas macro-economic data or strategy of retail may cause a global impact on the sales.

Conclusively, the fashion retailer should aim to integrate the most relevant factors in the forecasting model under development. Due to the variables' uncertainty, it is however a complex task to a) prioritize and b) quantify their impact. In addition, the correlation between variables further obstructs the understanding and modelling of the variables' impact on sales. Furthermore, some variables are not available, such as competitor data, nor predictable, i.e. weather data, and may thus not be integrated in the forecasting system.

Seasonality

Seasonality is of uttermost importance in every time series analysis (Thomassey, 2014) and is the most important variable for sales estimations (Armando and Craparotta, 2019). The fashion industry is especially exposed to seasonal influence because of the various different product characteristics (Thomassey, 2014). For example, products like swimwear and flip-flops are sold during warmer seasons while warmer jackets and boots are sold during winter time. Basic products do not demonstrate any peculiar periods for an increased sales likelihood. Hence, based on the sensitivity of the category in focus, the seasonality should be either more or less integrated into the forecasting model.

Life cycle of items

The life cycle of fashion items are, as previously stated, short in comparison to their long supply process (Choi, 2007). Moreover, for clothing items, the different product categories should be differentiated according to the nature of products. Basic items are sold throughout the year whereas fashion items are "one shot" items that are sold punctually during a short time period. In addition, there is a third category of "best selling items". These are sold each year, are slightly modified according to fashion trends and may be replenished during the season.

This high variance among products results in distinct differences with regards to life cycles, making it too simplistic to generalize a similar selling behaviour among all products. Hence, in terms of forecasting, basic items and best-selling items are commonly considered in the model while the fashion items are left out. It is hence suggested to develop specific sales forecasts for such items (Caro and Gallien, 2007). This is however an activity in a later stage of the fashion supply chain when the exact styles are to be determined, and should not be a focal area during the category sales planning.

The exogenous factors, seasonality and varying life-cycles cause the irregularity and randomicity of sales data to increase; making it more difficult to predict the future demand. To tackle such complexity, it is desirable to develop advanced forecasting models that are flexible and robust to handle the distinctive characteristics of the fashion sales data (Wong and Guo, 2010). To tackle this complexity, sophisticated AI techniques have received increased attention within the field (Choi et al., 2014).

3.3.2 Assortment planning

The second step in the assortment planning process is deciding what actual products to carry in the assortment, for a fashion retailer this is done in regards to styles, colors, patterns etc. To do this, the retailer must understand what products the consumers are demanding.
In fashion, products may be categorized into two product types - fashion and basic (The Parker Avery Group, 2020). Fashion products have a short life cycle meaning they will be included in a single selling season or less. Basic items however, have a long life-cycle and may be included in several selling seasons. They do not change, i.e. colours and features remain constant over the product's life and they usually have neutral colours and cuts and few embellishments (Abernathy et al., 1999). The different dimensions of the basic and fashion product characteristics are illustrated in figure 8. Even though the majority of the assortment planning process targets fashion products, basic products should also be considered in the assortment plan in order to provide a complete picture of the multi-channel product offering (The Parker Avery Group, 2020). Basic items are prioritized in the category sales planning while the fashion products are in focus in the assortment planning phase. It is difficult to make decisions about fashion products, i.e. what to include and what not to include, if you don't understand the entire product mix. What differentiates basic products and fashion products in the assortment planning is the level of planning. Basic products should target an aggregate planning level in which the portion of basic products in each class is determined. Assortment planning of fashion products should on the other hand be devoted to more resources in which specific attributes and number of pieces per location, amongst other things, are determined (The Parker Avery Group, 2020).

In forecasting product selection, three characteristics should be considered: style, color and size (Kang, 1999). Rosenberg (1993) has identified a product line as a compilation of products that has 1) similarities in satisfying needs, 2) matching potential with other items and 2) similar price ranges. Moreover, fashion retailers usually select between one to 100 colours. A common approach is to choose a few trend colours in combination with the brand's own color identities. Lastly, sizes should be chosen according to the fashion retailer's target market. Important to note is that sizes may vary across brands, hence it is important that the retailer is aware of how consumers perceive the brand's sizes, i.e. larger or smaller than what they usually purchase, when forecasting product selection.

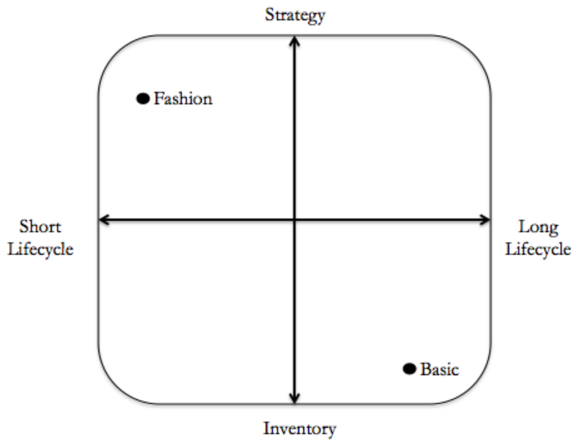

Figure 8. The relationship between fashion and basic products

The final product selection part of the assortment planning is a consumer choice problem, hence the retailer must understand how the consumer would choose from a set of alternatives characterized by their specific attributes (Klein and Bither, 1987). Retailers use different rules to decide what products to include/exclude, this is also referred to as choice logic (Kang, 1999). This includes the decision of what styles, colors and patterns to carry as well as how many of each. When understanding what products to offer, the short-term sales are forecasted in order to estimate the quantity to produce on an SKU-level. This should be done differently for basic products and for fashion products. Fashion products must be forecasted more often and allow for flexibility (Kang, 1999).

Throughout the entire assortment planning process, a retailer should consider the demand effects of product substitution and complementarity (Hübner, 2017). The total demand for a product is not only composed of its initial demand but also by how the consumer sees the product in relation to the whole assortment, hence how products substitute for each other and how they complement each other.

The assortment planning in the retail industry can be described using three factors presented by (Caro and Gallien, 2007). The retailer must in each period of a finite season decide the subset of products to be offered from a large set of options. When a product is sold, the retailer can gather data to better understand customer preference and demand for each article and hence add this to historical data to better plan future assortment. Kök et al. (2009) further defines the tradeoff between three elements that are required in assortment planning; breadth, depth, and how much of each SKU is stocked. The breadth of the assortment refers to how many categories the retailer chooses to carry while the depth is decided by how many SKUs exist in each category. Choosing breadth and depth is a part of the strategy that all retailers must consider. Some choose to have a wide variety of products, like department stores, while others choose to simply have a few categories with a great depth, for example, Toys 'R Us (Kök et al., 2009). Another aspect for retailers to consider when planning their assortment is the classical trade-off known as ”exploration versus exploitation” (Caro and Gallien, 2007). The trade-off refers to the decision the retailer must take before each season, to include products that are believed to sell good (exploitation) or products that will gather more demand data (exploration) and hence increase profitability in the long run. Caro and Gallien (2007) describe this issue as ”how to balance learning with immediate profit”. Supply and assortment decisions amongst retailers have historically been taken long before the selling season due to long lead times in product development, procurement, and production (Caro and Gallien, 2007). Today, Zara is an example of a retail company that is starting to implement new processes in their supply chain and development process that enables them to make better assortment decisions during the actual selling process by leveraging customer demand data (Caro and Gallien, 2007). Assortment planning for fashion retailers is thus crucial in order to compete in the fierce market of fashion that is driven by customers expecting excellent products and service (Liao et al., 2017; Lotfi and Torabi, 2011). Choosing the variety and quantity of products must be well managed as it affects the economic performance of the retailer. Deficient assortment planning leads to high costs as the retailer is left with excessive inventory of the products not sold and a rapid shortage of inventory on the popular products (Liao et al., 2017). Levering new techniques to tackle operational issues such as assortment planning is stated to be essential to maximize profits according to (Srivastava et al., 2020). Efficient assortment planning can further reduce operational costs and thus improve the overall financial performance of a retailer.

Substitution effect

A substitution in assortment planning is simply when a customer can't find the product he or she is looking for and chooses to settle for a similar product. How willing the consumer is to switch to another product is an important parameter to consider in assortment planning. It is for example less critical to have a great depth and a large stock if customers have a high tendency to substitute in a category (Kök et al., 2009). Consumer substitution can be divided in three types of patterns:

1) *Stock-out based substitution:* the consumer regularly shops for a product that one day is out of stock so another product is chosen instead.
2) *Assortment based substitution:*
    a) The consumer has a specific favorite product in mind but it is not carried by the retailer so another product is bought.
    b) The consumer chooses to buy the product that he or she prefers from a shelf with different products because it has a higher utility than the ”no-purchase”-option.

The latter case is most common in consumer durables like fashion apparel and the first two in daily consumables like grocery. In the third case, some products that could be first-hand options might already be out of stock as the consumer begins to shop, hence the consumer can substitute for a product without being aware that a substitution is actually made (Kök et al., 2009; Palmer, 2016).

Complementarity effect

The complementarity effect occurs when products provide greater utility together than when consumed separately. By considering such effects in the product selection problem, a retailer may increase sales by facilitating unplanned consumer considerations into purchases. In the product selection problem, the categories of the chosen subset are thus interdependent. Hence, ignoring the complementarity effects risks causing sub-optimal assortments (Ghoniem et al., 2013). Furthermore, retailers are aware of the fact that increased profitability may be obtained from the customers they already have, and that it is not only dependent on an increasing number of customers (Wong et al., 2013). This means that increasing the number of transactions per customer may result in growth in terms of profit and customer loyalty.

Above facts have guided retailers into using the strategies of complementarity effects, or cross-selling, i.e. selling additional items to a customer in relation to the items that the customer has/is intending to purchase. An item's selling performance in an assortment is hence dependent on its cross-selling potential (Gun and Badur, 2008). To actualize and optimize the strategy of cross-selling, retailers may use historical POS data to identify customer's preferences and purchasing behaviour (Wong et al., 2012). This may generate previously unknown insights surrounding products, and attributes, that perform well from a complementarity perspective; guiding the retailer to the best product selection during the assortment planning.

In the fashion industry in particular, a complete fashion outfit is often composed of several items. Such outfits can either include both basic and fashion products, or items from different categories such as tops, bottoms and accessories (Moon and Ngai, 2008). Thus, cross-selling in the fashion industry heavily relies on the unique product attributes to mix-and-match two products that appear to be esthetically appealing together. Usually, such activities are subjective in which human designers evaluate the performance of the mix-and-match from multiple perspectives. Hence, the procedure of fashion mix-and-match is a complex decision making process that involves matching, or complementarity, evaluation of multiple product attributes. Such problems are preferably solved using intelligent techniques processing large sets of product- and POS data, revealing hidden purchasing patterns (Wong et. al, 2012).

