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Big data management using artificial intelligence in the apparel supply chain: Opportunities and Challenges

La gestion du big data par l'intelligence artificielle dans la chaîne d'approvisionnement de l'industrie textile : Opportunités et défis

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I may not have gone where I

intended to go, but I think I have

ended up where I intended to be.

—Douglas Adams

Abstract

Big data management using artificial intelligence in the apparel supply chain: Opportunities and Challenges

Over the past decade, the apparel industry has seen several applications of big data and artificial intelligence (AI) in dealing with various business problems. With the increase in competition and customer demands for the personalization of products and services which can enhance their brand experience and satisfaction, supply-chain managers in apparel firms are constantly looking for ways to improve their business strategies so as to bring speed and cost efficiency to their organizations. The big data management solutions presented in this thesis highlight opportunities for apparel firms to look into their supply chains and identify big data resources that may be valuable, rare, and inimitable, and to use them to create data-driven strategies and establish dynamic capabilities to sustain their businesses in an uncertain business environment. With the help of these data-driven strategies, apparel firms can produce garments smartly to provide customers with a product that closer meets their needs, and as such drive sustainable consumption and production practices.

In this context, this thesis aims to investigate whether apparel firms can improve their business operations by employing big data and AI, and in so doing, seek big data management opportunities using AI solutions. Firstly, the thesis identifies and classifies AI techniques that can be used at various stages of the supply chain to improve existing business operations. Secondly, the thesis presents product-related data to create a classification model and design rules that can create opportunities for providing personalized recommendations or customization, enabling better shopping experiences for customers. Thirdly, this thesis draws from the evidence in the industry and existing literature to make suggestions that may guide managers in developing data-driven strategies for improving customer satisfaction through personalized services. Finally, this thesis shows the effectiveness of data-driven analytical solutions in sustaining competitive advantage via the data and knowledge already present within the apparel supply chain. More importantly, this thesis also contributes to the field by identifying specific opportunities with big data management using AI solutions. These opportunities can be a starting point for other research in the field of technology and management.

Keywords: Big data management, artificial intelligence, apparel supply chain, personalized offerings, data-driven strategies.

Abstrakt

Big Data Management och användning av artificiell intelligens i klädförsörjningskedjan: Möjligheter och utmaningar

Under det senaste decenniet har användning av big data och artificiell intelligens använts för att hantera olika affärsproblem inom klädindustrin. I takt med den ökade konkurrensen på marknaden och kundernas efterfrågan på mer individanpassade lösningar, letar klädföretag efter nya sätt att förbättra affärsstrategier så att de kan bli snabbare och mer kostnadseffektiva. Big data management ger möjligheter för klädföretag att få kontroll över sin leverantörskedja och identifiera big data-resurser som är värdefulla, sällsynta, svåra att kopiera och kan användas för att skapa datadrivna strategier samt förstärka dynamiska förmågor i en osäker miljö. Med hjälp av dessa datadrivna strategier kan klädföretag på ett smartare sätt producera kläder för att ge kunderna en produkt som är närmare deras behov, och som sådan, driva hållbar konsumtion och produktionsmetoder.

I den här kontexten undersöker avhandlingen fördelarna för klädföretag att använda big data och artificiell intelligens för att förbättra sin affärsverksamhet och samtidigt söka möjligheter med big data management med hjälp av AI-lösningar. Först identifierar och klassificerar avhandlingen AI-tekniker som kan användas i olika delar av leveranskedjan för att förbättra den befintliga affärsverksamheten. För det andra presenterar avhandlingen produktrelaterad data för att skapa en klassificeringsmodell och designregler som kan vara till gagn för att ge personliga rekommendationer eller kundanpassningar som möjliggör en bättre shoppingupplevelse. För det tredje tar den fram förslag baserat på bevis från branschen och befintlig litteratur, som kan vägleda chefer i att utveckla datadrivna strategier för att förbättra kundnöjdheten genom individanpassade tjänster. Denna avhandling visar att effektiviteten hos datadrivna analytiska lösningar via befintlig data och kunskap kan leda till konkurrensfördelar. Framför allt bidrar denna avhandling till fältet genom att identifiera specifika möjligheter med big data management med hjälp av AI-lösningar. Dessa möjligheter kan vara en utgångspunkt för andra forskningsarbeten inom teknik och management.

Nyckelord: Big data management, artificiell intelligens, klädförsörjningskedja, personifierade erbjudanden, data-drivna strategier

Résumé

La gestion du big data par l'intelligence artificielle dans la chaîne d'approvisionnement de l'industrie textile : Opportunités et défis

L'industrie de l'habillement a bénéficié, au cours de la dernière décennie, de l'application de big data et de l'intelligence artificielle pour résoudre divers problèmes commerciaux. Face à la concurrence accrue sur le marché et aux attentes des clients en matière de personnalisation, ces industriels sont en permanence à la recherche des moyens d'améliorer leurs stratégies commerciales afin d'accroître leur rapidité et leur rentabilité. A cet égard, les solutions de gestion de big data offrent aux enseignes de la distribution textile la possibilité d'explorer leur chaîne d'approvisionnement et d'identifier les ressources de données importantes. Ces ressources précieuses, rares et inimitables permettent de créer des stratégies axées sur les données (data-driven) et d'établir des capacités dynamiques à maintenir dans un environnement commercial incertain. Grâce à ces stratégies data-driven, les enseignes de prêt-à-porter sont en mesure de confectionner des vêtements de façon intelligente afin de fournir à leurs clients un article adapté à leurs besoins et, par conséquent, d'adopter des pratiques de consommation et de production durables.

Dans ce contexte, la thèse étudie les avantages de l'utilisation de big data et de l'intelligence artificielle (IA) dans les entreprises de l'habillement, afin d'améliorer leurs opérations commerciales tout en recherchant des opportunités de gestion de big data à l'aide de solutions d'IA. Dans un premier temps, cette thèse identifie et classifie les techniques d'IA qui peuvent être utilisées à différents stades de la chaîne d'approvisionnement pour améliorer les opérations commerciales existantes. Dans un deuxième temps, des données relatives aux produits sont présentées afin de créer un modèle de classification et des règles de conception susceptibles de fournir des recommandations personnalisées ou une personnalisation permettant une meilleure expérience d'achat pour le client. Dans un troisième et dernier temps, la thèse s'appuie sur les évidences de l'industrie de l'habillement et la littérature existante pour suggérer des propositions qui peuvent guider les responsables dans le développement de stratégies data-driven pour améliorer la satisfaction du client par des services personnalisés. Enfin, cette thèse montre l'efficacité des solutions analytiques basées sur les données pour maintenir un avantage concurrentiel grâce aux données et aux connaissances déjà présentes dans une chaîne d'approvisionnement de l'habillement. Plus précisément, cette thèse contribue au domaine textile en identifiant des opportunités spécifiques de gestion de big data à l'aide de solutions d'intelligence artificielle. Ces opportunités peuvent être une source de référence pour d'autres travaux de recherche dans le domaine de la technologie et de la gestion.

Mots clés: Gestion big data, intelligence artificielle, chaîne d'approvisionnement de l'habillement, personnalisation, stratégies basées sur les données (data-driven).

摘要

基于人工智能的服装供应链大数据管理：机遇与挑战

在过去的十年里，大数据和人工智能已经在服装业处理各种商业问题方面得到了应用。随着市场竞争的加剧和顾客个性化需求的增加，服装企业不断寻求改进经营策略的手段，以提高反应速度和成本效益。在这个领域，大数据管理解决方案可以为服装公司提供对自身供应链进行分析的机会，并识别有价值的、稀有的和不可模仿的大数据资源，并用来创建数据驱动的经营策略，建立动态的能力来应对不确定的商业环境。在这些数据驱动策略的帮助下，服装公司可以实现智能化服装生产，为客户提供与其需求更加匹配的产品，从而推动可持续的消费和生产。

本论文研究分析了服装企业采用大数据和人工智能的优势，用以改善其业务运营，同时利用人工智能解决方案寻找大数据管理的机会。首先，本文对可用于供应链不同阶段的人工智能技术进行了分析，并对其进行了分类，以改善现有的商业运作。其次，本文提出了产品相关的数据，在此基础上建立了分类模型和设计规则，可以为客户提供个性化推荐或定制化服务，为顾客提供更好的购物体验。第三，本文在行业实例和现有文献分析的基础上，提出了指导管理者制定数据驱动战略的建议，通过个性化服务提高客户满意度。最后，本文通过服装供应链已有的数据和知识分析，展示了数据驱动的分析解决方案维持竞争优势的有效性。本论文通过使用人工智能解决方案识别大数据管理的具体机会，为该领域的技术进步做出了贡献。这些机会可以作为技术和管理领域其他研究工作的起点。

关键词：大数据，人工智能，服装供应链，个性化服务，数据驱动策略

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Sheenam Jain

Borås, Sweden, August 2020

List of Appended Articles

This thesis is based on four articles enclosed at the end of this manuscript, and which are also referred to as papers or studies in this thesis.

Article A:

Giri, C., **Jain, S.**, Zeng, X., and Bruniaux, P., 2019. A Detailed Review of Artificial Intelligence Applied in *the Fashion and Apparel Industry*. *IEEE Access*, 7, pp.95364–95384.

Impact Factor 3.745, Scientific level 1 in Nordic list

Article B:

Jain, S. and Kumar, V., 2020. Garment Categorization Using Data Mining Techniques. *Symmetry*, 12(6), p.984.

Impact Factor 2.645, Scientific level 1 in Nordic list

Article C:

Jain, S., Peterson, J., Chen, Y., Wang, L., Zeng, X., and Bruniaux, P. (20xx) Modeling the knowledge of experts in the apparel industry using artificial intelligence. Submitted to *Sustainability*

Impact factor 2.576, Scientific level 1 in Nordic list

Article D:

Jain, S. and Sundström, M. (20xx). Toward a conceptualization of personalized services in apparel e-commerce fulfillment. Submitted- first revision to *Research Journal of Textile and Apparel*.

Scientific level 1 in Nordic list

List of Author Contributions

Article #	First Author	Second to the last author	Responsibility
A	Chandadevi Giri (CG), **Sheenam Jain (SJ)**	Pascal Brunaiux (PB), Xianyi Zeng (XZ)	SJ is the corresponding author. CG and SJ are equal contributing authors and conceptualized the study together with the help of PB and XZ. CG and SJ formulated the research framework, conducted the review process, and wrote the manuscript. SJ was responsible for the classification of apparel supply-chain stages and business-to-business (B2B) and business-to-consumer (B2C) activities, while CG was responsible for the classification of AI methods.
B	**Sheenam Jain**	Vijay Kumar (VK)	SJ is the first and corresponding author of the manuscript. SJ conceptualized the study with the help of VK. VK contributed to finalizing the methodology. SJ and VK conducted the experiment and compiled the results. SJ wrote the manuscript. VK contributed to analyzing the results and refinement of the manuscript.
C	**Sheenam Jain**	Yan Chen (YC), Lichaun Wang (LW), Joel Peterson (JP), Pascal Bruniaux, Xianyi Zeng	SJ is the first and corresponding author of the manuscript. SJ conceptualized the study with the help of PB and XZ. SJ conducted the experiments with the help of JP. SJ formulated the framework of the fuzzy inference system and did the programming. SJ wrote the manuscript. YC and LW helped SJ in the analysis of the results. JP, PB, and XZ contributed to the refinement of the manuscript and the development of the conclusions and discussions section.
D	**Sheenam Jain**	Malin Sundström (MS)	SJ is the first and corresponding author of the manuscript. SJ conceptualized the study with the help of MS. MS conducted the interviews with the retailers in Swedish, analyzed the interviews, and prepared transcripts. SJ conducted the literature study, combined the ideas from the interviews to formulate propositions and wrote the article. MS contributed to finalizing the framework and refinement of the manuscript.

Conference Publications

S. Jain, J. Bruniaux, X. Zeng, and P. Bruniaux, Big data in fashion industry, *AUTEX 2017*, World Textile Conference, Corfou, Greece, 29–31 May.

S. Jain, J. Bruniaux, X. Zeng, and P. Bruniaux, Knowledge Base Extraction from Fashion Big Data, *CLOTECH 2017, 11th International Conference on innovative materials & technologies in made-up textiles articles, protective clothing and footwear, Lodz, Poland*, 11–14 October.

S. Jain, X. Zeng, P. Bruniaux, M. Sundström, J. Peterson, Y. Chen, and L. Wang, Customer perception of mass customization in textile and apparel industry, *AUTEX 2018*, World Textile Conference, Istanbul, Turkey, 20–22 June.

S. Jain, M. Sundström, and J. Peterson, Mass-Customized Fashion: Importance of Data Sharing in the Supply Chain, *NRWC 2018, 6th Nordic Retail and Wholesale Conference*, Reykjavik, Iceland, 8–9 November.