3.4 Consumer Choice Models

Consumer choice models (CCM) can be used to model the purchase behavior of individuals based on reasoning connected to different constraints such as budget and taste (Reisch and Zhao, 2017). This section presents two different categories of CCMs that are applied in the literature on assortment planning.

Utility based models

Utility based models used to model substitution or complementarity effects are based on the notion that consumers see a utility of each product in a set $N \cup \{0\}$, where $\{0\}$ denotes a no-purchase option. The consumer then seeks to maximize the utility, hence choosing the first-hand choice if possible. The Multinomial Logit model is a discrete, utility based, consumer choice model and assumes that every customer sees a product with a given utility which they aim to maximize. The utility that is connected to the product that the customer chooses is defined as $U_i = V_i + E_i$. E_i is random noise following the Gumbel distribution and V_i is a constant. The probabilities are as follows:

$$P_i(S) = \frac{e^{v_i}}{1 + \sum_{j \in S} e^{v_j}}; P_0(S) = \frac{1}{1 + \sum_{j \in S} e^{v_j}}$$

Where P_i is the probability that a consumer chooses product i from an assortment S and P_0 is the no purchase option (Qi et al., 2020).

The *locational choice model* is another utility based model that differentiates from the MNL-model by seeing products as bundles as opposed to separate units with their unique utility (Kök et al., 2016). By seeing products with characteristics, or attributes, the products with similar characteristics can be grouped, hence why they are seen as bundles. In a characteristics space, each product can thus be represented as a vector that is made up of components representing each characteristic and its ”weight” of each product. A shirt’s components could for example be its sleeve length, size, or color. Based on his or her preferences amongst these characteristics, each customer has an ideal point in the characteristic space.

Exogenous demand models

The exogenous demand model specifies the demand for each product and the choice probabilities amongst a given set of products if the first-hand choice is not available (Kök et al., 2007). The consumer chooses from a set of products, N={1,2,…,i,…,k}. If the consumer's first hand-choice j, is not available, another product can be chosen according to a given substitution probability u_{ij} (Kök et al., 2007; Hübner et al., 2016). Using the parameter u_{ij} for substitution probabilities allows for differentiation between products with different substitution rates. Generally, the exogenous model allows one round of substitution, hence if the customer’s first-hand is not available, the sale is lost. When optimizing an assortment with the exogenous model, it is often assumed that customers arrive one at a time and that they make their decision based on how the quantities in stock have been updated at the moment of arrival (Palmer, 2016). The retailer in this case therefore aims at optimizing the quantity of each product in order to maximize profits.

4. Result

This chapter, presenting the result of this thesis, starts with the findings of the first research question. As these results are subject to confidentiality, this section is kept fairly short and general. Following that, the findings related to the second research question investigating AI techniques in the assortment planning process are presented. It is structured by first presenting the result connected to category sales forecasting and then the results on the subject of substitution and complementarity effects in assortment planning.

4.1. SCOR model and level of AI supported SCA

The first research question of this thesis, investigated through a case study, aims at understanding the extent to which AI supported SCA is integrated in a fashion retailer's decision making processes in the initial part of the FSCM, see figure 9. The findings on the level of integration of AI supported SCA are shown in figure 9, where red indicates no implementation of AI, yellow indicates low maturity of AI and green indicates that some AI technique is actively used in decisions related to the specific fashion supply chain process. Due to confidentiality, details about the decisions in each process of the supply chain can not be disclosed. The research however indicates that the decision making processes related to the "Quantify" stage receives maximum attention when applying AI techniques; "Develop","Purchase" and "Plan assortment" receives some attention while "Plan production" fully lacks any AI supported SCA. "Plan production" and "Plan assortment" are two processes very much interdependent and related. It was therefore decided in accordance with the case company to look further into how AI may support the decision making in these areas, where decisions concerning the assortment planning process are prominent.

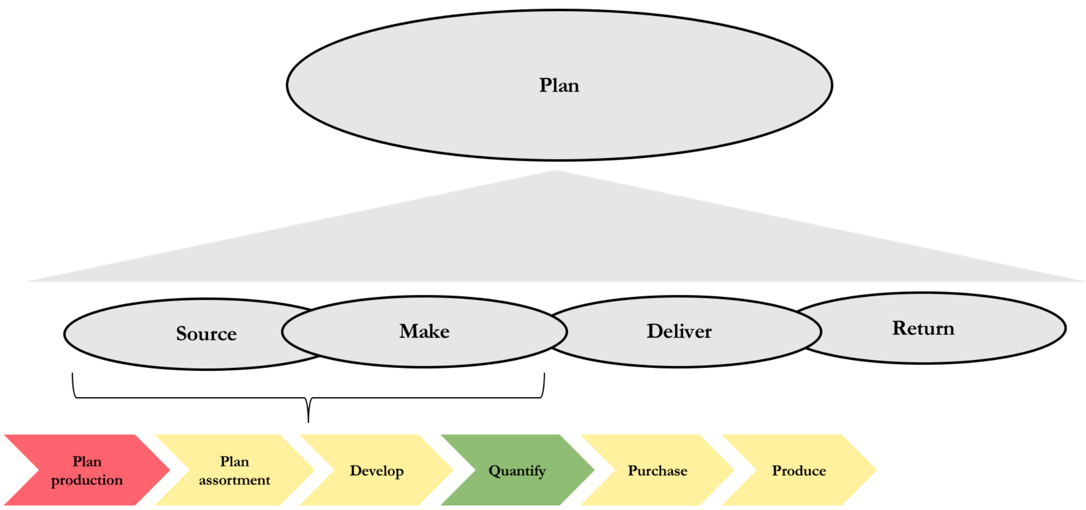

Figure 9. Level of AI supported SCA in the FSCM decisionmaking processes at the case company

4.2 The assortment planning process

This section presents the result of the systematic literature review conducted to answer RQ2. The findings are based on the review of 29 articles yielded from the SLR search string and the use of the snowballing method. Of all articles, 7 focus on the category sales planning block of the assortment planning process and 22 on the assortment planning block. The articles discussing assortment planning have further been divided into those accounting for substitution (15 articles) and those accounting for complementarity (7 articles). Table 6 presents the literature accordingly.

Furthermore, to answer RQ2, the AI techniques and methods presented in each paper have been identified and are demonstrated in table 7. Overall, machine learning dominates as the used AI-technique in the investigated papers. However, the different areas of the assortment planning process are approached with different solutions. Therefore, the methods used in the different blocks vary in regards to their granularity level. For the literature on category sales planning, the column "Methods/Models" in table 7 defines the approach to how the identified AI technique has been applied. For the assortment planning block, machine learning dominates as the used AI technique but through the use of consumer choice models (CCM). Therefore, the column "Methods/Models" on the assortment planning blocks presents the type of CCM used. Also for complementarity effects, machine learning is the dominating AI technique but most often through the use of data mining.

Table 7 furthermore presents the time dimension of the reviewed papers. This time horizon is equivalent to the one declared in the assortment planning process framework in the theory chapter of this thesis. Methods and models used at an early stage of the assortment planning process, e.g. before the assortment is produced have been categorized as mid-term. Methods and models used for the planning of an already produced assortment have been categorized as short-term.

To draw conclusions surrounding how the literature is divided between fashion specific research and general retail, all articles are also categorized based on what industrial sector (e.g. retail or fashion) the presented models are conformed to. One of the articles does not specify one industrial sector but focuses on the quick response supply chain. The fashion industry dominates the papers on category sales planning, while a general retail supply chain is most often prevalent in the papers on assortment planning. Lastly, all included papers are published between the years 2000-2020.

Retrieved literature related to the assortment planning process						
Block of planning process	**Authors**	**Year**	**AI techniques**	**Methods/Models**	**Time horizon**	**Industry**
Category sales planning	Thomassey et al.	2005	Machine learning, Expert System, Fuzzy logic	Fuzzy rule-based inference system: using 1) Takagi-Sugeno (T-S) type rules, 2) automatic learning and genetic algorithms for the learning process	Mid-term & short-term	Fashion industry
	Kalyanam et al.	2005	Machine learning	Hierarchical Bayes framework, MCMC sampling algorithm	Mid-term	Fashion industry
	Sun et al.	2008	Machine Learning (Artificial Neural network)	Extreme learning machine using back-propagation algorithms & normalization/unnormalization	Mid-term	Fashion industry
	Xia et. al	2012	Machine learning (incl. Artificial Neural network)	Extreme learning machine using adaptive metrics of inputs (k-nearest neighbor method), and the Levenberg-Marquardt optimization algorithm	Mid-term	Fashion industry
	Wong and Guo	2013	Machine Learning (Artificial Neural network), Evolutionary optimization techniques	Extreme Learning Machine using Harmony search learning algorithm and heuristic fine-tuning process	Mid-term	Fashion industry
	Kaya et al.	2014	Machine Learning (incl. Artificial Neural Network), Expert systems, Fuzzy Logic, Evolutionary optimization techniques	Forecast combination employing adaptive weights and a fuzzy rule-based inference system using Takagi-Sugeno (T-S) type rules Forecasting models: Seasonal pattern based-, Evolutionary neural networks-, and Extreme Learning Machine based forecasts	Short-term	Fashion industry
	Armando and Craparotta	2019	Machine learning (incl. Artificial Neural Networks)	Forecast combination of: Seasonality-based multivariate linear regression model, Time-series model: Holt-winters method & prophet, Neural network using feed-forwarding and back-propagation, an autoregressive neural network	Mid-term & short-term	Fashion industry
Assortment planning (substitution effects)	Smith and Agrawal	2000	Machine Learning	Exogenous demand model	Short-term	Retail
	Ryzin and Mahajan	2001	Machine Learning	Utility based model (MNL)	Short-term	Retail
	Rajaram	2001	Machine Learning	Exogenous demand model	Mid-term & short-term	Fashion industry
	Kök and Fisher	2007	Machine Learning	Exogenous demand model	Short-term	Retail
	Karabati et al.	2009	Machine Learning	State-space-based estimation model	Short-term	Retail
	Miller et al.	2010	Machine Learning	Utility based model (MNL)	Mid-term & short-term	Retail
	Vaagen et al.	2011	Machine Learning	Exogenous demand model	Mid-term & short-term	N/A
	Ulu et al.	2012	Machine Learning	Utility based model (Location choice model)	Mid-term & short-term	Retail
	Hübner et al.	2016	Machine Learning	Exogenous demand model	Mid-term & short-term	Retail
	Liao et al.	2017	Fuzzy Logic	Fuzzy optimization model & Hybrid genetic algorithm	Mid-term & short-term	Fashion industry
	Saberi et al.	2017	Machine Learning	Data fusion techniques, APORTU Mathematical modelling	Mid-term & short-term	Retail