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1. Introduction

This chapter introduces to the reader the practical and theoretical background of the research problems. It clarifies the position of the thesis by first discussing the practical reason for conducting the research and then providing the background to the research questions by highlighting previous research in the area. The chapter starts by providing the research aim and the focused research questions. Finally, the context of the coming chapters in the thesis is presented for readers to gain a better understanding of the contents of the chapters to follow.

1.1. Toward Big Data Management in the Apparel Supply Chain

Contemporary society is driven by mass marketing, mass production, and mass distribution. Even our apparel has been created for the broadest possible appeal to maximize efficiency and profitability (Godley, 1997). The business of making clothes for the masses is what constitutes today's apparel industry, and in this modern economy, like most of the manufacturing industry, apparel is also based on large-scale business strategies, standardization, and mass marketing. Paraphrasing Holbrook & Hulbert (2002)—"Imagine that you seek to buy a pair of trousers. It would be a miracle if you were able to find a style that you like with a pattern that suits your taste in the right color and the appropriate fabric, all in a size that happens to fit you perfectly." (Holbrook and Hulbert, 2002).

However, this was not always the case. Before the age of mass production, customers went to their tailor and specified relevant details concerning their required garment (the size, the shape, the fabric, the color, the style, etc.). The tailor kept in stock the raw material and then constructed the garment to match the exact specifications provided. This was a time consuming and expensive way of producing clothes, and to many, it was a consumer luxury to visit the tailor (Rasmussen, 2010). During the world wars, when necessity outgrew desire, mass production of clothing was invented—i.e. manufacturers started producing clothing in fixed styles, colors, and sizes (Godley, 1997). This was acceptable for a long time until the twentieth century when society acknowledged social and cultural changes, designers started establishing themselves in manufacturing businesses, and customers became willing to spend more on the clothing they chose to wear. Consequently, the apparel industry needed to adapt to the changes and manage the supply of the latest style trends to fulfill consumer demand (Bhardwaj and Fairhurst, 2010a)

In the quest to achieve this, some apparel retailers gave rise to fast fashion, which inculcates a feeling of non-permanence among customers (Abrahamson, 2011; Barnes and Lea-Greenwood, 2006). They take inspiration from the latest trends showcased during fashion weeks taking place all over the world and produce and provide a massive quantity of inexpensive, trendy garments for customers, increasing the number of seasons from quarterly to as much as weekly (Joy et al., 2012; Tokatli and Kizilgün, 2009). Therefore, it was important to have agile production systems in place that could rapidly adapt to new trends, maintaining the effectiveness and efficiency of supply-chain operations (Sull and Turconi, 2008). For instance, the Spanish fast fashion retailer Zara moved its production to Spain making the time-to-market shorter by taking advantage of flexible manufacturing and lean inventories (Tokatli, 2008). Furthermore, the proliferation of the internet and e-commerce added online retail channels to the traditional brick and mortar outlets, making it easier and more appealing for customers to purchase these new trends (Hammond, J. and Kohler, 2000). Today, customers can make a purchase without visiting a store, try on garments at their leisure at home, and return them if not satisfied. This behavior has led to an increase in textile waste, both due to impulse buying as well as product returns, contributing negatively to a sustainable society and reducing business profitability (Ofek et al., 2011).

With this backdrop, there are several challenges for apparel retailers, producers, customers, and society as a whole. Retailers and producers have to face the costs incurred by returns and keeping sufficient inventory, as well as dealing with overproduction and waste (Mehrjoo, M. and Pasek, 2016). Even though apparel is offered in a gamut of choices, often the customer does not get the product that meets their expectations. Due to this, apparel companies have to deal with an approximately 40% return rate globally (Reagan, 2016). As such, the global apparel industry has become energy-consuming, polluting, and wasteful (Glynis, 2015), and the obligation for the industry to bring change to its supply-chain operations has become the need of the hour. Managers in apparel firms need to re-think the idea of mass marketing, as contemporary customers do not demand more, but more relevant apparel. At the same time, manufacturers need to move toward economies of scope (efficiencies formed by variety, not volume) and modify their processes by using available resources based on upcoming technologies. This would require managers to look into their supply chains for existing resources to develop their capabilities to handle uncertain customer demands and create competitive advantage in a changing business environment (X. Wu et al., 2006). Managers need to adopt digital technologies that can automate decision making, and vouch for meaningful actions such as demand forecasting and smart manufacturing (Bertola and Teunissen, 2018; Luo et al., 2015). Technologies such as AI and big data analytics (BDA) have a key role to play in change management, enabling companies to understand their customers' shopping behavior and garment preferences to reduce the possibility of overproducing inventory and to optimize product development, design, and sourcing (Shang et al., 2013). This would not only support the managers in making strategic analytics-driven decisions but it would also get the industry embarked on the journey toward a sustainable supply chain, which would increase business profitability, and contribute to consumer satisfaction. However, there are various challenges that management will face when employing digital technologies. A few of these are finding the right technologies, acquiring and assembling data, the current lack of skilled resources, the appropriate organizational structure, and doing these on a limited budget (Della Corte et al., 2020; Fischer, 2018).

An important step toward overcoming some of these challenges is the use of big data management integrated with AI solutions within a robust data management environment (Oliver, 2019). To achieve this, managers in apparel firms need to find relevant big data that has the potential to uncover new opportunities to generate revenue. In this age of digitalization, where customers can interact with companies online, and a great deal of information between industry stakeholders is exchanged digitally, it is not difficult for companies to find big data, but it is difficult to find the right data and use appropriate analytics and AI techniques to find valuable insights (Bughin et al., 2017). For instance, customers have always been contributing to this big data every time they make a purchase or choose to enroll in a loyalty program. They can now see the utilization of AI when something they searched for on Google appears in the form of advertisements in their Instagram feed. Some other contributors to big data within the apparel industry are the collections of products that have been produced since the beginning of record-keeping, production data that can help improve efficiency, product data related to the material, color, and style, and data related to body sizes. Every stage in the apparel supply chain and the corresponding actors work on and produce some data. Therefore, there is a clear opportunity to exploit this big data, as it is generally perceived as a valuable resource to increase the efficiency and effectiveness of business operations, to provide the right products at the right time to the right people with minimum waste, thereby generating more value for the business and customer (McAfee and Brynjolfsson, 2012). However, there are also challenges with big data management such as data security, storage, the management of unstructured data, the extraction of insights in a timely manner, and the organizational resistance that makes it difficult for businesses to readily adopt big data and create data-driven strategies (Pînzaru et al., 2016, Labrinidis and Jagadish, 2012; Sivarajah et al., 2017). In the future, companies that pioneer big data management using AI and overcome the accompanying challenges may prove exciting as new paths to profitability emerge.

1.2. Research Background

With the emergence of globalization and digitalization, the concept of big data management and AI to connect businesses globally has gained attention (Kim and Lee, 2018). Big data, in its simplest form, is a massive amount of data that is available in various forms (image, text, audio) and is often stored in distributed systems or in the cloud (Ward and Barker, 2013). While big data management entails the organization, handling, and use of this big data, it usually requires specific technologies and analytical methods (De Mauro et al., 2016). AI is one of the technologies that can help in big data management. It uses the information gained from big data to allow machines to do things that were once only the domain of humans (Hutter, 2012). Big data management and AI have existed as concepts for decades, but the lack of data management strategies has obstructed their growth. However, today, there is simply an enormous amount of data available in various formats. Several organizations in the automobile, travel, grocery, confectionery, and other similar industries have used advanced analytics on big data to help managers to accelerate businesses growth, support smarter decision making, strengthen customer relationships, and improve team management (Akter et al., 2016; Kache and Seuring, 2017; Mazzei et al., 2017; Raguseo and Vitari, 2018; Ram et al., 2016). The successful use of big data and AI requires a comprehensive strategy for using these technologies and the deployment of appropriate technical capabilities and architecture (Barton and Court, 2012). However, business leaders often struggle with having an organization-wide view of the opportunity, making it difficult to make an attractive case for analytics and to get the organization to commit itself to the potential changes big data management might bring about (Chin et al., 2017).

Apparel firms, which operate on a delicate balance of different factors such as changing trends, distributed supply chains, and challenges such as the fluctuations in customers' purchasing power and demands, the absence of unified sizes etc., is just beginning to use big data and AI as a tool to solve these problems. Over the last decade, the apparel industry has utilized big data and AI to a certain extent for improving supply-chain processes such as apparel production (Lee et al., 2012), fabric inspection (Nasira and Banumathi, 2014), distribution (Chen, Wang, et al., 2014), and sales forecasting (Craparotta et al., n.d.; Giri, Thomassey, et al., 2019). Today, research studies report additional customer data sources since collection methods in the industry have become systematic, storage systems have taken digital form, and analytical approaches come from the latest modern technologies to gain consumer insights (Reinartz et al., 2019). For instance, tracking customer movements in a store with the help of RFID and computer vision, or tracking customer movements on a website using eye-tracking technology, are contemporary methods of actively collecting data (Bonetti and Perry, 2017). Since, data is also becoming available from individuals leaving digital footprints such as online-based business transactions and data from social media sites or mobile applications, the importance of AI techniques has become even greater (Grewal et al., 2017). The amount of data available from actively collected data methods and passively gained data is huge and can provide companies with opportunities to track customer behavior and gain insights for trend predictions. By collecting a large volume of data from different sources in every step of the apparel supply chain and turning them into useful information, companies can quickly make important decisions based on the most popular styles, colors, fabrics, and sizes (Ericsson, 2011; Ericsson and Sundström, 2012).

In addition to customer data, there are other sources of data to be found at the various stages of the apparel supply chain that can be collected. Data can come from the collections created by the product development team, providing rich information helpful to carry out predictive analyses. The data related to raw material used in the production is another essential data source helpful to plan inventory. The data related to the garment and its design, including details about the different garment categories and attributes are useful for efficient production planning (Mok et al., 2013). Manufacturers can use big data and AI techniques to identify the top-selling products to adjust production activities and provide designers with useful insights. Furthermore, retailers can decrease the volume of initial purchases, minimize inventories, and plan season collections based on real sales by shifting to demand-based offers from offer-based demand (Ericsson, D. and Sundström, 2015; Ericsson, 2011).

Some existing apparel businesses have recognized the above needs and are proactively adopting AI techniques to increase business profitability. For example, two large and well-recognized actors within retail are experimenting with these technologies: Myntra and Zalando. Myntra has adopted deep learning to train classification models that can recognize garment attributes in an image (Singh Adhikari et al., 2019). Zalando has implemented AI to build recommendation systems that can provide personalized recommendations to the customers (Freno, 2017). However, new standards of service and experience are constantly being demanded by customers, which requires businesses to becoming even more data-driven and manage AI and other advanced analytics with the purpose of offering customer-centric propositions.

Following the line of thinking described above, another business recognizing the need for big data management is StitchFix, which is using data to provide a personalized assortment of mass-produced garments to the customer based on their style profile (Zielnicki, 2019). Other activities based on the idea of tailored mass production have been showcased by several companies allowing customers to co-create garments, which are then produced in a mass-customization setting (i.e. flexible production systems that lead to higher productivity and variety at a lower cost) (Peterson, 2016). From a broader perspective, the above described examples from the industry represent two different ways of organizing and managing individualized offerings. Firstly, one approach provides customers with an opportunity to create a “style profile” by responding to a few questions regarding their body type and measurements, favorite colors, styles, and other fashion preferences. Here, the data source is the customer’s personal style preferences. The recommendation algorithm uses such data to select items that can be suggested to the customer, while the feedback of the customer can then be used to automatically recalibrate its recommendations, subsequently reducing return rates (Vaccaro et al., 2018). These are all operations aimed at providing personalized style advice, where the garments are styled according to personal preferences, yet they are still mass-produced. Secondly, the other approach offers its customers the ability to co-design the garments using a web-based configurator that has limited styling options which the consumer can choose to put together a garment of their choice. The garments are produced in a flexible manufacturing system similar to a mass production process, even though the garments are customized. Here, the sources of data are related to production as the focus is to maintain production efficiency while providing the customer with an inexpensive product.

Both ways of organizing individualized offerings have some limitations. In the former, the inventory cost is high for the business, while the customer pays a higher price for style advice and receives a mass-produced garment. In the latter, there is added production complexity for the business, while higher lead times and the difficulty in co-creating garments due to the customer’s lack of professional knowledge remain problematic. Consequently, a major problem with many big data management approaches in the market is that they are one-sided (Guan et al., 2016). There are limitations on how cost efficient they can be, especially considering they mostly depend on one or two data sources. Imagine what could be achieved by realizing the strength of integrating more important data sources. Such an approach might facilitate smarter and faster decision-making and revamp the apparel supply chain into a *demand chain process* of producing garments. Diversified data sources, more additional big data, and advanced AI use within the context of apparel big data management suggest a possible data-driven strategy to achieve a higher level of consumer satisfaction, improved production operations, enhanced business profitability, and a move toward a greener supply chain.

Consequently, a supply chain integrated and managed with data is one of the more important solutions necessary to bring improved effectiveness and efficiency in the way an apparel supply chain operates and gains competitive advantage. Big data management with AI has much potential to create and maintain such a way of re-thinking the apparel supply chain, such as providing new means of interactive communications, improved supply-chain organization, and a digitally connected supply chain. It can help in providing personalized services and products to customers. One way of providing customers with products that meet their demands is shown in Figure 1-1.

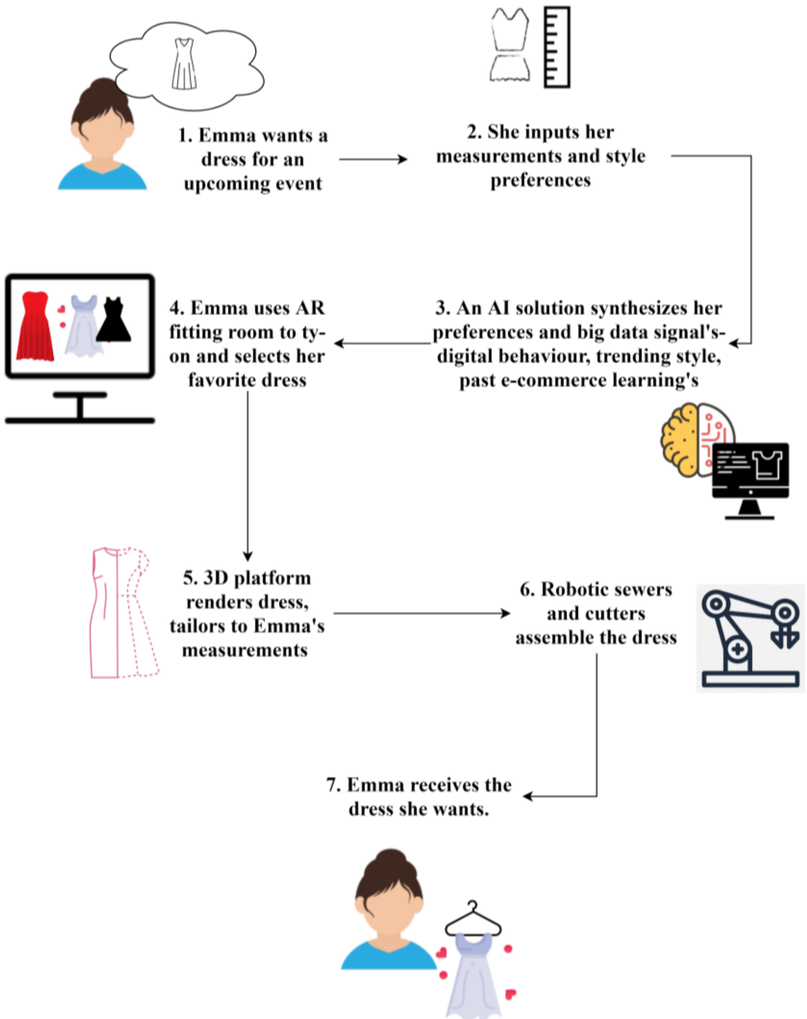

Figure 1-1. A data-driven management strategy for apparel supply chain (CBIInsights, 2019)

In the figure, a data-driven strategy is depicted, where data management is infused with various digital technologies, including AI, to provide the customer with personalized products, experiences, and services. With this type of strategy, business leaders might find new ways of organizing their businesses and building competitive advantage. However, it is crucial to investigate the benefits and challenges of such a big data management strategy to improve business operations. It is thus one of the more important reasons why this dissertation has been completed.

1.3. Research Gaps

As per the discussion in the previous section, it is clear that the apparel supply chain is one of the world's most dynamic supply chains and is facing numerous challenges due to globalization, technological advances, and varying customer needs. While competing in global markets for supplying the latest trends to customers, supply-chain managers are constantly looking for ways to improve business strategies to improve speed and cost efficiencies (Bhardwaj and Fairhurst, 2010a). With increasing customer demands for individualization, the complexity of the product and thereby supply-chain operations tends to increase, becoming more difficult to manage (Shang et al., 2018). This requires newer strategies to manage supply-chain operations, and the need for improved knowledge on big data management within the apparel industry. The big data generated in the supply chain provide a lucrative tool to optimize the operations and stimulate agility, but applied research within the domain is lacking.

The domain knowledge of senior executives in a business is critical to extract the right opportunities from data, and there is a strong need to support the industry with academic knowledge on managing big data and exploit AI. Managers need to ask the right questions and define precise goals. In a data-driven business, there is requirement of managers who themselves are reliant on data-driven decisions, to identify opportunities, think creatively, comprehend market developments, and suggest better offerings, but academic contributions to such requirements are currently insufficient. Contemporary technology within big data and AI can uncover hidden patterns, but managers need a new understanding of those patterns and the knowledge to create and manage data-driven business strategies to make intelligent decisions. Nevertheless, managing big data does not come without challenges. It is difficult to handle a huge volume of real-time data if appropriate platforms are not in place. Since the data comes from multiple sources, its security is questionable and can lead to problems for businesses if best practices for data security are not employed. Moreover, there is the challenge of translating the business goals developed by managers into actions that can be deployed using data analytics and support data-driven strategies. It is important for managers in apparel firms to understand emerging techniques that can handle this data effectively and streamline not only product development but also other supply-chain operations.

Therefore, combining technological knowledge and management approaches within the apparel industry might support businesses to reap the full benefits from big data, while also contributing to the academic domain of big data and AI.

This poses the question: which of these technologies can help to manage and process big data captured in the supply chain, and convert it into a valuable resource for the business. Moreover, puts emphasis on the need to provide evidence on how these technologies can be adopted successfully to support big data management. In this context, the research gap identified here, is threefold. Firstly, since there is no proper research documented where one can identify the current work done in the domain of big data using AI techniques in the apparel supply chain, it is important to first find evidence among existing studies. Thus, the thesis identifies and classifies AI techniques that can be used at different stages of the supply chain to improve existing business operations. Secondly, little attention has been given to data sources based on manufacturing and product development variables such as product-related data, and so this thesis presents product-related data to create a classification model and design rules that may be an opportunity to provide personalized recommendations or customization enabling better shopping experiences for customers. Thirdly, the absence of a framework based on big data-driven management strategies that can assist apparel e-commerce retailers to provide personalized services remains a challenge. Thus, the thesis draws from the evidence in the industry and existing literature to suggest propositions that may guide managers in developing data-driven strategies for improving customer satisfaction using personalized services.

1.4. Research Aim and Questions

With regards to this, the thesis aims to investigate whether apparel firms can improve their business operations by employing big data and AI, and in doing so, seek opportunities with big data management using AI solutions. The research questions that will help in achieving this purpose are shown below, as well as in Figure 1-2:

1. *What are the AI techniques that can be used at different stages of the apparel supply chain to improve business operations*?

2. *How can AI techniques be used to develop data-driven solutions using product-related data furnished by apparel product manufacturers and designers?*

3. *How can big data assist in providing personalized offerings to customers through apparel e-commerce retailers?*

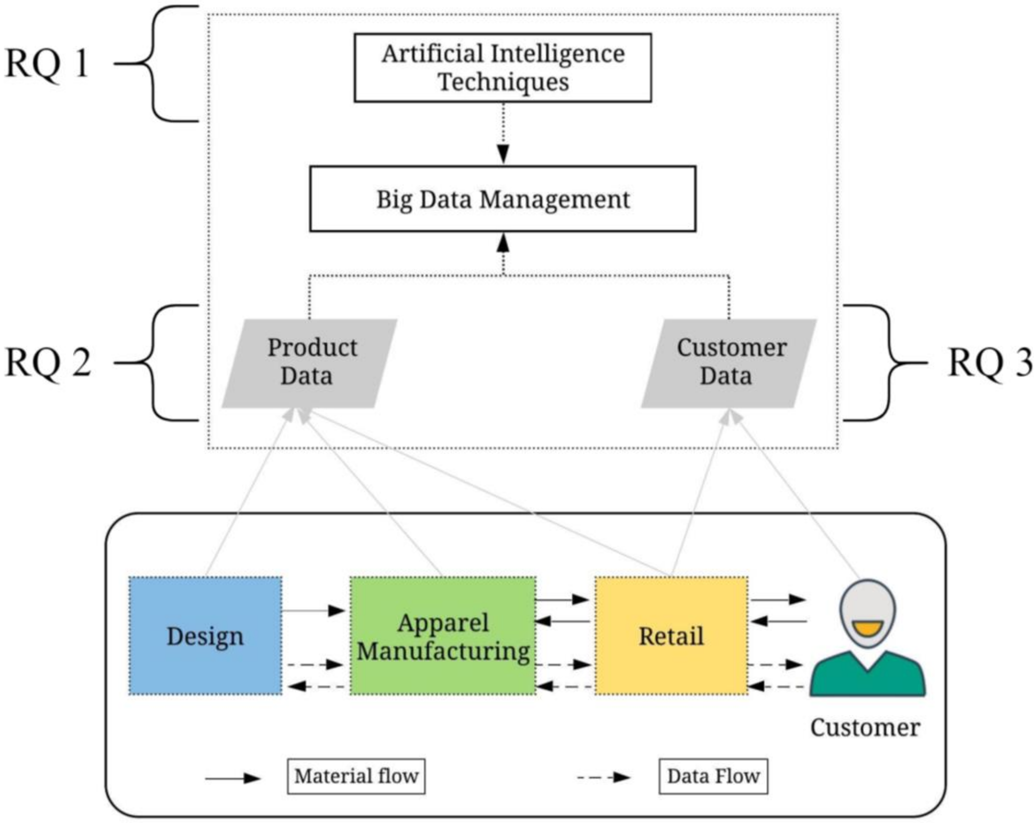

Figure 1-2. Positioning research question on the big data management system in apparel supply chain

As shown in Figure 1-2, the bottom half of the diagram outlines the supply-chain actors on which this thesis is focused. The reason for choosing these actors was their contribution in producing products and customer-related data as well as the availability of data from these sources. Research question 1 (RQ1) focuses on identifying the AI techniques that can be used to manage big data in the apparel supply chain, research question 2 (RQ2) focuses on managing and analyzing product-related data with AI techniques, and research question 3 (RQ3) focuses on identifying how big data can support apparel retailers to provide personalized services to its customers.

1.5. Outline of the Thesis

This thesis is composed of the cover essay and four appended articles. The structure of this thesis is outlined in Figure 1-3.

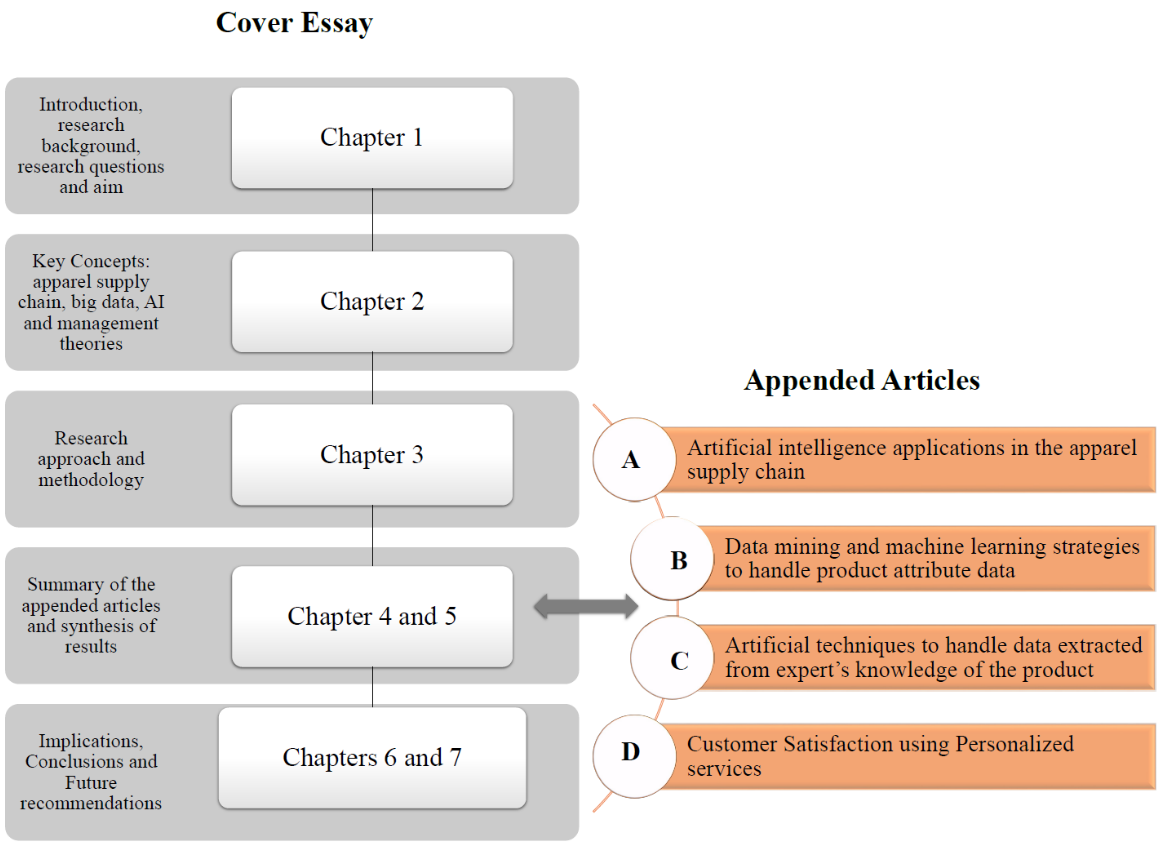

Figure 1-3. Structure of the thesis

The cover essay consists of seven chapters. Chapter 1 introduces the research topic and background and presents the research gap, aim, and questions. This introductory chapter is followed by a description of the key concepts that the thesis touches upon and takes support from. This chapter describes the current state of the apparel supply chain, defines big data management in the apparel industry, and presents the different data that are derived from the supply chain, various ways of managing AI applications in the apparel supply chain, and the management theories to examine big data management using AI solutions. Chapter 3 provides an overview of the research design of the thesis, including the data collection process and units of analysis. Chapter 4 offers a summary of the appended articles and their contribution to the thesis, and Chapter 5 provides a synthesis of these contributions and discusses findings related to the research questions. Finally, Chapter 6 discusses the implications of the thesis' findings, while Chapter 7 provides limitations, and suggestions for future research.