	Hübner	2017	Machine Learning	Exogenous demand model	Mid-term & short-term	Retail
	Castro et al.	2018	Machine Learning	Utility based model (Reference point logit)	Short-term	Retail
	Bernstein et al.	2019	Machine Learning	Utility based model (MNL)	Mid-term & short-term	Retail
	Srivastava et al.	2020	Machine Learning	Clustering (K-means & FCM), Knapsack algorithm	Short-term	Retail
Assortment planning (comple -mentarity effects)	Brijs et al.	2004	Machine Learning (Data mining)	Association rule mining, PROFSET model	Short-term	Retail
	Chen and Lin	2007	Machine Learning (Data mining)	Multi-level association rule mining, PROFSET model	Short-term	Retail
	Gun and Badur	2008	Machine Learning (Data mining)	Association rule mining, PROFSET model	Short-term	Retail
	Nafari and Shanrabi	2010	Machine Learning (Data mining)	Multi-level association rule mining	Short-term	Retail
	Wong et al.	2012	Fuzzy Logic	Fuzzy screening module, fuzzy linguistic rating scale	Short-term	Fashion industry
	Bai et al.	2015	Machine Learning (Data mining)	Association rule mining, PROFSET model	Short-term	Retail
	Agarwal	2018	Machine Learning (Data mining)	Association rule mining, Apriori algorithm, clustering	Short-term	Retail

Table 6. Gathered literature from SLR on the assortment planning process

Figure 10 moreover synthesizes and summarizes the information presented in Table 6. This maps the discovered AI techniques - and models found within the two blocks of the assortment planning process.

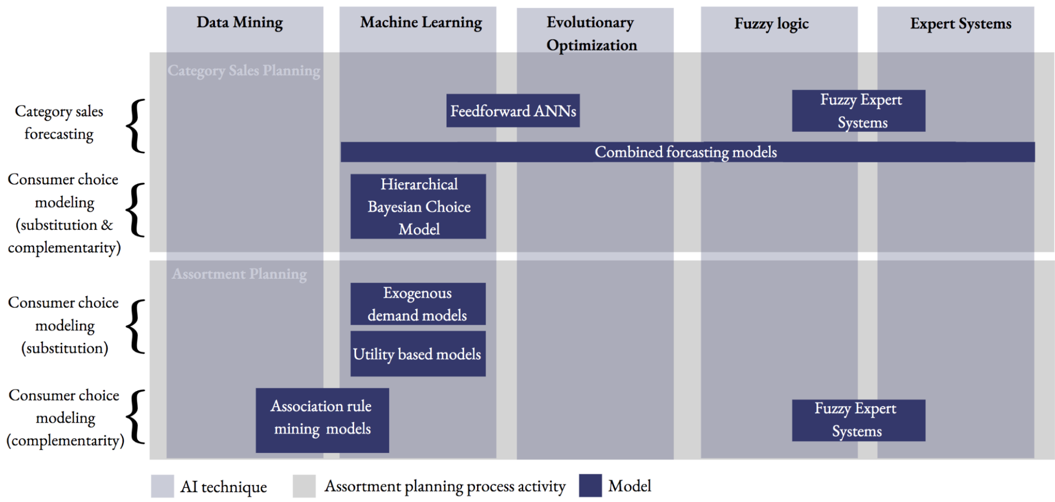

Figure 10: Illustration of the literature's findings of AI techniques- and models in the assortment planning process

Following parts of the result chapter will go deeper into the literature on category sales planning and assortment planning.

4.3 Category sales planning

The literature of category sales planning in the fashion industry covers the following AI techniques: 1) machine learning, including ANNs, 2) expert systems, 3) fuzzy logic, and 4) evolutionary optimization algorithms.

All research included in the SLR within the field of AI techniques in category sales planning is conformed to the fashion industry, see table 6. This is due to the fact that the snowballing method was predominantly used for studying this subsection as there was a scarce number of resulting articles in the initial search result. The specific characteristics of the fashion industry presented in the theory section heavily impacts the success of sales forecasting methods (Thomassey, 2010). Hence, the authors decided to solely include the research of category sales forecasting found within the fashion industry, excluding the general retail industry.

The resulting articles on the topic of category sales planning include one consumer choice model (Kalyanam et al., 2007) and six category sales forecasting models (Armando and Craparotta, 2019; Kaya et al., 2014; Sun et al., 2008; Xia et al., 2012; Wong and Guo, 2010; Thomassey et al, 2005). In the research field of AI, the articles are considered fairly new as they are published in the 21st century whereas the concept of AI evolved in the 1950s (Giri et al., 2019).

Within category sales forecasting, different versions of ANNs are the most commonly employed technique. However, the trend in the last decade tends to move towards the development of combined forecasting models, incorporating various of the mentioned AI techniques (Kaya et al., 2014; Armando and Craparotta, 2019). Consequently, all papers have developed models targeting a mid term time horizon for planning the assortment, ranging from months to one year. This is in line with the existing theory of the prioritized hierarchies of category sales planning (Hübner, 2017; Fildes et al., 2019).

Below sections aim to report the findings and methods discovered within category sales planning, including a) modeling consumer choice behaviour and its impact on category demand and b) forecasting category sales levels in the fashion industry.

4.3.1 Consumer choice demand model

Kalyanam et al. (2007) develops a consumer choice demand model for an apparel category using machine learning; implementing a Hierarchical Bayesian framework. The model considers both substitution and complementarity effects. The aim of the model is to generate a measure of each apparel item's contribution to the attractiveness of the entire assortment by analyzing category sales. This is realized by utilizing historical Point-Of-Sale (POS)- and stock data to deconstruct the impact of an out-of-stock item into three dimensions: 1) lost sales, 2) cross-item impact, and 3) category demand impact.

The research of Kalyanam et al. (2007) main contribution is the discovery of how the presence of an item in an assortment would impact sales of the assortment or category over, and above, its own sales. It is also discovered that the stock-out, i.e. absence, of an item impacts category sales to a larger negative extent than the cross-item effects or loss of own sales.

Moreover, it is found that a few key items, i.e. the best-selling items, generate a big impact on the sales performance of the whole category. Interestingly, it is also discovered that the absence of *each* item, regardless of it being a key item or not, also has a significant effect on the category sales. Thus, the peculiar concept of retailers needing a broad assortment to sell the category, while only a few items are major sellers, is confirmed. As a subsequent finding, the conventional definition of key items being the best-selling items is challenged. Kalyanam et al. (2007) find that the best-sellers are not necessarily the items with the most critical impact on the sales volume of the category and assortment. Rather, due to the complex correlation between products in an assortment and category, key items for assortments should be redefined for each individual assortment. An item may for example contribute to the aesthetically pleasing display of a category within an assortment, and the absence of certain items may lessen category demand due to potential erosion of the aesthetic value of the category presentation. Hence, it is suggested that retailers use product data and sophisticated techniques to determine such key items, and their role in the assortment, when simulating consumer behaviour's impact on the category demand by implementing the presented model.

4.3.2 Category sales forecasting in the fashion industry

Category sales forecasting uses historical POS data to predict future sales levels. When historical data exists, time series forecasting is a common approach used by practitioners. Time series forecasting models assume there is a functional relationship between the future value and past observations. Historical observations of sales within each category are hence used to determine a model to capture the underlying relationships and extract the maximum information possible from the past years' time series (Thomassey, 2014). Such information usually includes trend and seasonality, but also the impact of exogenous factors.

The parameters impacting, and critical for, the performance of the sales forecasting models mainly concern the suitability of the chosen techniques with respect to the considered multidimensional hierarchies and treatment of the specific characteristics of the fashion industry (Thomassey et al., 2005). The following section thus aims to report the multidimensional hierarchies and fashion market characteristics considered in the reviewed literature of category sales forecasting. Consequently, this is followed by an in-depth presentation of the discovered models and AI techniques suggested by the literature to be suitable for such forecasting systems.

Table 7 presents the fashion category sales forecasting models, setting the focus at their consideration of 1) the multidimensional hierarchies (Fildes et al., 2019), and 2) the specific market characteristics in the fashion industry (Thomassey, 2010; Little, 1998). The discovered models cover the multidimensional hierarchies of a) year, season, month and week with respect to *time granularity*, b) SKU, category and style (basic, fashion products) with respect to *product aggregation* and, c) market and store with respect to the *supply chain dimension*. Moreover, all articles succeed in incorporating a critical number of the fashion market characteristics. Conclusively, the majority of the research resembles the conceptual theory of category sales forecasting in the fashion industry.

Multidimensional hierarchies and fashion market characteristics in the literature of fashion sales forecasting				
	Multidimensional hierarchies			
Authors	Time Granularity	Supply Chain	Product aggregation	Considered fashion market characteristics
Thomassey et al.	Year, Week	Market	Category	Trend, seasonality, exogenous factors
Kalyanam et al.	Month	Market	Category	Color, size, price
Sun et al.	Month	Store	Style (Fashion, basic)	Trend, seasonality
Xia et. al	Year, season, month	Store, market	Category	Trend, seasonality, exogenous factors
Wong and Guo	Year (Weekly aggregation)	Store	Category, SKU	Trend, seasonality
Armando and Craparotta	Year (Weekly aggregation)	Store	Category	Trend, seasonality, exogenous factors

Table 7. Multidimensional hierarchies- and fashion market characteristics discovered in the literature of fashion sales forecasting

Artificial Neural Networks (ANNs)

ANNs has been widely explored in the literature of forecasting models (Zhang, 2012) and has proved to substantially improve the accuracy in comparison to linear methods (Chu and Zhang, 2003). The nonlinear structure of neural networks is useful for capturing the complex underlying relationship in the fashion sales data. ANNs have the capacity to learn from the environment, without using expert knowledge required in the statistical models, by approximating any continuous function in a data-driven self-adaptive way. This makes them powerful in detecting complex patterns, including nonlinear trends and seasonal patterns. The most widely applied type of ANN in forecasting time series is the single hidden-layer feedforward model (Choi, 2016; Sun et al., 2008) using evolutionary optimization algorithms for learning such as gradient descent (Alon et al., 2001; Xia et al., 2012). However, there are claims that these ANN models have been slow in performing the forecasts (Choi et al., 2014; Sun et al., 2008). In the fashion industry, the high product variety causing complex data increases this weakness of the ANN model.