2. Literature Review

This chapter gives insights into the relevant literature, provides a frame of reference and lays a foundation for the purpose of this thesis. Section 2.1 provides the context of the apparel industry, the challenges within the apparel supply chain, and a deeper understanding on how it has been studied and researched. Section 2.2 lays the groundwork for the RQs and provides a summary of managing big data and AI in the apparel supply chain. Section 2.3 discusses the resource-based view (RBV) and dynamic capability view (DCV) of the firm to examine big data management and AI in the apparel supply chain.

2.1. The Apparel Industry

The apparel industry has one of the largest household consumptions. In 2017, the estimated purchase of clothing and textile by households in the EU was € 510.9 bn (Statista, 2019). This is influenced by the low prices of products and the reduction in the manufacturing and delivery lead times of garments to the customer. According to Nikolina, (2019), apparel contributes 2–10% of the waste in the EU. Most of the clothes are thrown away or added to landfills. Globally, the apparel industry is responsible for 10% of carbon emissions and remains the second largest commercial polluter, second only to oil (Conca, 2015).

This industry represents a dynamic sector in global trade as it is characterized by unpredictable demand, short product life cycles, quick response times, a large variety of product, and a volatile, inflexible, and complex supply-chain structure (Guemes-Castorena, D. and Ruiz, 2017; Lam and Postle, 2006; Ren et al., 2019; Silva et al., 2018). With globalization, it has become even more fragmented and competitive, with not only several major players but also countless niche stores and private companies that cater to specific demographics. There is a constant race to achieve lower cost and volume by bringing flexibility to the operations related to design, production, and delivery (Bhardwaj and Fairhurst, 2010a; Moon et al., 2017).

The consumer in the contemporary apparel industry enjoys increased awareness and associated preferences related to the latest styles and designs (Bhardwaj and Fairhurst, 2010b). This is highly influenced by the proliferation of social media and the internet (Manyika et al., 2011), which is a pervasive medium, ideal for the dissemination of information related to the latest fashion trends, upcoming fashion weeks, and popular celebrities. Due to this, the apparel supply chain has had to rapidly change its collections to fulfill growing consumer demand (Bhardwaj and Fairhurst, 2010b). Therefore, understanding consumer buying behavior and engagement has become essential. Instead of pushing the supply to the customer, it is now becoming demand-driven i.e. customer requirements are first taken into consideration, and the product is developed accordingly, then assembled, and sold (Ericsson, D. and Sundström, 2015; Pfahl and Moxham, 2014).

Changes in customer behavior and consumption patterns have highlighted the need of businesses to broaden their supply chain strategies appropriately to efficiently respond to customer needs within a short period of time and to manage the complexity of the product design process (Bhardwaj and Fairhurst, 2010b). This indicates a shift from "supplier-driven" to "demand-driven" supply chains, with production becoming more sensitive to the needs of customers (Morris, 2011). In a demand-driven supply chain, the product development process is focused on the customer's needs and demands (Ahmed and Shepherd, 2010). It requires the customers to be engaged much earlier in the product development process and entails active interaction between the customer and the producers.

2.1.1. The Apparel Product

The byproduct of the apparel industry is a garment. A basic garment, such as a round neck t-shirt or a formal shirt, does not change radically over time, it is the fashion and seasonal garments that change with market demands and trends. The changes in seasonal apparel products are influenced by the prevailing weather, seasonal events, and cultural traditions. The changes in a fashion product largely depend on the adoption of a certain set of attributes and the styling of a garment by a large group of people within a specific period of time (Glock and Kunz, 2005). The task of effecting changes in these garments rest with the designers and their teams, and their responsibilities vary depending on the type of apparel business (Gwilt, 2012). For instance, the designer labels—led by the designers themselves—manage all aspects of the business, whereas in the case of mass produced garments, various stakeholders are involved in managing the production process and the design team is often referred to as the product development team (Renfrew and Renfrew, 2009). The strategies of the product development process and the supply chain can be modified to fit the needs of diverse market segments. In this thesis, the apparel business involving various actors who perform different operations to create the fashion apparel product itself, is studied.

2.1.2. The Apparel Supply Chain

An apparel supply chain includes activities such as design, production, marketing, distribution, and customer support as depicted in Figure 2-1. As identified in the study by (Ariyatum, 2003), these supply-chain activities are performed with five factors that differentiate the apparel supply chain from other industries. The first is that the product development phase is driven by seasonal and fashion demands. The second is its focus on showcasing a collection of garments to the world. The third is that the product development process is iterative. The fourth emphasizes frequent planning and development due to the short life cycle of garments. Finally, the retail buyers make the ultimate decision regarding the final products. Owing to the considerable direct involvement of retailers in the new product development cycle, retail buyers are considered to be the key decision-makers on specifications governing fabric quality, style, color, sizes, and the quantity to be manufactured (Gereffi and Memedovic, 2003).

The activities that comprise a supply chain—as depicted in Figure 2-1—can be managed within a single firm or divided among different firms (Gereffi and Frederick, 2010). Along with these, there are four primary management roles in apparel firms, namely planning, organizing, leading, and controlling, and these are performed at every stage of the supply chain. *The designers* employed by the retailers determine the product information, which includes details such as the type and design of garments, their technical specifications, sizes, and the colorways in which the garment needs to be produced, the type of fabric to be used, and the quantities of fabric and garments (Goworek, 2010). The *garment manufacturers* follow these instructions to create prototypes, in direct communication with the retailer. Meanwhile, the *fabric manufacturers* follows the same instructions to produce the required fabrics (Bruce and Daly, 2011). Most of the time, fabric approval is required much earlier in the process, since the bulk production of fabrics requires significant time. During fabric production, the fiber is converted into a fabric with a series of value-added activities. Once the garment prototypes are approved, the managers at the production houses begin production planning which provides instructions for pattern making, cutting, sewing, assembly, finishing, inspection, and packaging (Nayak and Padhye, 2015). The creation of a pattern is one of the most important steps as it produces a template for the fabric cutter (Glock and Kunz, 2005). After cutting, the fabric pieces are sewn together with the addition of yarn, trims, and accessories.

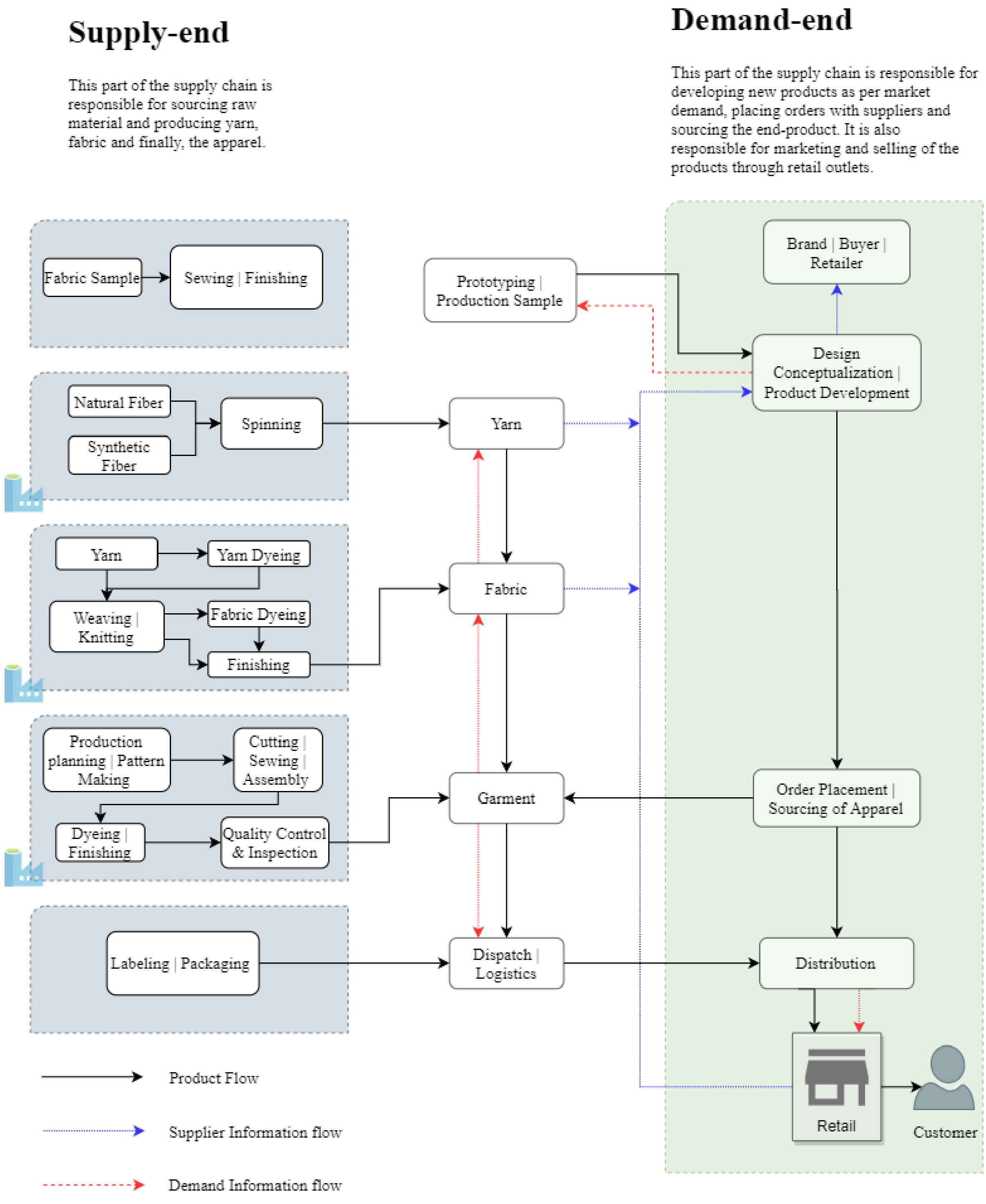

Figure 2-1. Traditional apparel supply chain (Mahmood and Kess, 2014)

Finally, the produced products are distributed by *distributors or logistic providers* to different warehouses both locally and globally according to the plans created by managers at the retail firm (Nayak and Padhye, 2015). The *brand owner* creates marketing plans and sells through one of its retail channels to customers (McCormick et al., 2014).

In general, there are two types of supply chains: supplier-driven and buyer (customer)-driven. The apparel industry is a typical example of a supplier-driven supply-chain with substantial power asymmetries between the suppliers and retailers (or brand owners) of the final apparel products (Gereffi and Memedovic, 2003)—see Figure 2-1. While this way of doing business has resulted in a generation of great social and economic value, it has had an adverse effect on the environment (Akter, Ji, et al., 2020). The culture of "fast fashion" is one of the major reasons for this, as it has encouraged consumers to buy increasingly inexpensive garments leading to the proliferation of textile waste (McNeill and Moore, 2015). One of the challenges faced by apparel firms has been to reform the manner in which the current supply chain is driven. As already discussed, the apparel supply chain is increasingly shifting toward a demand-driven supply chain that requires digital solutions to provide customer-centric products. However, the groundswell of big data management solutions for creating such data-driven strategies still lack recognition from top management.