A more recent learning algorithm for a single layered ANN, called Extreme Learning Machine (ELM), has been proposed (Huang et al., 2004) and extensively researched for the purpose of sales forecasting. ELM tends, especially, to provide better generalization performance and faster learning speed than the previous gradient descent learning algorithms (Huang et al., 2004). Sun et al. (2008) confirm this claim in their development of an ELM-based ANN. The most significant factors affecting the sales amount are chosen as the input layer. The output is the sales amount. The training data is used to determine the input and output weights of the network and the predicted sales series of new data is consequently generated. Sun et. al (2008) demonstrate that their model produces a smaller predicting error and quicker training time in comparison to two well established backpropagation networks. However, the ELM's forecasting outputs are unstable in comparison to the traditional ANN and statistical models (Huang et al., 2006). This is because it randomly decides on the input weights and hidden biases, resulting in more hidden neurons which may impact the generalization performance of the network (Wong and Guo, 2010). Due to the irregularity and randomness of the POS-data in the fashion market, this industry is especially vulnerable to this. Similar to other flexible nonlinear estimation methods, the ELM may suffer from underfitting or overfitting. Underfitting may occur when the network is not sufficiently complex, failing to detect the signal in a complicated data set. Overfitting occurs when the network is more accurate in fitting the training data while performing worse for new data. In addition, in case of low availability of training data, the ANN forecasting model may be more likely to be overparameterized and overfitted since it may exaggerate minor fluctuations in the data (Xia et al., 2012). This reduces the performance of the forecasting results since an overfitted model generally has poor predictive performance.

To overcome mentioned challenges of ELMs, Wong and Guo (2010) has developed a methodology to forecast the total sales amount of each fashion item category using a Hybrid Intelligent (HI) model. The HI forecaster employs a meta-heuristic evolutionary optimization technique: the harmony search (HS) algorithm (Mahdavi et al., 2007). This is believed to generate optimal ANN weights and obtain increased generalization performance. As illustrated in figure 1, the data preprocessing consists of a) detecting and removing outliers, b) interpolating missing data and, c) normalizing sample data. Consequently, the HI forecaster initially generates several forecasts using the HS-ELM learning algorithm-based ANN. Using these initial forecasts, a heuristic fine-tuning process is utilized to generate the final sales forecasts (figure 11). The HS-ELM learning algorithm demonstrates an improvement of ANN generalization while the heuristic fine-tuning process further improves the forecast accuracy through the elimination of unreasonable forecasts and averaging of multiple ANN forecasts. The results prove that, on the whole, the HI model exhibits superior performance over both the statistical ARIMA model and other ANN forecasting models.

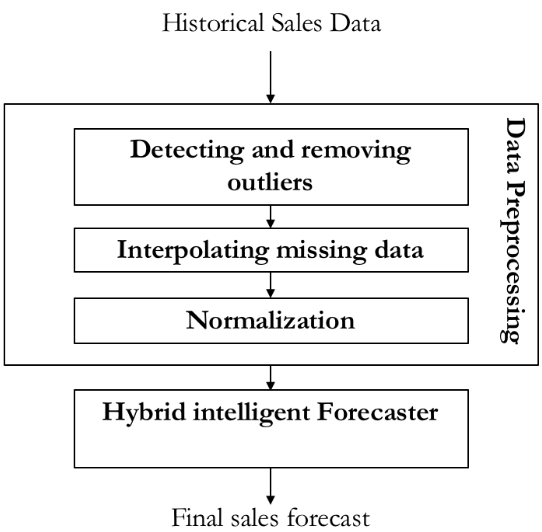

Figure 11. The hybrid intelligent forecaster (Wong and Guo, 2010)

Xia et al. (2012) have also combated the problem of overfitting within ELM by using adaptive metrics of inputs: the AD-ELM. Their model handles the adaptation to local variations of trends and amplitudes, which according to the authors are the most important factors for the forecasting system. In the adaptive metrics method, the inputs of the network are chosen to be close to the historical data. In this way, the forecasting error is reduced since the difference between the training and the testing data is smaller. The simulation results demonstrate that the AD-ELM produces smaller prediction errors in relation to other forecasting methods using gradient-descent learning algorithms.

Fuzzy Expert Systems

In the setting of uncertain knowledge related to exogenous factors and non-linear, irregular and incomplete data, utilizing the computational intelligence of fuzzy logic is proved to be effective (Zadeh, 1997).

Thomassey et al. (2005) has developed a model that builds on the model developed by (Thomassey et al., 2001). They developed a HFCCX model, implementing a Fuzzy Inference System (FIS) to treat the influence of explanatory variables on category sales. However, this model employs an expert's manual intervention when defining the inference rules. It is preferable to avoid the requirement of expert's judgement since it, at times, lacks reliability (Stewart, 2001), imply biases (Poulton, 1989) and are expensive and time consuming in the fashion industry. To combat the problem of the reliance on expert's knowledge, Thomassey et al. (2005) has extended the HFCXX by developing an automatic HFCXX model, (AHFCCX). Henceforth, exploiting machine learning to integrate automatic learning becomes valuable (Kuo, 2001). Usually, automatic feature detection is as accurate as an expert's judgement. Automatic identification is moreover especially crucial in the fashion industry since the time series are numerous and strongly affected by the explanatory variables, making the manual tuning of models laborious and delicate. The AHFCCX is based on an automatic learning of Takagi-Sugeno FIS using historical data and easily interpretable linguistic rules (Takagi and Sugeno, 1985). Furthermore, they find that the influence of explanatory variables differentiates amongst the considered category that the model is targeting; requiring a learning process of the model for each category. The FIS training generally requires an important time series to optimize the prediction of the new data sets. To increase the training data number and improve the performance of the model, Thomassey et al. (2005) develop a clustering technique to classify behaviour among categories. The goal is to cluster categories that have similar behaviour with regards to the explanatory variables. The learning process is consequently performed on all historical category sales of the same cluster rather than the same category.

The AHFCCX consists of three stages: 1) sales data are deseasonalized from the influence of explanatory variables, 2) resulting data generates baseline sales and enable prediction of next year using a basic forecasting based on seasonality average and 3) sales forecasting are reseasonalized with influence of explanatory variables related to the next year (figure 12).

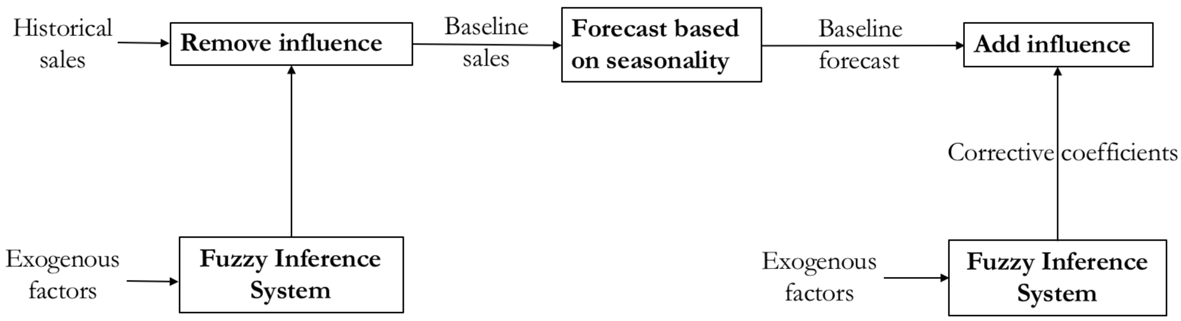

Figure 12. Principle of forecasting system with fuzzytreatment of exogenous factors (Thomassey et al.,2005)

The FIS is implemented in the first step to compute the corrective coefficients of sales by removing the influence of explanatory variables. The same system is repeatedly used in the last step to re-add the influence of new explanatory variables. The influence rules used in the FIS to modify the coefficients may be extracted from the historical database using genetic algorithms. Such algorithms are used for the structure learning of fuzzy inference models (Kim and Kim, 1997), allowing for an easier interpretation of the system by deleting rules that damage accuracy (Zadeh, 1997). In this case, price, holidays and time period are the selected rules from which the coefficients are corrected.

In this model, 322 different items are used and compared with other forecasting models, including 1) classical Holt-Winters method (Hyndman and Athanasopoulos, 2014) not considering exogenous factors, 2) the linear ARMAX (Autoregressive ARMA method) considering the same exogenous factors as the FIS, and 3) a naive approach of simply reproducing last years' sales. The results demonstrate that the FIS model globally improves the accuracy of the mid-term forecast in contrast to the former forecasting models. The successful results may be explained by the FIS possibility to extract the influence of several explanatory variables and the seasonal behavior of sales; two very important dimensions that are critical for sales forecasts in the fashion industry.

Combined models

Two research groups, Kaya et al. (2014) and Armando and Craparotta (2019), develop methods combining both linear and non-linear forecasting models by utilizing multiple AI techniques. This is beneficial since demand characteristics of a fashion product evolve over time; causing the accuracy of different methods to change. Methods that perform well under stable demand conditions may fail when demand fluctuations occur.

Kaya et al. (2014) have developed a forecast combiner to predict category sales on a weekly basis on a SKU store level. Initially, the authors use the Seasonal Pattern Based (SPB) forecasting method developed by Choi et al. (2014). This model identifies a repeating seasonal demand pattern for a product category. This is achieved by using the following algorithm: 1) The unsatisfied demand is calculated using past week sales, 2) Systematic events such as holidays are considered to be a natural component of the seasonal pattern and are left to be included in the data, whereas non-systematic events like punctual promotions are replaced with the closest weeks sales, and 3) the price effect is identified and removed from the data to arrive at a definitive seasonal pattern. The model lastly generates an estimation of pieces sold at a future price estimation. The other forecasting methods used include the contributions of Au et al. (2006); Sun et al. (2008) and Yu et al. (2011) ; applying evolutionary neural networks and ELM based forecasts. Consequently, the forecast combiner of Kaya et al. (2014) periodically updates the combination weights of the different forecasting methods based on their relative forecast error performance. The combination of weights utilizes fuzzy logic, motivated by the aim of not being too strict with the definition of forecast accuracy. The authors conclude that while the SPB method generates satisfactory results, the combined forecasts achieve better accuracy than any of the individual forecasts.