To fully comprehend and implement a demand-driven strategy within the context of big data management, another challenge faced by apparel business leaders is the need to diversify their ecosystems and realize the power of data in meeting customer demands, on top of running efficient and effective operations. Achieving agility is an important challenge in implementing a demand-driven strategy and requires processing a large and varied quantity of information (Akhtar et al., 2018; Yang et al., 2021). This process is possible with the latest digital technologies such as big data, AI, and other advanced analytical techniques (Nayak and Padhye, 2018). However, just like IT applications (Sambamurthy et al., 2003; Weill et al., 2002), these new digital technologies do not automatically improve agility. There needs to be an understanding of the techniques and the accompanying challenges such as poor data quality, limited analytical expertise, infrastructure to store and manage the data, and data security to improve the current business operations (Labrinidis and Jagadish, 2012; Sivarajah et al., 2017). Consequently, considering these challenges, the purpose of this thesis is to investigate whether apparel firms can improve business operations by employing big data and AI, and in doing so, seek opportunities with big data management using AI solutions.

2.2. Big Data and Artificial Intelligence

Big data is precisely what it sounds like: information on a large scale. But more generally it means a large collection of unstructured or structured data that are assembled together digitally and organized in a manner that makes it convenient for humans to rapidly obtain valuable insights (Oussous et al., 2018; Syed et al., 2013). In this way, big data can be one of the solutions to answer previously unexplainable questions about what customers buy, when and how they buy, and the process through which they pay. As such, businesses can make better decisions related to pricing and the assortment of products, minimize inventory costs, and reduce markdowns by analyzing big data in real time or over a specific period (Aktas and Meng, 2017; Fisher and Raman, 2018). However, big data alone cannot help to achieve this, it requires assistance using advanced analytical techniques such as AI. More precisely, big data is the fuel that underpins AI performance. The greater the quantity of data fed into these AI processes, the better their performance.

2.2.1. Big Data

Data is not new and have been around even before computers and databases came into existence. What has changed today, is how that data are stored and managed. Today, in this digital age, most data are available digitally. Data are generated every time there is a digital action, and so the amount of data being created continues to grow rapidly. The term 'big data' corresponds to the huge amount of data that can be collected and used advantageously with the help of appropriate technologies (Matthias et al., 2017). The analysis of big data can derive valuable conclusions by combining data from different sources and converting it into information to create knowledge, make better predictions, and tailor services, which otherwise could not be accomplished using traditional data and methods (Henke et al., 2016). A basic understanding of the difference between traditional and big data is shown in Table 2-1.

Table 2-1. Difference between traditional and big data (modified from Hu et al., 2014)

	Traditional Data	**Big Data**
Volume	Tens of terabytes or less	Constantly updated (100 terabytes to petabytes)
Data Flow	Static data	Constant flow of data
Data Structure	Pre-established structures	Semi-structured or unstructured in nature
Data Source	Internal to the organization; centralized	Internal and external; distributed
Data Integration	RDBMS	HDFS, NoSQL
Data Storage	Interactive	Batch or near real time
Type of Analysis	Diagnostic or descriptive	Predictive or prescriptive

A standard definition of big data comes from Laney (2001), where big data means:

> "*High-volume, high velocity, and high-variety information assets that demand cost-effective innovative forms of information processing for enhanced insight and decision making*."

This definition emphasizes the three-V model of big data, where the three Vs are volume, velocity, and variety. *Volume* means that the data can be collected from myriad sources. There is a lot of unstructured data coming from social networks, websites, sensors, and mobile networks in comparison with structured data, but the ratio of useful information is reversed in favor of the latter (Russom, 2011). Information of relevance needs to be obtained from the huge volume of data collected, usually with the help of analytics tools, and it needs to be stored in special storage facilities such as data lakes and Hadoop open-source storage frameworks (Chen, Mao, et al., 2014). *Velocity*, which is the speed aspect of big data, corresponds to its generation, collection, and analysis. As already discussed, data can be gathered from multiple sources, however, its collection in real time is what makes it the "right data at the right time". The speed with which data is gathered directly impacts the accuracy and timeliness of business decisions. The analysis of data requires appropriate hardware and software solutions to process streaming data promptly. Management needs answers to the questions posed from the virtual marketplace in real time (McAfee and Brynjolfsson, 2012). Albeit that volume and velocity are important aspects of big data, it is also essential that big data comprises data from varied sources and in different formats. *Variety* relates to the many formats in which the data is available—from unstructured text, emails, video, and audio to structured, numerical data. Big data platforms must recognize these varied formats to uncover hidden opportunities and provide additional value (Gupta and Gupta, 2016).

However, there are different perspectives on the definition of big data, and one of the most influential definitions is that given by the International Data Corporation (IDC) in 2011 (J Gantz, 2011), which defines big data as:

> *"Big data technologies describe a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high-velocity capture, discovery and/or analysis."*

With this definition and suggestions from other research, the characteristics of big data can be defined by combining two additional Vs, veracity and value (Assunção et al., 2015; Rumsfeld et al., 2016; Yang et al., 2017; Yin and Kaynak, 2015). *Veracity* is associated with data quality, as it is a big challenge today to get credible data (Emani et al., 2015). Before insights can be derived from data, the quality of the data must be evaluated as it may not be relevant or there may be discrepancies in the data sample processed. Due to its ample quantity and speed, there is a high probability that not all data is accurate in nature and contains noise, which can impede the integrity of that data. Therefore, holding a big dataset does not guarantee that it is clean and accurate, it must be integrated, cleaned, made compatible, and be timeously accessible to get the best out of it (Gandomi and Haider, 2015). V*alue* is the most crucial feature of big data, as it turns large quantities of data into commercial value, advancing the business and gaining it a stronger competitive position (Ji-fan Ren et al., 2017). This is also where BDA comes into play. Even though many companies invest in data storage and integration facilities, they fail to understand that this does equate to creating added value (Henke et al., 2016).

Another view of big data can be found in the definition given by the US National Institute of Standards and Technology (NIST) which defines big data as:

> *"Big data shall mean the data of which the data volume, acquisition speed, or data representation limits the capacity of using traditional relational methods to conduct effective analysis or the data which may be effectively processed with important horizontal zoom technologies."*

This perspective of big data places emphasis on the technological aspects and shows that knowledge of efficient techniques and technologies is required to process and analyze big data. The use of advanced analytical techniques such as AI permits meaningful insights to be drawn, adding value to the decision-making process (Gandomi and Haider, 2015). The decision to use BDA should be based upon a cost-benefit analysis by computing the cost of processing big data and comparing it with the potential revenue that it will generate—it is crucial to know the various advanced techniques that can help businesses to generate this value. As per a McKinsey report, a successful BDA plan contains three elements: interlinked data inputs, analytical models, and decision-support tools (Biesdorf et al., 2013). A big data technology architecture is shown in Figure 2-2. The figure shows two stacks each for parallel computing and data analysis. With the use of distributed file systems, resources such as memory, storage, and processing power can be managed centrally. With these modules, applications such as AI, statistics, and database management can be performed on exceptionally large datasets in real time.

BDA, when defined as a process, depends on various disciplines to reveal hidden knowledge. BDA research utilizes either exploratory data analysis to generate hypotheses or propositions, or pursues predictions relying heavily on advanced AI, data mining, and statistical algorithms (Dhar, 2013). In this thesis, BDA research that implements AI, statistics, and visualization techniques to collect, process, analyze, visualize, and interpret results is taken into consideration.

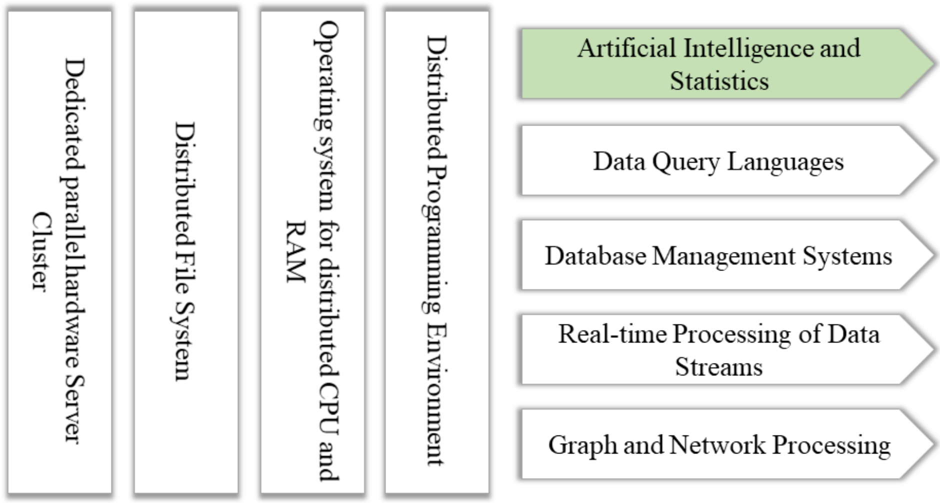

Figure 2-2. Big data technology architecture, modified from (Kaufmann, 2019)

2.2.2. Big Data Management in the Apparel Supply Chain

Big data management refers to collecting, organizing, storing, and utilizing big data using advanced analytics to improve business operations (Rossi and Hirama, 2015). The most critical aspect of big data management is the data itself. Much like most industries today, the apparel supply chain is home to a huge quantity and variety of data. As already mentioned, the byproduct of the apparel industry is the garment itself, which comprises style, material, and color, and is produced to specifications reflecting consumers' requirements. Each one of these corresponds to the intrinsic knowledge of fashion designers, textile designers, pattern makers, production planners, managers, and consumer behavior analysts. This knowledge is an important source of data in the industry. The historical data that manufacturers and retailers hold, related to a garment's design, production, and distribution, is another source of data (Jain et al., 2017). This kind of data is dynamic in nature and is available in various forms such as images, transactions, customer feedback, and keywords. There exists a relationship between these data that can be acquired, stored, and managed to make smart decisions that can help business leaders create competitive advantage (Dong et al., 2020; Zeng et al., 2013). Every supply-chain actor produces, uses, and manages certain data. There are various systems that are used to manage, record, and share traditional data among different supply-chain actors. However, when dealing with big data, it is necessary to have the appropriate tools for effective and efficient management. In this thesis, three data sources have been taken into consideration, namely the retailer, design, and apparel manufacturer. All three sources contribute to the production and management of product-related data. The reason for using product-related data stems from the findings of the literature review, suggesting that there has been limited research conducted for managing product design and customer data using AI, while the reason for choosing these actors was the availability of data from these sources.

By starting with data that are already available, the managers of the apparel supply chain can learn more about their data quality and the gaps in it (Kwon et al., 2014). This, in turn, can help them understand their technology priorities, including how much data history may be needed at what level of detail or aggregation, as well as how often is it updated (LaValle et al., 2011). The key is to build a use-case road map around the organization's current data capabilities and enhance it over time, which then enables the business to pursue more complex scenarios as shown in Figure 2-3 (Kwon et al., 2014; Wang et al., 2016). This means that managers can begin with the internal data and seek revenue-generating opportunities. Once that is successful and the organization has sustained itself in an uncertain environment, managers can go one step further i.e. acquiring data from external sources to further their growth, and similarly, take another step forward by integrating these disparate data sources to provide customer-centric offerings.

2.2.3. Artificial intelligence

Market demands and trends are highly variable and businesses face ample competition in an increasingly saturated market. Consequently, big data alone is not enough to make a tangible difference (Biesdorf et al., 2013). To compete efficiently and effectively and grow, businesses need to rely on both their expertise and the data available to them (Bughin et al., 2017). They are required to ask the right questions and to know how to act on the answers they receive. Big data may be able to provide retailers more than they had ever imagined, but there has to be appropriate ways to collect and store this data (Bradlow et al., 2017; Grewal et al., 2017).

To acquire this data, AI techniques can offer retailers powerful tools to create data models and maximize the use of data (Bughin et al., 2017; Henke et al., 2016; Kersting and Meyer, 2018). These models can use supervised learning to differentiate one product type from another.

Techniques such as neural networks employ supervised learning algorithms to learn to derive patterns and features from complicated data by impersonating how human brains process information (Ibrahim, 2016). Such techniques can be used to recognize specific patterns and shapes when processing apparel images.

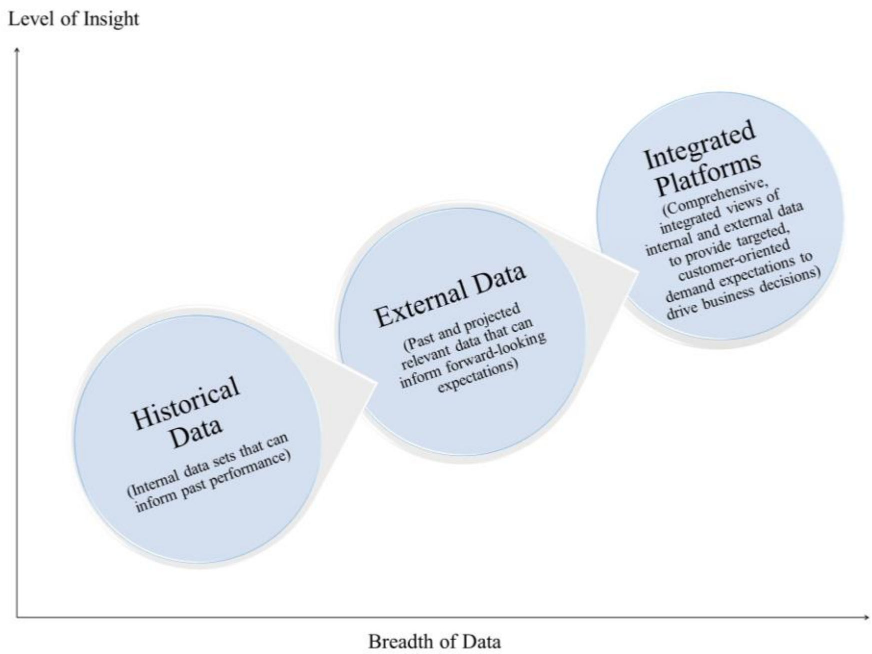

Figure 2-3. Step-wise big data management based on current organization capabilities (Fox et al., 2018)

Similarly, all other AI techniques require a large amount of data for the effective training of algorithms. For instance, the efficiency of a self-driving car increases as the number of data instances increases, since this ensures that the algorithm learns numerous scenarios and is able to react faster and better when they occur in reality. Likewise, the understanding of customer needs and behavior will become richer with the availability of more data. Utilizing data from various sources, AI can create a knowledge base that will ensure accurate predictions. Techniques such as machine learning and deep learning are using data inputs to learn and create rules for business analytics (David Kreyenhagen et al., 2014; Plummer, 2017; Tehrani and Ahrens, 2016). The problem here is to have the right data, i.e. data free of noise (O'Leary, 2013). Accordingly, AI algorithms are often combined with additional analytical techniques to prepare and process the data for business problems related to prediction, classification, and generation. A simplified characterization of AI techniques is shown in Figure 2-4.

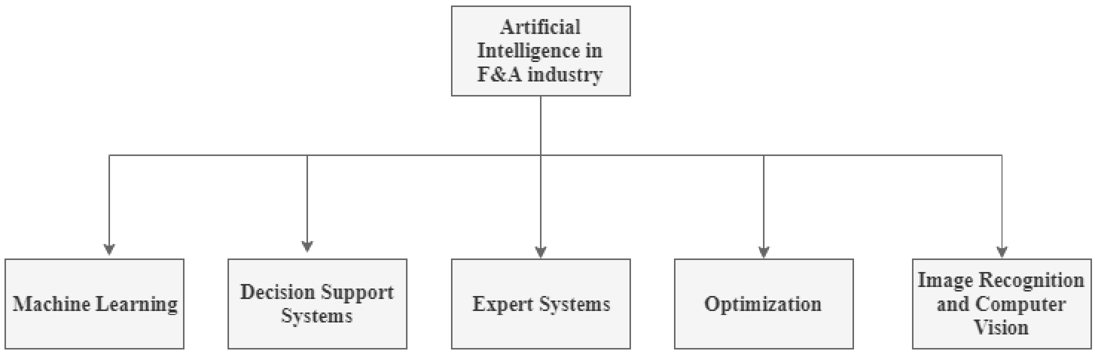

Figure 2-4. Artificial intelligence techniques characterization (Paper A, (Giri, Jain, et al., 2019))

2.2.3.1. Machine Learning

Machine learning is a technical process by which computers are trained to perform assigned tasks without human intervention and learn from the patterns of the data itself. Mathematical models are built on historical data to predict and identify hidden patterns to make future decisions (Bishop, 2006). Machine learning can be classified as supervised or unsupervised learning. Supervised learning is a parametric model and it has inputs (independent variables) and target variables (dependent variables) (Stuart and Norvig, 2009). A supervised model's performance can be improved by optimizing the model parameters through iterative processes (Mohri et al., 2012). Based on the research problem, it could be a classification or regression task, and this relies on dependent variables whether categorical or numerical. Unsupervised learning models have only input attributes or independent variables, with the main task of grouping similar data points. This grouping of similar pattern data points is called clustering and the process creates its own labels (Bishop, 2006).

Supervised machine learning is one of the most powerful engines that enable AI systems to make business decisions faster and more accurately than humans. It turns big data into real, actionable insights, and enables organizations to use data to understand and prevent unwanted outcomes or to boost desired outcomes for their target variables.

2.2.3.2. Decision Support Systems

The decision support system (DSS) is used in organizations at a commercial level for making mid-level or high-level managerial decisions. It can be automated or regulated by a human or a blend of both. Several authors consider a DSS to be a software tool whereas others consider it to be a system that can be integrated with business lines to make decisions (Keen, 1980). Research in (Sprague, 1980) suggests that DSS combines mathematical models with conventional data retrieval methods; it is flexible and adapts to the organizational environment as per the defined strategy.

2.2.3.3. Expert Systems

In AI, an "expert system" is a system that makes a decision without human intervention (Jackson, 1999). It uses a reasoning approach to solve complex problems, characterized by "if-then" rules. The first system of its kind was developed in the 1970s before gaining popularity in the 1980s (Leondes, 2002). They were considered to be the first popular software applications in the field of AI (Stuart and Norvig, 2009). An expert systems can be classified as an inference engine and a knowledge base. The "knowledge base" works on the principle of facts and rules, while the "inference engine" uses the rules to learn the facts and derive new facts (Stella, N. and Chuks, 2011).

2.2.3.4. Optimization

Artificial intelligence has the ability to solve complex problems and find numerous solutions by means of intelligent searching (Luger and Stubblefield, 1993; Stuart and Norvig, 2009). Classical search algorithms start with some random guess which is improved using an iterative process. Hill climbing, beam search, and random optimization are some of these methods (Poole et al., 1998). Machine learning algorithms use search algorithms, which are based on optimization techniques. Simple exhaustive searches (Luger and Stubblefield, 1993; Nilsson, 1998) are too slow and therefore the heuristics approach has been adapted to serve as a technique to find a solution. The limitation of the heuristics search approach is that it fails to work with smaller datasets (Tecuci, 2012). An evolutionary algorithm is another form of optimization search, which starts with initial guesses of the population permitting them to mutate, recombine, and then select the best one while discarding others. Popular evolutionary algorithms include genetic algorithms (GA), gene expression programming, and genetic programming (Holland, 1975; Holland et al., 1992). Distributed search methods can also be done using swarm intelligent algorithms.

2.2.3.5. Image Recognition and Vision

In AI, computer vision is a scientific area which trains a machine to achieve high-level interpretation of images or videos. These images or videos can come from many sources, such as the medical field, global position sensing, cameras, etc. (Ballard and Brown, 1982; Sonka et al., 2008). The principal tasks of computer vision algorithms are the extraction, pre-processing, and exploring of high dimensional data as well as the creation of supervised or unsupervised models (Jahne, 2000). Models use the concept of geometry, statistics, physics, and machine learning theory to obtain insights into understanding the images being processed (Forsyth and Ponce, 2003). Object recognition, video tracking, and motion estimation are some of the sub-areas in the field of computer vision (Tim Morris, 2004).

In this thesis, the focus has been reduced to using supervised machine learning algorithms and techniques falling under DSSs to manage and analyze big data and to create data-driven AI solutions in articles B and C. The reason for choosing these techniques was because of the type of data being collected and the fact that the selected techniques have been successfully employed in other similar studies, with beneficial results.

2.2.4. Managing Apparel Supply Chain Operations with Artificial Intelligence

By managing supply chain operations with the help of AI, managers in apparel firms can achieve higher efficiencies in some business operations (Ngai et al., 2014; Waller and Fawcett, 2013). For instance, managing logistics visibility with AI can help in tracking supplies and products faster (Sodero et al., 2019). The managers first need to identify how and where AI can achieve the greatest business impact (Abd Jelil, 2018). They need to scan all areas of the supply chain to identify the largest analytics opportunities, as well as those that are most critical to the organization's strategy (Guo et al., 2011; Nayak and Padhye, 2018). This is in line with the idea presented by Figure 2-3 that managers should begin with their existing capabilities before acquiring new ones. It is also in line with RQ1, which seeks to find the different AI techniques that can be or are being used at different apparel supply chain stages. As per the different stages of the supply chain presented in Figure 2-1 and the different AI techniques presented in Figure 2-4, the following discussion provides some insight into which techniques have been applied at different stages to manage apparel supply chain operations.

2.2.4.1. Apparel Design

This stage of the apparel supply chain can get some benefits from the application of AI for managing big data. However, there are only a few studies that have been working in this direction. For instance, Kim and Cho, (2000) developed a system based on an interactive genetic algorithm to support fashion design using domain-specific knowledge. The users could interact with the system by providing their preferences, while the system provided the nearest design based on the user requirements. A similar study presented an intelligent design system based on a genetic algorithm and a neural network that allowed the user to find clothing combinations (Lin, 2007). More recently, Li et al., (2017) proposed a new model to evaluate the appearance of a fashion product. They used neuro-based design technology and eye-tracking equipment to collect data and data mining techniques were used to analyze the product attribute preferences. The results obtained could be used for making better production decisions.

2.2.4.2. Fabric Production

This is the supply chain stage that has been most popular in research for realizing AI applications. There has been much research conducted on automatic fabric inspection, where the machine learns different fabric defects with the help of different AI techniques such as image recognition, computer vision, and the support vector machine. (Darwish, 2013; Ghosh et al., 2011; Khalifa et al., 2012; Nasira and Banumathi, 2014; Siegmund et al., 2016). Other applications realized at this stage predict the behavior of fabrics, modeling the descriptors of the fabric handle, optimizing fiber to yarn spinning, and classifying fabrics. (Admuthe and Apte, 2009; Koustoumpardis et al., 2007; Li et al., 2012; Pavlinić and Geršak, 2004; Soufflet et al., 2004).

2.2.4.3. Apparel Production

Like fabric production, this stage has also attracted attention in research related to AI. There has been much research in supporting and automating pattern making operations, and improving the efficiency of the fabric cutting process, which is directly related to the fit of the garment. For instance, using anthropometric data to predict body dimensions (Liu, Wang, et al., 2017) and ensure efficient fabric utilization during cutting (Vorasitchai and Madarasmi, 2003; Wong and Leung, 2008). There are several studies using machine learning algorithms for classifying clothing styles (David Kreyenhagen et al., 2014; Li et al., 2010; Wang et al., 2011). Moreover, there has been the adoption of AI techniques such as artificial neural networks for predicting the performance of the sewing operation on fabrics (Hui et al., 2007), fuzzy logic for production resource planning (Lee et al., 2012), the genetic algorithm and neural networks for garment defect classification (Wong et al., 2009; Yuen, Wong, Qian, Chan, et al., 2009), and the genetic algorithm and association rule mining for quality assurance (Lee et al., 2013, 2016). Furthermore, the application of DSSs and knowledge-based expert systems have also been realized in research for reducing the environmental cost by helping management making better decisions (Metaxiotis, 2004), for providing the fashion mix and match suggestions (Wong, W.K., Zeng, X.H. and Au, 2009), and for selecting the best material and corresponding supplier i.e. supplier selection and resource planning (Chen et al., 2005; Rabenasolo and Zeng, 2012).

2.2.4.4. Distribution and Retailing

Retailing is one of the most important operations for gathering information on the behavior of customers and turning them into valuable insights that can add more value. Today, there are more retail channels available than simply the traditional physical outlet, including e-commerce, social commerce, and mobile-commerce, providing more ways of collecting data for the retailers (Cao, L. and Li, 2015; Rodríguez-Torrico et al., 2017). This is also the reason for the increase in research related to retail innovation using digital technologies (Pantano et al., 2017; Pantano and Vannucci, 2019). In this era of digital commerce, garments are tried after their purchase, which clearly involves the possibility of product return.