Armando and Craparotta (2019) build on the approach used by Kaya et al. (2014) by developing another category forecasting model; combining an additional number of base forecast models.
The forecasting methods included in the meta- model are: 1) a seasonality-based multivariate linear regression model 2) the SBP (Choi et al., 2014), 3) two different time-series techniques using Holt-Winters method (Hyndman and Athanasopoulos, 2014) and the prophet method (Taylor and Letham, 2018), 4) a feedforward ANN 5) an autoregressive neural network (Hyndman and Athanasopoulos, 2014) , and 6) a simple method of averaging all weekly category sales data from previous years. Armando and Craparotta (2019) consequently utilize the error metrics to find the best model for each dataset, being the true essence of the meta-model. Ultimately, the meta-model determines a chosen model combination, accompanied by the error indicators, which creates the final 52 week forecast. Testing the meta-model on an European fashion retailer, the metamodel proves to reduce the forecast error on the year category forecast by 24%. Moreover, since any forecasting algorithms may be added to, or removed from, the metamodel to suit the purpose; the researchers suggest that it is an extremely powerful tool to use in the field of forecasting.

4.4 Assortment planning

This section presents the result of assortment planning. Most articles yielded from the SLR search investigate assortment planning while taking substitution and complementarity effects to account. Complementarity and substitution effects are very much related as they both consider how the customer chooses between products in the assortment depending on different factors. The review of articles investigating substitution and complementarity in assortment planning shows that there are two parts to the selection of an optimal product mix. First, the substitution and complementarity effect on demand must be modelled to capture how the customers choose between different products in regards to the whole or part of the assortment. This is most often done through a consumer choice model (CCM) that estimates how the consumer would choose between different products. Secondly, this estimated behaviour feeds into the actual function choosing what products to include that maximizes profits or sales (Rajaram, 2001): the assortment optimization. This gives the retailer the optimal quantity or variety of products to carry. The process is illustrated in figure 13.

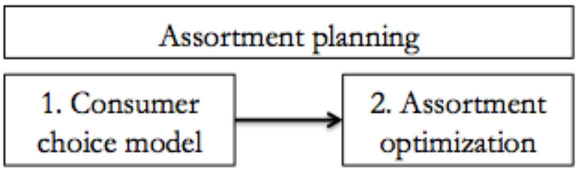

Figure 13. The two steps of assortment planning

Gun and Badur (2008) states that any analytical assortment planning process must begin with a consumer choice model and some estimation of parameters. As substitution and complementarity effects are two prominent areas in the assortment planning literature but most often discussed separately, this section is divided thereafter. First, techniques and models used in the literature to plan an assortment with substitutable products are presented. Secondly, the same is done for an assortment with complementarity effects.

4.4.1 Optimizing an assortment accounting for substitution effects

As the actual product selection with substitution effects is included in the CCM, less attention is given to the assortment optimization models in this study. This section describes the most frequently encountered CCMs in the literature review and then summarizes how they are used by researchers in the field. Most models were applied to a general retail supply and not a fashion supply chain and the investigated articles are published between 2000 and 2020.

The findings show that utility based models and exogenous models are dominating as used CCMs in the covered articles. However, even though this study looks at substitution, it was noted that some authors choose to take multiple factors into consideration in the CCM, such as pricing, shelf-space and inventory. There is not one single article focusing on how to incorporate substitution behaviour at a mid-term time horizon solely, rather short-term is dominating even though some authors discuss both. Most articles, even though they might focus mainly on the short term, discuss methods that are also applicable also long-term. The articles discussing stock-out based substitution or substitution in an already produced assortment are categorized to the short-term time horizon. Fashion forecasting, which is a part of assortment planning, is not included in the papers discussing CCMs or optimization models.

According to Hübner and Kuhn (2011) the CCMs most frequently used in assortment planning for estimating demand substitution are multinomial logit models (MNL), which are utility based, and different types of exogenous models. However, the MNL model has certain limitations and short-coming that has led authors to consider other utility based models such as the Location Choice Model and the Nested Logit Model (Kök et al., 2006).

In the context of assortment planning, newsvendor models are often recurring. The newsvendor model conceptualizes an optimization problem that sellers can face in the case of varying demand for a product that becomes obsolete by the end of the day, such as newspaper, for which the quantity of product to stock for maximized expected profits must be decided (Petruzzi and Dada, 2011). The optimal solution to this problem is found at the point where the supply quantity makes the expected cost of potential overstock equal to the expected (opportunity) cost of understocking. This model is the source of a vast amount of theories and literature that will not be further discussed but mentioned to give a background to the term.

Utility based models

The MNL model is mentioned by a majority of the authors in the field of assortment planning. The closed-form expression in the MNL makes it an ideal option for modeling consumer choice in analytical settings (Kök et al., 2006). Mahajan and van Ryzin (2001) develop an MNL model that assumes that the consumers choose their preferred product when they see the assortment and if that product is out of stock, no substitution is made. This means that the probability for choosing a product is independent of the inventory status of the other products in the set. Some authors model assortment-based substitution while other authors, like for example Mahajan and van Ryzin (2001) evaluate the problem in an environment with stock-out based substitution (Kök et al., 2014). A similar approach is taken by Vaidyanathan and Fisher (2005) with the difference that their model uses a more general demand distribution and a heuristic to optimize the assortment. Miller et al. (2010) focus their study on optimizing and evaluating a retail assortment for infrequently purchased products. They consider customer preference shifts and develop a choice-model mainly based on the MNL and optimize using a mixed integer, linear programming (MILP). The authors point out their inclusion of both heterogenous MNL utilities and the fact that they also consider how the consumer's choice is affected by the assortment. In order to allow for sudden changed customer preferences, they consider two alternative choice models to the MNL that they present in their paper. Bernstein et al. (2019) propose a cluster-based method for the development of a personalized assortment that focuses on online implementation and real-time data. They apply the MNL model as the underlying consumer choice model.

Although the MNL-model is frequently used in the literature, several authors address its shortcomings. (Kök et al., 2007) states that the model "in its simplest form" creates limitations due to the fact that the "rate of substitution is determined by the utility of the no-purchase option with respect to the utility of the product in S", where S is the product alternatives. This makes the MNL-model overlook critical aspects of the substitution behaviour as two categories of products that can not have the same purchase incidence but different substitution values. Vaagen et al. (2011) also states that a big limitation of the MNL-model is its Independence of Irrelevant Alternatives-property (IIA). This refers to the requirement that the ratio of the choice probabilities must be independent of the choice set. If a new product is added to the assortment, the proportions are altered in regards to the already existing products due to the probability properties in the MNL which are a result of the IAA (Miller et al., 2010). A new product thus "steals" market shares from already existing ones. The IIA property of the MNL makes it less suitable in agile environments with complex characteristics. Palmer (2016) further states that in practice there are limited possibilities for the MNL model to give sufficiently good results. Because of the MNL model's simplicity of prediction, predicting the revenue for a given assortment is quickly modeled for smaller assortments. When the assortment grows and multiple different sets of the assortment must be considered, the model becomes complex and difficult to use for evaluating all different assortments. Some authors, like Mahajan and van Ryzin (2001) therefore propose to compute the optimal assortment more efficiently by setting the hypothesis that all products have the same price. This method allows for easier computations as the number of evaluations decreases. However, using the hypothesis of identical pricing on all products limits the method to a few cases (Palmer, 2016). Miller et al. (2010) discusses the stability of the utility estimates as another potential shortcoming of the MNL. The problem lies in the possibility that the consumer can change his or her preference after seeing the assortment as visiting the store (or website) closer could add additional information about the products (Kahn and Lehmann, 1991). However, this is contradicted by (Simonson, 1999) that states that even when consumers have all disclosed information about products, the choice is not based on clear preferences. Further, this shortcoming is only present in the case where substitution is modeled on a short-term horizon and the products are produced. Castro et al. (2018) approach the substitution problem in assortment planning by using POS data to estimate the substitution probabilities between products. The authors further present a reference point dependent preference structure that eliminates the property of IIA.

As for example (Miller et al., 2010), some authors alter the MNL model to avoid its limitations. Others use alternative utility based models, often the location choice model which is one out of the three models that (Kök et al., 2009) presents in their literature review on assortment planning. The locational choice model can not assume the substitution effect that is a result of the IIA property and allows for any two products to be substituted for one another. Instead, this is only possible for products that are close to each other in the characteristic space and thus have similar properties. By setting locations either near or far apart, the retailer can control the rate of substitution between products (Kök et al., 2016). Ulu et al. (2012) develops a locational choice model and uses a Bayesian framework to model customer preferences in a dynamic assortment setting. The authors focus on how to understand consumers' preferences better, such as color, size, pattern type, etc. They examine different types of existing consumer choice information that the retailer has at hand and find that it is optimal to alternate between exploration and exploitation. To some extent, offering an assortment that leads to short-time loss can be valuable long-term as the knowledge gained can optimize future assortment and in that way generate higher profits in the future (Ulu et al., 2012).

Exogenous demand model

Contrary to the MNL, the demand in an exogenous demand model is aggregated on a product level as opposed to on an individual consumer preference level (Vaagen et al., 2011). Vaagen et al. (2011) discuss the modeling of consumer-directed substitution in quick response supply chains, by approaching the problem on a market level and then proposing an exogenous demand model. Smith and Agrawal (2000) develop an exogenous model that they classify to be a multi product inventory model, hence in this case both inventory levels and substitution are considered. They define their choice set by different ”retail subclasses” (Smith and Agrawal, 2000). In the fashion industry, a subclass could for example be made of a specific type of pants. The authors state that this is in some cases a highly simplified model of consumer substitution behavior but that it ”introduces a level of realism that is currently missing from independent-item multi product inventory models”. Another exogenous model is presented by Rajaram (2001) which uses a nonlinear integer programming model for the assortment choice and an efficient heuristic to solve the problem. (Rajaram, 2001) model maximizes the total expected profits in the choice amongst a subset of products. When testing the model at a fashion retailer specializing in women's apparel the model managed to choose the assortment in a way that significantly decreased overproduction and thereby also deadstock and markdowns. The authors further state that the model managed to reduce lost margins due to stock-outs.