For this reason, distribution and retailing have been a research area of interest. There are instances of DSSs developed to monitor on-time delivery (Nakandala et al., 2013) and order allocation for logistics operations carried out at a global level (Chen, Wang, et al., 2014), which is an important factor in enhancing the customer experience for an e-commerce retailer. There are also DSSs under development designed to maintain and replenish stock levels for apparel fast fashion retailers, to avoid dead stock scenarios and reduce logistics costs (Hu and Yu, 2014; Martino et al., 2016; Sugumaran and Sukumaran, 2019). However, most of the AI applications have been aimed at trends, sales, and demand forecasting for apparel retailers such as using mobile sales data to analyze sales at different locations (Min, 2013), using a combination of neural network and fuzzy logic for predicting demand (Aksoy et al., 2012), and for forecasting color trends using advanced techniques (Hsiao et al., 2017; Yu et al., 2012). There are additional studies related to the area of forecasting using various AI techniques (Brahmadeep and Thomassey, 2016; Kumar and Poonkuzhali, 2018; Martins et al., 2016; Yesil et al., 2012; Yu et al., 2011). There are studies to strategize price points based on future demand prediction that can lead to an increase in revenue (Ferreira et al., 2016) and which can also be used to optimize supply chain operations (Martino et al., 2017).

Recently, there has been an increase in sentiment analysis using customer reviews and feedback posted on social media sites by adopting techniques such as text mining and the Naïve Bayes classification algorithm (Fiarni et al., 2016; Giri et al., 2018). Another area of the application of AI can be found in developing recommendation systems that can help in providing improved suggestions for cross-selling products and enhancing sales performance (Wong et al., 2012). When buying apparel products through online channels, obtaining the correct size can become tricky, and it is one of the most frequent reasons for product returns. Hence, there has been much work done to further develop virtual trial room technology by improving the alignment of virtual garments with the virtual 3D avatars of customer's bodies (Yuan et al., 2013), and by improving the virtual try-on fit evaluation using machine learning techniques (Liu, Zeng, et al., 2017).

2.3. Management Theories Applied in Big Data-Related Research

As important as the understanding of the various tools and techniques is in creating big data models, it is vital to understand the different theories to answer the question of why we need these models and how can they help businesses to grow. Theories are significant tools that assist in analyzing various issues, and can facilitate deeper arguments (Glaser and Strauss, 2017). Moreover, some theories can help in supporting findings and discussions regarding the implications of big data management within the context of the apparel supply chain. Hence, contemplating the importance of theories, the study presented by de Camargo Fiorini et al., (2018) discussed the literature up until 2017, related to how different management theories could be implemented to improve the understanding of the impact of big data on organizational performance. Taking inspiration from this, this thesis presents appropriate theories, below, that are focused on understanding and evaluating big data, using management theories. In total, from a selection of 204 identified articles within the domain, 60 theories were identified that have been employed within research to improve the understanding of big data management and AI. For instance, Zeng and Glaister, (2018) studied the process of value creation by managers using big data and provided a framework for the same grounded in the knowledge-based view (KBV). Under the lens of contingency theory, studies have found a positive association of big data and AI on supply chain agility and the attainment of competitive advantage (Dubey et al., 2019; Jeble et al., 2018). Jain et al., (2018) combined the Technology Acceptance Model (TAM) and the theory of reasoned action to understand customer behavior on e-commerce platforms toward the hyper-personalization of women's ethnic-wear garments. They implied that positive customer experiences could be achieved by using big data and analytic techniques to provide personalization on e-commerce platforms. Roßmann et al., (2018) built on the organizational information processing (OIPT) theory to examine the role of BDA and organizational change in finding a fit between the information processing requirements and the capabilities in an agile business environment. However, in this thesis the RBV and the DCV of the firm were chosen, as they were judged to be the most appropriate for compiling this thesis. These theories were selected as they individually provide insights into the phenomenon of big data and collectively provide a framework to examine big data management using AI in the apparel supply chain. One of the critical resources in big data management is the data itself, and the RBV offers the value, rarity, imitability, and organizational (VRIO) framework to consider strategic resources (Barney, 2001; Cardeal and António, 2012). Dynamic capabilities refer to the manner in which organizational processes are organized and continuously re-organized to achieve lucrative rewards. It suggests ways for those organizations that desire to use big data to reconfigure their resources so that big data initiatives are replicable by them and can sustain uncertain situations. These theories are explained in detail below.

2.3.1. Resource-Based View (RBV)

The concept of the RBV was first proposed by Barney, (1991). It provides a connection between diverse resources controlled by an organization, the mobility of the resources within the specific industry, and the competitive advantage possessed by an organization (Barney et al., 2001). It strives to understand the reasons an organization grows and diversifies. An organization's resources are used to assist it to establish strategies to progress its overall effectiveness and performance. These resources that preserve value in the context of the given organization's markets are difficult to replicate by other firms (Meso and Smith, 2000). An organization's access to resources and capacity to assemble and combine these resources in particular ways determines its capability in a given product area. As an organization gathers resources for one business, these resources will, to varying extents, be sufficiently compatible for use in other product areas (Capron and Hulland, 1999). The proponents of this view believe that organizations should look for sources of competitive advantage within the company instead of looking for it within the competitive environment (Hoopes et al., 2003; Peteraf, 1993).

There are immense opportunities for big data research taking on the theoretical lens of resource-based theory, as many studies have adopted this for different business problems. The study by (Saleem et al., 2020) adopted the RBV to propose that BDA was positively associated with technological innovation and the performance of small and mid-size enterprises (SMEs). Big data is often associated with value and has been used to examine the effect of data on an organization's financial performance with the help of market performance and customer satisfaction data (Raguseo and Vitari, 2018). Srimarut and Mekhum, (2020) employed the RBV to show the positive role of supply chain connectivity in building BDA as a competitive resource. Moreover, it suggested that BDA had the capability of making the supply chain self-reliant during market fluctuations. This perspective also holds true with regards to this thesis as it advocates gaining supply chain agility and fulfilling growing demands with the help of existing big data resources and AI.

In a similar fashion to how the RBV has helped understand the concept of big data management in other industries, it can also be used in the apparel supply chain. As discussed in section 2.2.2, managers in apparel firms must scrutinize the existing operations, data produced, and way they are managed. In doing so, they can understand their existing data capacity, analytics capabilities, and the gaps in the organizational infrastructure. This is the starting to discover opportunities of creating new ways of managing supply chain operations with the help of big data using AI. This approach of strategy development starts with the organization's resources and relates those to capabilities together with configuration and re-configuration processes, which is a general outline of the DCV.

2.3.2. Dynamic Capability View (DCV)

Dynamic capability is "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997). The DCV focuses on an organization's competitiveness in a dynamic market of "rapid and unpredictable change" (Eisenhardt and Martin, 2000). The dynamic capabilities framework presumes that the core competencies should be employed to adapt to short-term competitive situations that can be utilized to construct long-term competitive advantage. It is also an extension of the traditional RBV of the firm. When dynamic changes occur in an uncertain environment, the traditional RBV lacks a proper description of capabilities. This gap is tackled by the DCV by planning appropriate resources and capabilities to quickly respond to specific circumstances (Eisenhardt and Martin, 2000). The basic premise of the DCV is that an organization has the capacity to use its processes to respond to market changes and uncertainties, and to design new strategies of value creation to integrate, establish, and reconfigure organizational resources (Ambrosini and Bowman, 2009; Teece and Pisano, 2003).

A study by Van Rijmenam et al., (2019) found BDA to be an important dynamic capability that supports strategic decision making during market fluctuations and uncertain environments. The study by Akter, Gunasekaran, et al., (2020) combined the RBV, the DCV and BDA to create and confirm a service system analytics capability model and its impact on competitive advantage. In another study, Fosso Wamba and Akter, (2019) also combined the RBV and the DCV to develop a model for supply chain analytics capabilities (SCACs) driven by big data. They found that analytics-driven supply chain agility to be an important moderator between the SCAC and an organization's performance. There have been discussions about the importance of big data quality and value in the literature (Günther et al., 2017; Lakshen et al., 2016). In this context, Shams and Solima, (2019) developed a data incubator to strategically deal with challenges in big data management related to data value and data veracity. Many studies have combined the RBV and the DCV to investigate the impact of big data.

Similarly, this thesis, as per the DCV, proposes the use of AI to find opportunities within the organization's data, to design and refine the business models and realign the structure during uncertain environments to make business operations more agile. With the help of big data management, an organization gains the capability to implement changes to operational and tactical activities. For instance, while managing big data using AI, if an organization finds an alternative way of organizing supply chain activities to gain benefits, it must be able to reconfigure the corresponding capabilities.

2.3.3. Positioning the Research

The importance of achieving agility in business operations for the apparel supply chain by using AI to create better business decisions with big data management, which may result in sustainable competitive advantage, has been discussed in this chapter. For this reason, I will use both the RBV and DCV to examine how big data management and AI can be used as valuable resources by the managers of an apparel supply chain. The advocates of the RBV reason that organizations should look inside the company to find the sources of competitive advantage instead of looking at the external competitive environment (Ji-fan Ren et al., 2017). The key concepts within this perspective are therefore organization resources and sustainable competitive advantage.

An organization's resources can be defined as "*all assets, capabilities, organizational processes, firm attributes, information, and knowledge controlled by a firm that enables it to improve its efficiency and effectiveness*" (Barney, 1991). With respect to this thesis, these resources are considered to be "*product-related data, and customer data already available within the apparel supply chain, and AI capability"*. To transform these resources into sustainable competitive advantage, they must have four attributes that can be estimated using the VRIO framework developed by Barney (Barney, 2001) as depicted in Figure 2-5. The title of this framework is an acronym composed of the first letters of its elements, namely value, rarity, inimitability and organization. While the first three words are used to evaluate the organization's resources, the last word is used to evaluate its dynamic capability (Cardeal and António, 2012), i.e. the output of how well an organization integrates its resources is its dynamic capability.

To evaluate the resources considered in this thesis on these four elements, the framework presented in Figure 2-5 must be followed. Firstly, it starts with assessing whether big data management using AI enabled the organization to attain value by exploiting new opportunities for its growth and development. If the answer is "Yes," then the resource can be considered valuable. Secondly, whether the big data and analytics strategy provided the organization with a unique capability should be investigated. Thirdly, whether the big data solutions developed were difficult or almost impossible to duplicate by the organization's competitors should be examined. And finally, it should be established whether the organization has the capability to capture, exploit, and generate value from its valuable, rare and costly-to-imitate big data.

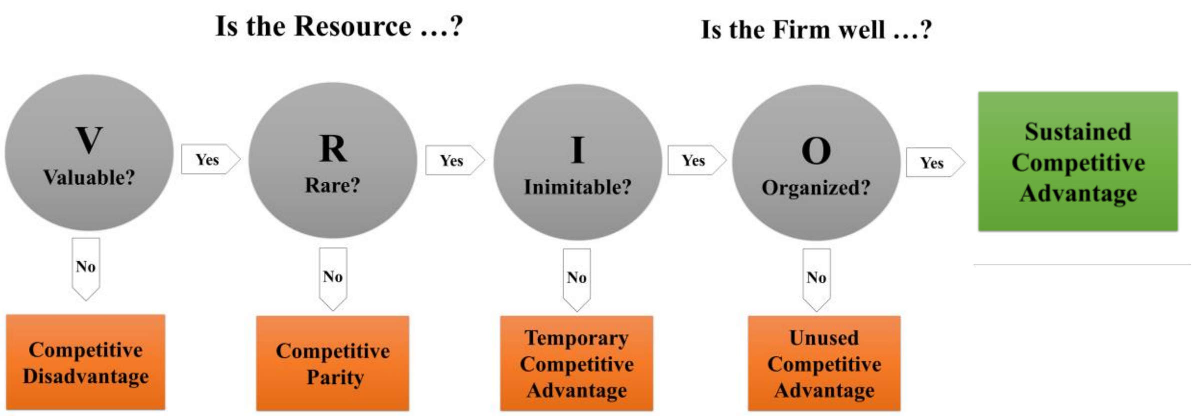

Figure 2-5. The VRIO Framework

3. Research Methodology

This chapter provides an overview of the methodological choices, research perspective, and processes followed to find answers to the research questions. After presenting the research approach for the thesis— explaining the systematic literature review approach and the choice of quantitative and qualitative approaches, the chapter discusses the research process including the different data sources and tools used for data analysis.

3.1. Research Approach

This thesis follows the use of multiple methods to gain knowledge from a combination of qualitative and quantitative techniques. Such an approach allows to position individual methods in the appended articles, and develop a comprehensive understanding of the research area within the context of the methodology (Abowitz and Toole, 2010). It is also a methodological choice widely adopted in implementation (Palinkas et al., 2011) and applied research in distinct domains (see i.e. Nogry and Varly, 2018; Sutton, 2018).

This thesis is a compilation of four research articles. While it adds to the fundamental knowledge and understanding of big data and AI in the apparel supply chain, it is primarily driven by specific industrial problems related to keeping pace with evolving customer needs, and finding new ways of creating competitive advantage, and in doing so contribute toward the larger societal issue of greener production and consumption practices. The thesis covers current emerging technologies, more specifically the tools and techniques falling under the umbrella of AI, which is believed to be an efficient technology to deal with big data (Kersting and Meyer, 2018). Further, it adopts the VRIO framework within the RBV and the DCV management theories to compile the findings from the appended papers. The thesis is interdisciplinary in nature and contributes to the engineering and social science field. Consequently, a combination of relevant methods, both from the social and engineering sciences, were chosen as they synthesize the substantive expertise of an engineer with those of social science expertise, highlighting social research problems in technology research with the utility of a mixed rather than a single methodological approach.