The exogenous model takes substitution probabilities as input, however the literature focuses little on how the required substitution behaviour parameters should be estimated compared to the amount of attention put on the actual models using them. Vaagen et al. (2011) states that available methods for estimating substitution probabilities are often based on inventory and sales transaction data but that it is unclear how the substitution shares can be appropriately estimated. This is for example done by Karabati et al. (2009): the substitution rates are estimated using POS data. Vaagen et al. (2009) further discuss the estimation of the substitution probabilities as a possible problem since they are, according to literature, not directly connected to the newsvendor based inventory and assortment planning models. An inconsistency arises due to the fact that these estimations require dynamic data such as real-time inventory or sales transaction data and in contrast, the nature of most assortment planning models are static (Vaagen et al., 2011). In this case, the optimization is done before the actual stock-out occurs and is different from the case when substitution effects on products are incorporated in assortment planning before production, from a non-inventory perspective. Zara, one of the world's biggest fashion retailers, in contrast to the academic environment, solves this problem by having a quick-response supply chain. The company has learned through a qualitative understanding of market drivers, what assortment updates are needed to be done and manages with their agile supply chain to alter the assortment thereafter (Vaagen et al., 2011). How to effectively translate these qualitative characteristics to numbers and incorporate them into analytical or numerical models is at this moment unclear.

Kök and Fisher (2007) propose a news-vendor model approach for estimating the customer substitution and demand parameters that work even if only sales summary data can be collected. They then solve the assortment planning issue using an iterative optimization heuristic. Hübner et al. (2016) focus their study on assortment planning and substitution behavior for perishable and non-perishable products by following the structure of the model presented by Kök and Fisher (2007). They conclude that even though literature has seen a growing interest in assortment planning there is not yet an effective and efficient solution approach to assortment planning with substitutional effects. Most models can only handle narrow assortments of less than 100 items. Hübner et al. (2016) develop their own model called CAP_SDS that also is based on a multi-item newsvendor model and takes into account both out-of-assortment and out-of-stock. Even though Hübner's et al. (2016) model seeks to diminish shortcomings present in previous models, they also have assumptions that limit their model. It assumes fixed restocking costs and unlimited transportation and capacity.

Apart from the utility based and exogenous models, there are some authors with more recent published articles proposing other approaches. Saberi et al. (2017) uses data fusion techniques and mathematical modeling together with data gathering from Google Trend and Google Correlate to understand trends and thereby model substitution. Srivastava et al. (2020) propose data mining and clustering techniques such as K-means for assortment planning. Their main focus is not on substitution, even though customer preference is taken into consideration they also include constraints such as space and cost. There are also authors like Liao et al. (2017) using fuzzy optimization models and a hybrid genetic algorithm to find an optimal assortment. These approaches do not dominate among the articles yielded from this literature review. However, as they are the most recently published, the use of these techniques seems to be a growing trend.

4.4.2 Optimizing an assortment accounting for complementarity effects

As demonstrated in table 6, there is a consensus surrounding the current state-of-the art AI techniques of solving the analysis of product selection with regards to complementarity effects in the retail industry. To model consumer choices, data mining is utilized to mine association rules between items in an assortment from past POS data (Bai et al., 2015; Gun and Badur, 2008; Brijs et al., 2004; Nafari and Shahrabi, 2010; Chen and Lin, 2007; Agarwal, 2017). Consequently, using the detected associations, the authors suggest different mathematical optimization models to generate the best products to include in the assortment (figure 13). The majority of the papers optimize for maximized profit. The remainder of this section will set the main focus on reporting the techniques and models used to understand consumer choice behaviour and exclude, if any, the optimization model.

All resulting research bases the model development on a short term time horizon. The focus is hence set on optimizing the product selection from an already developed assortment rather than forecasting the product selection for a future assortment. Such short term operations may include store-, inventory-, and shelf space allocation. The results thus suggest there is a lack of research done on integrating aspects of complementarity effects prior to developing a new assortment.

Association Rule Mining

According to Gun and Badur (2008), data mining is a set of automated techniques that are utilized to withdraw unknown information from large databases. Using different criteria, patterns and relationships may be detected. In retail, data mining may yield, inter alia, information surrounding associations and clusters. Within associations, Association Rule Mining (ARM) has proved to be the dominant data mining technique. This is a popular rule-based machine learning method for discovering interesting patterns among different items in a collection of transactions or market baskets. This involves building knowledge regarding purchase patterns, i.e. finding relationships between purchases (Bai et al., 2015). Analyzing complementarity effects, ARM is hence a suitable method.

The ARM approach explores the frequency of items, A and B, occurring together in a transactional database. A and B are itemsets, containing at least one item. The association rules between itemsets are discovered by using two thresholds called *support* and *confidence* (Nafari and Shahrabi, 2010). The support of an association rule indicates how frequent an itemset occurs in the data i.e. the proportion of transactions including both A and B. The confidence is an indication of how often a rule is true, i.e. the proportion of transactions that contains A also contains B (Brijs et al., 2004). A minimum value for support and confidence is defined prior to mining the associations to find frequent itemset. A frequent itemset is thus an itemset whose support is greater than or equal to the value of the minimum support. Frequent itemsets with high confidence is what is searched for.

Brijs et al. (2004) has developed a model, referred to as the PROFSET model for the product selection problem based on product-specific profitability. This model analyzes complementarity effects, considering the profit of both basic and added (i.e. fashion) products, using frequent itemsets obtained from ARM. The researchers' conclude that their proposed model is able to select products that are interesting for the retailer in terms of both qualitative, i.e. including certain mandatory items in the assortment to remain the business image, and quantitative, i.e. minimum profitability requirements, criteria. Secondly, the retailer may quantitatively analyze the profitability impact of the product assortment decisions proposed by the model. However, the model is simplifying the concept of profit allocation to the frequent itemsets. This means that the whole profit of a transaction is owed to that frequent itemset, and that if the model does not select one of the items in the itemset {A,B}, all related profits to the set are lost. This does not reflect the reality as customers do not always purchase certain product combinations intentionally. A fraction of the sales related to that itemset may be recovered, and will depend on the availability of substitute products in the store or nearby area.

Gun and Badur (2008) improves the profit allocation approach used in the PROFSET model of Brijs et al (2004). They argue that it is more important to understand what the trigger of the specified sales transaction is; i.e what are the effects of other items in a sales transaction of a specified item? In their model, the profit allocation is made iteratively. This implies that for each transaction containing frequent itemsets, the profit is redistributed over the specific items that are included in those frequent itemsets. This is done by utilizing the support value to sort the rules and itemsets, allocating the profit share to each item accordingly. Additional improvements include an increased implementation of business constraints into the decision system, such as product limits per category to support diversity. A minimum threshold of sold quantities within a category is also implemented. Moreover, the ARM methodology takes category dependency into account by making the association analysis at the category level to understand what categories are purchased together. Lastly, the contribution of Gun and Badur (2008) considers volume generation of items independent of their sales revenue. This aids retailers in keeping volume generating items, with regards to quantity rather than revenue, in the assortment.

Chen and Lin (2007) have also improved the PROFSET model by introducing a multi-level association rule mining model to capture a higher level of abstraction of the products, including category, subcategory (style for example) and items. By mining multi-level association rules, retailers can allocate the product categories, subcategories and items with regards to their associations and profits. With the estimated gross margin of frequent item sets, the profit of a selected product mix can be derived. The assortment model of Chen and Lin (2007) also implements a sophisticated method of adding and analysing the impact of added, i.e. fashion, products by using the association between product items.

Fuzzy Expert Systems

Wong et al. (2012) has developed a hybrid intelligent system called Intelligent Product Cross-selling System (IPCS). The IPCS is designed to assist fashion designers to optimize the mix-and match pairs of items; increasing sales through cross-selling. Before the season starts, the IPCS incorporates expert knowledge to propose initial recommendations regarding products that demonstrate high potential in achieving complementarity effects. At its core, the goal of the IPCS is to optimize cross-selling by comparing the degree of importance of the item attributes with one another. The study demonstrates that the attributes that were important to consider when cross-selling products (with a level of importance) were: 1) type, color (extremely high), 2) size and occasion (very high), 3) length, texture, trend and silhouette (high) and 4) pattern (medium). Price is not taken into consideration since the focus of the product is its features in the context of complementarity and mix-and-match purpose.

The IPCS consequently integrates a rule-based expert system and a fuzzy screening technique. Fashion designers define the rules to be used, such as matching satisfaction levels of different items and the above-mentioned importance of each attribute. The integration of fuzzy logic is effective in treating the imprecise and inherent subjectiveness of the designers. The inference engine, carrying out the reasoning processes in which the expert system reaches a solution, is consequently evaluating the matching performance of each product attribute and the overall performance of fashion pairs. This is done by assigning each item pair a Fashion Matching Satisfaction Index (FMSI). The pairs with the highest FMSI is then suggested to be used for the purpose of cross-selling products.

Wong et al. (2012) proves that the time required for the initial matching, previously performed by fashion designers' intuition, may be shortened using the IPCS. It has thus contributed with a more standardized approach of cross-selling techniques in the fashion industry. The research also proceeds to implement the IPCS in stores. In fitting rooms, RFID technology is used to send real-time data to the IPCS system regarding the customer's current chosen product. Installing digital interfaces, the IPCS consequently recommends other articles based on the FMSI.

6. Discussion

This section contains a discussion of the reviewed AI models' applicability at the case company as well as their feasibility when integrated in the thesis' suggested framework of the assortment planning process. To challenge the approach of such static assortment planning, the aspects of dynamic assortments and quick-response supply chains are further discussed.

The case study investigating the utilization of AI supported SCA at a major fashion retailer concludes that the degree of such implementation targeting pre-production processes in the "Source" and "Make" blocks of the FSC is low. This includes all levels of decision-making, i.e. operational, tactical and strategic. Proceeding the discussions with the case company regarding this matter, these findings suggest that the majority of AI initiatives have been concentrated in the latter processes of the FSC, targeting damage control rather than damage prevention. This includes, inter alia, sophisticated AI solutions for markdowns of non-sellable products in order to reduce daunting losses. However, despite the short term savings achieved by such solutions, the long term gains derive from reducing the bullwhip effect and increasing the alignment between the supply and marketplace demand by improving the critical business decision making in the initial stages of the fashion supply chain. Following these findings, the case study reveals that the interest and ambition for a higher adoption of AI supported SCA at such initial FSCM processes is strong as several initial initiatives and discussions for increased integration exist. One such area of interest and high priority at the fashion retailer is the procedure of planning a new apparel assortment. To achieve the objective of increasing the alignment between supply and marketplace demand in this early-stage FSCM process, the SLR of the thesis discovers that the assortment can be improved by early integration of detected customer needs, enabling accurate forecasting of both demand and product selection. In particular, using AI techniques that are exploiting big data to 1) forecast mid-term (one year to - a season) category sales levels for markets, and 2) determine the role and attractiveness of each category, and specific item, in the assortment by modelling substitution and complementarity effects should be prioritized in the FSCM processes of "Plan Production" and "Plan assortment".

Forecasting category sales demand is dominated by the AI techniques of machine learning, including computational intelligence of the feedforward artificial neural networks and the use of fuzzy logic. This trend is in line with MIT's review of the development of AI in recent years demonstrating a rise in the popularity of machine learning in the 2010s, and ANNs in particular in 2015, due to the massive growth of big data (Hao, 2019). Despite the successful result of ANNs and oftentimes superior performance in contrast to the linear models, the technique is however criticized for being time-consuming due to, inter alia, slow convergence speed (Choi et al., 2014; Xia et al., 2012; Wong and Guo, 2010; Huang et al., 2006). This statement should however be challenged. In the last decade, the availability of cheap computing power and GPUs has enabled machines to train networks in reasonable time frames (Dilmegani, 2019).

At times, there also exists a raison d'etre for more basic forecasting models such as linear regression models, since the demand characteristics of a fashion product evolve over time;

causing the accuracy of different methods to change. Methods that perform well under stable demand conditions may fail when demand fluctuations occur. To allow for such variations, the trend in the latest years of developing forecasting systems tends to move towards combining several AI techniques and different levels of complexity in the models. This seems to be the superior approach as it is concluded that the combined forecasting models achieve better accuracy than any of the individual forecasts. It is however important to note that different works never achieve a benchmark with real forecasts of retailers, which could be the only criteria for retailers in the decision of implementing the model or not. Moreover, regardless of the robustness of the techniques used, all models' success relies on the existence, relevance and reliability of data of the fashion retailer. This is oftentimes a common, and major, cause of inaccurate forecasts in the fashion industry (Thomassey, 2010). Thus, the fashion retailer must complement sophisticated models and systems with efficient technological infrastructures and platforms to enable collection of the required data; meeting the desired level of the three dimensions of volume, velocity and variety. For optimal integration and maximized benefits of utilizing AI supported SCA, it is furthermore desirable that all supply chain members are interconnected in a technological ecosystem enabling a) a seamless flow of data shared between all members, and b) sharing of the models insights and recommendations for all members to be up-to-date and aligned on the decisions that are to be made.

Moreover, as suggested in the framework of the assortment planning process, see figure 5, the forecasting of category demand and product selection should preferably be complemented with a trend forecasting model. This allows the fashion retailer to make better forecasts by a) studying market conditions and consumer buying behavior early on, b) evaluating current fashion trend information, and c) discovering street fashions of target customers (Frings, 2002). Conclusively, before developing sales forecasts, the fashion retailer needs to firstly identify their target customers, understand their purchase behaviour and gain knowledge of the trends affecting the markets from both a long-term and short-term assortment planning perspective. Consequently, the fashion retailer may integrate such critical learnings and aspects in the forecasting models of expected sales. This would potentially increase the accuracy of the forecasts since information about future market and customer behaviour is considered to a greater extent.

The literature reveals that substitution and complementarity are without a doubt important to consider in product selection to best cater to the needs and wishes of the consumer. However, few articles develop models for product selection that simultaneously consider both aspects to the same extent. It is concluded that the consumer choice models, including the utility based and exogenous models, demonstrate successful results when modeling substitution effects in retail assortments. Discussion with the case company regarding the result of this study revealed the utility based models are not used in any decision process in the supply chain. However the current models used today for different customer recommendations, e.g in emails, online etc. are similar to the utility based models as they also have the ability to model customer specific preferences. Hence, there is a possibility that the utility based models could work for modeling how to best capture consumer behavior and thereafter make consumer specific recommendations. Further, looking at the entire framework of the assortment planning process it is believed that the exogenous demand models used in the assortment planning are similar to the forecasting models used on category sales level, with the difference of time and product aggregation level. Both models aim to forecast consumer choice but on different time-horizons. Thus, it is the belief of the authors of this thesis that valuable insights on how forecasting consumer choice behaviour can be gained from the literature on both category sales planning and assortment planning.

Furthermore, using machine learning in combination with data mining and association rule mining to understand consumer purchase behaviour is efficient when modelling complementarity effects in the retail industry (Bai et al., 2015; Gun and Badur, 2008; Brijs et al., 2004; Nafari and Shahrabi, 2010; Chen and Lin, 2007; Agarwal, 2017). Since these models discover patterns and hidden information without either human intervention, nor industry specifications, it is believed that the same methodology could be transferred in the modelling of complementarity effects in the fashion industry. However, important to consider when utilizing association rule mining is the business applicability of the mined purchasing patterns. A pattern in the data is interesting only to the extent in which it is utilized in the decision-making process of the business to increase the utility; whether it be the aim of increased profitability or other business parameters (Cabena et al., 1998). Hence, it is crucial that the fashion retailer clearly investigates and specifies the business constraints and targeted objectives that are to be integrated in the models prior to developing a new apparel assortment. To shed additional light on the business perspectives in combination with sophisticated technologies, the question of the optimal assortment breadth and depth transpires. From a complementary perspective, it might be proven to be superior to develop and produce a rather wide assortment including many categories. However, a wider assortment might be more costly for some retailers due to for example a less specialized production line. Hence, the resulting business profitability might not be improved despite the seemingly profitable item combinations of a broad assortment.

The framework presented in this paper maps the two aspects of substitution and complementarity as part of the forecasting of the product selection process, see figure 5. Hence, according to this, substitution and complementary effects are to be considered at all times prior to production of any physical assortment. However, the investigated articles in this thesis' SLR focus mainly on how to deal with substitution and complementarity on a short-term perspective, i.e. after the assortment plan is set, to optimize operational activities such as marketing and handling of stock-outs. This is problematic in two ways. Firstly, when combining several models and implementing them at different time horizons in a waterfall type process, the problem of suboptimization arises. This refers to the practice of focusing on one component of a total, making changes with the intention of improving this one component while ignoring the effects of the remaining system components. It is thus required that all recommended models co-exist and that agile model development, at all time horizons, is adhered to. Secondly, the models for substitution and complementarity effects presented in this thesis may be considered somewhat obsolete for the purpose of such an agile, more long-term, strategic and tactical forecasting of product selection. It is however believed that the concepts of the reviewed models can inspire model development at the earlier stage in the FSC, integrating accurate AI techniques and exploitation of big data of high volume, velocity, and variety. Such data includes, inter alia, 1) historical POS-data, and 2) granular data on the product attributes of the new products to be included in the assortment. The former type of data could be utilized to a) use machine learning incorporating consumer choice models to understand underlying patterns on how consumers historically have substituted and complemented products, and b) learn what product attributes are critical in such consumer behaviour. Integrating such methodologies in the strategic and tactical process of forecasting and consequently planning the assortment is believed to decrease the risk of stock-outs, overproduction, and unwanted products. Thus the operational activities related to such damage control, requiring heavy resource investments, could be mitigated and reduce both costs and waste. Conclusively, it is believed that the best-case scenario would be to use AI techniques to 1) forecast substitution and complementarity effects before producing the assortment by adapting the models to be implementable at a mid term horizon, and 2) optimize inventory and store assortments post-production by applying discussed models on a short-term basis.

However, regardless of the robustness of the techniques used for forecasting product selection, the static assortment planning strategy that entails assortment decisions long in advance without any major assortment modification in-season may fall short. The assortment risks becoming outdated or miss calculated as trends and demand in the fashion industry change rapidly. It is believed that the best strategy for a fashion retailer going forward is to minimize the time delta between the development and launch of a new assortment by adapting a QR supply chain. Such a supply chain design puts emphasis on, and allows for, the strategy of dynamic assortment planning, as suggested by Caro and Gallien (2010), with shorter lead-times and quicker time to market. The importance of adapting to the accentuated volatile and dynamic fashion industry is a consequence of the ever-increasing fierce competition and customer demands. A critical share of fashion retailers are either redesigning or entering the industry with a supply chain employing a QR strategy. This namely enables the fashion retailer to implement dynamic assortment planning; increasing the ability to more efficiently tackle the volatile market. Incorporating the effects of substitution and complementarity on a real-time in-season assortment entails collecting real-time data to quickly alter the assortment while it is available on the market; further aligning the supply with the current customer demand and purchasing behaviour. The utilization of real-time data to analyze the performance of assortment can significantly enhance the decision-making tied to assortment optimization. In contrast to the retail industry, the seasonality and trends in the fashion industry causing distinct assortment variations in each new season makes it difficult, and non-optimal, to equate historical products to new ones. Thus, it is increasingly critical to incorporate techniques and strategies taking advantage of real-time data in the quest of optimizing the fashion assortment.

Valuable real-time big data for such objectives consists of several types, including a) real-time POS, 2) website clicks, 3) in-store RFID-data tracking the customer interaction with products, and 4) social media. Building sophisticated models utilizing such data may generate valuable insights to the fashion retailer regarding consumer choice behaviour in real-time while realizing increased abilities for exploration purposes. Naturally, as previously discussed, implementing dynamic assortment planning utilizing these methods requires strategic, tactical and operational alterations of the entire FSC. However, the critical question surrounding the survival-, growth- and profit potential of an inflexible and non-agile fashion retailer in today's fashion marketplace cannot be discarded.

As only one case company was investigated, it is difficult to generalize these findings. However, by interpreting the literature, various fast fashion retailers have managed to shift towards a higher degree of AI implementation by either being agile and innovative or being internet born. Being data driven in combination with a QR supply chain allows the retailer to achieve higher accuracy and alignment between supply and demand at a shorter period of time. This in turn creates cost-savings, less overproduction and higher customer satisfaction. The rise of QR strategies in FSCs disrupt the traditional supply chain strategy of offshoring production to low-cost countries. For the case company studied in this thesis, the production would need to move closer to the market in order to realize the strategies of a QR driven supply chain and monetize on fast delivery that satisfies the rapidly shifting customer demand. However, this comes with higher production costs that must be put in relation to potential financial benefits. Further, if, as in this case, the fashion retailer is a global player, the potential growth of the low-cost countries' markets must be recognized. Moving production might decrease the chance of gaining substantial market shares if these markets are to grow in the future. Hence, to not lose one's position in these markets it might be strategically beneficial to optimize the location of production to be closest to the current and up-and-coming markets.

7. Conclusion

This chapter concludes the findings of this thesis by first presenting the research questions and how they were approached. Following that, the findings on AI supported SCA in fashion supply chain management are presented. Consequently, a brief summary of the most common AI techniques and models used to support the thesis' suggested approach of the assortment planningprocess in the fast fashion industry is presented.

The purpose of this thesis was two-fold, including 1) to synthesize the knowledge regarding the industrial level of implementation of AI supported supply chain analytics in the FSCM decision making, and 2) to report the literature's body of knowledge of AI techniques- and models implementable in the process of planning an apparel assortment.

To fulfill its purpose, the thesis investigated the following questions:

1) What supply chain management processes of a fast fashion retailer are lacking AI supported supply chain analytics in their decision making?

2) What AI techniques- and models are used to support the assortment planning process in the retail and fashion industry according to the literature?

The first question was answered by conducting a case study at a global fashion retailer, while the second question was examined through a systematic literature review.

The findings of the thesis suggests that the use of AI supported supply chain analytics in the "Source" and "Make" block of fashion supply chain management is rather low across all levels of decisions, i.e. operational, tactical and strategic, at the investigated fashion retailer. The majority of AI solutions have thus far been prioritized and implemented in the later stages of the chain, i.e. post production, focusing on damage control rather than damage prevention. Despite the short term proceeds that is achievable by putting out fires in the end processes of the supply chain, the real long term gains are realized by reducing the bullwhip effect by increasing the alignment of supply and demand in the initial stage of the chain. Even though the current AI supported supply chain analytics is limited in this phase, the studied fashion retailer has initiated initiatives targeting AI model development in some crucial processes pre-production, including quantifying, purchasing material and developing the apparel items. Despite the long way to go until this is fully implemented, the potential benefits of an increased implementation of AI throughout the entire chain is thus clear and desired by the fashion retailer. The goal is to implement AI supported supply chain analytics for all business decisions by 2025.

The second research question of this paper consequently addressed the retail- and fashion industry literature's applications of AI techniques in one of the major decision making procedures pre-production: planning the apparel assortment overlapping the processes of "Plan Production" and "Plan assortment". The study's developed approach and framework used to tackle this combined process focused on two major blocks of planning; namely category sales planning and assortment planning.

The review of the literature demonstrates that there is extensive research done in the field of AI supported activities within category sales planning in the fashion industry; especially forecasting category demand on a mid- and short term horizon. The dominating AI techniques used is machine learning, including computational intelligence of the feedforward artificial neural networks and the use of fuzzy logic. At times, there also exists a raison d'etre for more basic forecasting models such as linear regression models, since the demand characteristics of a fashion product evolve over time; causing the accuracy of different methods to change. Methods that perform well under stable demand conditions may fail when demand fluctuations occur. To allow for such variations, models combining several AI techniques and models have been developed. It is concluded that the combined forecasting models achieve better accuracy than any of the individual forecasts. It is however important to note that different works never achieve a benchmark with real forecasts of retailers, which could be the only criteria for retailers in the decision of implementing the model or not. Moreover, regardless of the robustness of the techniques used, all models' success relies on the existence, relevance and reliability of data of the fashion retailer. This is oftentimes a common, and major, cause of inaccurate forecasts in the fashion industry (Thomassey, 2010). Lastly, no forecasting model is integrated with trend forecasting models as suggested by the thesis' framework. This would potentially increase the accuracy of the forecasts since information about future market and customer behaviour is considered to a greater, and more precise, extent. More research in this field is thus desired.

The literature of AI techniques, including machine learning and data mining, used to model substitution and complementary effects in the literature is applied in both the retail- and fashion industry. The discovered AI techniques found in the retail industry may inspire similar modeling in the fashion industry since the concepts and methods for modelling substitution and complementarity effects, including consumer choice modelling, are similar regardless of the industry. The most common consumer choice models used to capture the effect of substitution and optimizing the assortment thereafter are utility based models and exogenous demand models. These findings are in line with what was concluded by Kök et al., 2006. There are many alterations and versions of these models fitted to the specific needs that a retailer can have. However, even though these are studied methods, the fashion specific articles have shortcomings caused by the large number of products and varieties, as well as the dynamic characteristics of the fashion industry. This causes challenges as many models are static and insolite when handling big assortments. Moreover, association rule mining is mainly used to model complementarity effects amongst purchases in an assortment. Despite this effective technique, business constraints must be carefully considered and accounted for when putting the models to work. The successful purchase patterns between both items and categories must be mined and prioritized, by the retailer itself, in such a way that the costs of implementing the suggested breadth, i.e. number of categories, versus depth, i.e. number of individual items, to realize the discovered complementarity effects are 1) profitable for the specific retailer's production strategy, and 2) do not distract the business image of the retailer.

In the assortment planning, reviewed articles indicate that substitution and complementary effects are the most accounted for factors when modelling optimal product selection. Despite this, there is limited research done on models considering both effects simultaneously. Moreover, the majority of the papers consider these effects solely on a short term horizon, targeting issues such as stock-outs without accounting for their impact prior to developing and producing a new assortment. This has several implications for the problem of sub optimization. Developing models in isolation, implementing them at different points in time, might be suboptimal as they risk ignoring effects impacting the entire system. Hence, despite the valuable contributions of the literature's suggested models, including both blocks of category sales- and assortment planning, there is a need to investigate how all reviewed models are to be integrated in one individual form.

One of the main contributions of this paper is the established framework (figure 5) developed from the literature as well as the synthesisation of the body of knowledge on applicable AI techniques in the assortment planning process. Further, the thesis discusses the practitioner's view and utilization of the suggested AI techniques- and models, thus bridging the gap between industry and academia. For practitioners, this thesis may inspire increased utilization of AI and big data in the assortment planning process. By employing the suggested approach in the procedure of defining a future assortment, implementing the reviewed AI techniques- and models, the alignment between supply and marketplace demand is likely to increase. For academia, the findings can inspire new research that is more in line with the industry by emphasizing the need for one holistic approach adapted to the characteristics of the fashion and a dynamic assortment planning.

Although the findings are considered valuable, the thesis has some limitations. First of all, having only investigated one company in the fashion industry, the generalizability of the findings concerning the level of industrial implementation of AI supported supply chain analytics pre-production is limited. For further studies, it would be valuable to investigate additional fashion retailers to gain deeper and broader insights into the issue. This would reveal a) additional learnings about the industrial AI maturity to reveal potential lack of knowledge and skills, b) the obstacles for increased implementation such as limited amount of data and deficient technological infrastructure and ecosystems, and c) the areas where academia may learn from the industry to direct research in the desired direction and excel the adoption rate of AI support in critical business decisions. Moreover, another limitation is the ignorance of the economic and sustainability aspects of where increased AI support in such decision making renders most business value. It is thus desirable to incorporate an evaluation method assessing such dimensions amongst the identified FSC processes- and decisions to further establish prioritized use cases of AI supported SCA.

Secondly, only two databases were used for the systematic literature review's article generation while other valuable databases could be relevant. Furthermore, no articles in languages other than English were utilized. Surely, there may be valuable research in other languages. Also, despite the rigorous research targeting the relevant taxonomy of AI in the fashion industry for article retrieval, the study might have missed some valuable research due to a different taxonomy being used by other researchers.

Lastly, despite the valuable contribution of this thesis, it is limited to the process of the static assortment planning taking place prior to the development of an assortment. For full assortment optimization, it should be complemented by processes for altering the assortment in real-time, i.e. dynamic assortment planning. Collecting real-time data on the items' market performance, it can be analyzed to generate business insights regarding what products to remove from, or add to, the assortment. Compensating for missed out fashion trends or misaligned demand forecasts can thus be realized to help further improve the alignment between the supply and marketplace demand. Due to the ever increasing competition- and customer demands, the shift towards dynamic assortment planning in quick response supply chain strategies is becoming increasingly apparent and desirable for fast fashion retailers. This also includes implementing supply chain processes that increase the accuracy of the offered assortment by minimizing the time between producing a new apparel assortment and launching it in the market. This is likely to reduce waste and costs while increasing revenues. However, the requirements of realizing this strategy successfully demand vast amounts of high quality historical- and real time data, equally satisfactory technological infrastructure- and ecosystem for collecting such data as well as sophisticated AI techniques and models to analyze and generate the desired insights and optimal guidelines for the fashion retailer to exploit. Being at the dawn of a new technological era, the fashion industry has hence yet much to wait in its innovative evolution towards a more sustainable marketplace.

Future research

For further research, several areas are suggested. Firstly, there seems to be a gap between how the literature portrays the implementation of AI in the fashion industry compared to how it is actually used in the industry today. One reason for this might be the lack of more recent articles from the latest years. Overall, all AI techniques are discussed in the literature except deep learning. In the last decade, the technique of deep learning has received increased attention. This may be explained by the soaring usage of ANNs as a result of the exponential growth of big data. It has also been stated by industry experts that deep learning is an attractive technique gaining momentum. Thus, the industry would benefit from increased research in such progressive AI techniques areas while researchers may gain traction in their field through the increased alignment with the industrial reality. More exhaustive studies might also show that the gap between industry and academia is less existent than indicated since AI implementations in the industry can be seen as a competitive advantage and thus they are kept from being subject to research.

Secondly, another identified gap in the literature is the lack of existing models for forecasting product selection to understand complementarity and substitution effects in the early stages of assortment development. Most of the studies investigated in this thesis targeted short term time horizons of existing assortments, with the main objective of optimizing inventory levels, shelf-space allocation, stock-outs and marketing activities. It is believed that the alignment of the supply and marketplace demand in the FSC would be increased by not only integrating consideration of substitution and complementarity effects at a finished assortment on a short-term horizon but also at a mid-term time horizon before defining the final items to be included in the assortment. This could potentially enable the fashion retailer to optimize the combination of products within the assortment; ensuring that all products contribute to acceptable sales levels.

Lastly, future research may investigate solutions for solving the suggested approach of assortment planning by consolidating the reviewed AI models into one single model. Namely, this implies simultaneously incorporating consumer choice behaviour models, assessing both substitution- and complementarity effects, and fashion forecasting in the forecasting system of category and item-level demand. Thus, the risk of suboptimization in the product selection process of an assortment may be mitigated.

9. References

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