The appended papers in the thesis adopt qualitative and quantitative methods mainly focused on collecting and analyzing big data and the knowledge available in apparel supply chains using AI techniques. This is also in line with the idea of investigating whether apparel firms can improve business operations using big data and AI, and in doing so, seek opportunities with big data management using AI. There are times when the method most appropriate to achieve the objectives of a research study cannot be used because of the constraints such as a lack of resources and/or required skills. In such situations, one should be aware of the problems that these limitations impose on the quality of the data. Hence, the choice of a method depended upon the purpose of the thesis, the resources available, and the skills of the researcher. As mentioned earlier, each appended article in this thesis is based on individual research work and includes its own methods and empirical data.

At first, the thesis used an exploratory research approach i.e. reviewing the existing literature related to big data and AI within the context of the apparel industry, to identify the gaps, define the research problem, and limit the scope of the research. This exploratory research was necessary as the field of big data management using AI in the apparel supply chain is a research domain with vast research avenues. Moreover, considering the purpose of the thesis, it was important to find evidence in the literature to show the applicability of big data management and AI in the apparel supply chain. Additionally, conducting an exploratory study using a structured method such as a systematic literature review (SLR) provides a good opportunity for the researcher to comprehend the various studies done and find gaps that could be filled. Next, the research took on an empirical stance, where quantitative approaches for data collection were considered. An empirical stance was employed to seek opportunities with big data management using AI solutions. Several sources of data collection were explored such as product-related data from apparel companies, consumer fashion preferences surveys through social media, and interviews with retailers providing mass customization of garments. However, these efforts were deemed inappropriate due to introduction of the GDPR law. Since it was still in its nascent stage, companies were reluctant to share data. This led to a change in the approach of collecting data, and therefore other sources were explored. The product-related data was collected from an open source database widely used in research related to the apparel industry. Since, companies could not share their product data directly, this approach helped us to get a dataset that was very close to the real data. Moreover, collection and preparation of similar data from a company takes longer and using an open source dataset eliminates that delay. As the apparel product requires human intervention in its conceptualization, another source of product-related data considered was product development experts. These data helped to build empirical models, driven by AI and big data. While these methods helped to provide AI solutions to manage big data, there was still a need to find evidence for whether apparel firms could use big data management to improve business operations. Due to this, a qualitative approach was used to interview apparel firms considered to be pioneers in managing big data. The interviews were conducted as part of a bigger research project by other researchers and were found to be applicable to this thesis. The data collected from this source was thoroughly studied and combined with theoretical knowledge to build a conceptual model that could further strengthen the theoretical underpinnings. The results from these studies were deliberated to identify a common thread that could tie these into one unit. After careful consideration, the RBV and the DCV were chosen to explain these findings as a single unit. The reason for this decision was that the different articles employed data that were already present within the apparel supply chain and were unique to different firms. Using such data, firms could create data-driven strategies that could help them in achieving a sustainable competitive advantage. A summary of the different approaches and methods followed in the appended articles is shown in Table 3-1 and described in the subsections below.

Table 3-1. Summary of methods in the appended articles

Article #	A	B	C	D
Topic	AI at different stages of apparel supply chain	Modeling product data in apparel using data mining	Modeling data from experts using AI	Satisfaction through personalized services
Data Source	Scientific articles	Scientific open source database	Experts in academics and industry, scientific articles	Three Swedish retailers, scientific articles
Context	Apparel industry	Apparel industry	Apparel industry	Apparel industry
Method of Data Collection	Systematic literature review	Open source database	Sensory evaluation experiments	Personal interviews
Analysis Method of Unit of analysis	Classification	Data mining & machine learning algorithms	Fuzzy Logic	Middle-range theorizing
RQ Answered	**1**	**2**	**2**	**3**

3.1.1. A Literature Review Approach

Systematic literature review (SLR), has been used for a long time to get an idea of the recent advances in the related research field (Okoli, 2015), even though an SLR is a time-consuming process and usually requires more than one researcher. However, a well-constructed SLR can be considered to be a major contribution to the literature and helps in answering various questions (Mallett et al., 2012). Therefore, in this thesis, an SLR was used in article A as an information source to focus on the big data and AI methods used in the apparel industry. An SLR was chosen to make the research more rational, transparent, and reproducible (Booth et al., 2016). To an extent, big data management goes hand in hand with AI, as AI depends heavily on big data for success. While reviewing the literature, it was found that relatively less research adopted big data to create empirical models. Since one of the inclusion criteria to consider an article in the review process was that it must have designed an empirical model, the focus was reduced to AI, while looking for instances of big data within these articles.

The review process commenced with collecting and preparing data from two scientific databases—Scopus and Web of Science. The detailed article selection and review process is provided in the appended article A. In employing this course of action, 149 research articles were thoroughly reviewed to answer the **paper research questions** (PRQ) posed in the article and reproduced below.

"*PRQ1. What is the impact of AI on the fashion and apparel industry over the past decades?*

PRQ2. Where has AI been applied in the fashion and apparel supply chain?

PRQ3. To what extent has research addressed the supply chain problems from a B2B and/or B2C perspective?"

By scrutinizing the literature, various interesting findings related to the adoption of AI techniques in research and their realization as practical applications came to light. Hence, conducting an SLR imparted the thesis with a pertinent discussion on the influence of AI at different stages of the apparel supply chain. In addition, it also provided a clear classification of supply chain stages and AI, discussed in detail in the appended article A. As a result of these categorizations, research gaps were identified in the application of AI techniques, at the supply chain stages and from a business (B2B and B2C) perspective. Based on these gaps, the prospects of the AI in this domain were identified.

3.1.2. *Quantitative Methods*

A data modeling-based approach is one of the most commonly used quantitative methods in engineering science. It includes creating physical, conceptual, or mathematical models which help scientists to replicate the reality under investigation through simplification (Saaty and Alexander, 1981). However, one limitation related to this approach is that these models can sometimes be an over-simplification of the reality, and so their applicability in practical scenarios becomes less practical. In this thesis, a more recent development—computer-based modeling—was adopted that takes advantage of the impending technological progress in computer programming which makes the models robust and easily applicable. The reason for choosing this as an approach was the increasing processing speed and power of computers, and their ability to manage big data with ease. Besides, it is easier to combine computer modeling with other scientific research methods due to their nature of being perceivable, operable, understandable, and robust. The models thus developed were determined by establishing mathematical relationships between variables that described numerically using computer programming. This was used to fulfill the purpose in the appended article B, which aimed to develop a classification framework for predicting garment categories and sub-categories given the product attributes. The article employs four machine learning techniques, namely Naïve Bayes, decision trees, random forest, and Bayesian forest.

Sensory evaluation is intended to provide a systematic and objective method for carrying out a perception-based analysis of a product's design (Ruan and Zeng, 2004). It can identify the relationship between human factors and product elements, and has been applied in the food, cosmetic, and automotive industries to evaluate consumer's perceptions of a product (Amerine et al., 2013; Civille and Oftedal, 2012). An apparel product is also made considering human needs and perceptions; therefore, sensory evaluation can be used to analyze expert's knowledge of it. This analysis can support product development and design. Despite the benefits, sensory testing is prone to errors and biases that can lead to inaccurate results. To eliminate some of these limitations, comprehensive instructions were provided, and participants were situated in separate rooms. In this thesis, the sensory evaluation method was utilized in article C, where the aim was to evaluate distinct apparel styles and real fabric swatches to characterize the relationship between product designers' knowledge and product design parameters.

To do this, the sensory evaluation process was carried out in three phases. It started with the analysis of existing literature to identify and select relevant fabric handles, apparel styles, and product parameters. Next, 25 appropriate images were chosen, corresponding to each of the nine apparel styles and were further reduced to five in each style by conducting an online survey among fashion designers from France, Germany, India, China, and Sweden. The method for distributing the survey was in line with a snowballing approach, where it was shared with a list of designers who then forwarded it to their contacts. With the responses from 67 designers, mood boards for nine styles were created, as discussed in article C. In the final phase, face-to-face experiments were conducted, where 20 participants from China, Sweden, and India were chosen. The participants were experts in the industry and academia within fashion design, textile design, and product development. During the experiment, each participant was provided with five real fabric swatches and mood boards of nine apparel styles, along with a brief questionnaire to fill in their evaluation of various sensory parameters such as fabric handle, season, the occasion of wear, and anthropometric points. They assessed the fabric, apparel styles, and sensory product attributes using linguistic terminology and recorded their responses on a Likert scale.

3.1.3. Qualitative Method

The qualitative method employed in this thesis was an interview-based approach. There are a range of interview formats, conducted with both individuals and groups, where semi-structured interviews are becoming increasingly prevalent in research (DiCicco-Bloom and Crabtree, 2006; Rowley, 2012). Qualitative interviews afford researchers opportunities to explore, in an in-depth manner, matters that are unique to the experiences of the interviewees, allowing insights into how different phenomena of interest are experienced and perceived. Qualitative research interviews are selected when the researcher attempts to comprehend the interviewee's subjective view of an aspect rather than generating generalizable understandings of large groups of people. However, conducting interviews is time consuming and resource intensive, and requires appropriate interviewing skills (Rowley, 2012). For this reason, the interviews were conducted as part of a bigger research project and performed with the help of experts, resulting in transcript versions of the interviews. For this thesis, seven of the qualitative interviews from three companies were analyzed to get an in-depth understanding of how apparel e-commerce retailers used big data to provide personalized services to their customers. The three retailers were chosen based on their experience in the online apparel business and are considered to be pioneers in the field of providing tailored or mass-customized product offerings.

Once the interview data was collected, the data transcription began. The most common form of transcription in qualitative interviews is verbatim transcription, which refers to the word-for-word reproduction of verbal data, where the written words are an exact replication of the audio-recorded words (Poland, 1995). Transcribing data from qualitative interviews is very time consuming (Halcomb and Davidson, 2006). Furthermore, the process yields vast amounts of material, which must be iteratively scrutinized and waded through when analyzing the data. In addition, the transcription of the interviews by the researchers themselves allows them to identify analytical structures, similarities, and dissimilarities between various interviewees' perspectives. Despite its advantages, one common and important weakness of this method is that it might not be possible to generalize the findings to other industries or settings, since some factors remain unique from one business to another. Moreover, sometimes questions are raised regarding the credibility of the results obtained. However, the use of triangulation, in the form of different investigators increases the possibility of obtaining credible results (Lincoln and Guba, 1985).

In the appended paper D, an analysis of transcript interviews based on a semi-structured personal interview approach was adopted. The empirical data used in paper D, was part of another research project between 2016–2018 owned by the Swedish Institute for Innovative Retailing (SIIR) at the University of Borås, and commissioned to collect practice-oriented cases to serve as illustrations and/or explorations of the retail phenomenon, customer experience, and customer satisfaction. During the research project, semi-structured interviews were conducted with key employees in ten different types of retail companies, including industries such as apparel, cosmetics, home textiles, and home electronics. The companies operated different channels that included bricks-and-mortar stores, online, and both online and offline sales. This study purposefully selected the empirical findings from three of these companies as they were matching pairs and offered online strategies and apparel. The cases were audio-recorded and labeled based on the company name, informants' designation and function, description of the session, and duration (as depicted in Table I in article D). The interviews were conducted with key employees from the three companies, performed in Swedish, and then translated into English. To avoid bias, the informants were selected based on their experience and knowledge, and from different hierarchical levels and functions. The data consisted of seven in-depth interviews with employees at the three firms, both at a senior and junior management level, as well as handling operational functions such as logistics and supply chain management.

The empirical data was analyzed using conventional techniques from qualitative research. Firstly, the data collected through the interviews and extensive review of the literature were analyzed in depth by breaking the interviews down with the help of a general theoretical foundation, bridging the domain with the help of middle-range theory. This resulted in an empirical generalization of personalized services within apparel e-commerce fulfillment that could be supported and verified using the suggested conceptual framework. Thus, the theory-driven analysis captured empirical claims with the help of a foundational premise that could extend the notion of personalized services in apparel e-commerce.

3.2. Research Process

The research process began in September 2016 under the framework of the Erasmus Mundus Joint Doctorate Program, “Sustainable Management and Design for Textiles (SMDTex),” funded by the European Commission. The research conducted in this thesis had a pre-defined topic and mobility in two European and one Chinese university set by a collaboration between the partner universities and the funding agencies (European Commission Education, Audio-visual and Culture Executive Agency, and Chinese Scholarship Council). The three specialized departments for this research project at each university were: a. The Human-Centered Design Department (HCD) at the École Nationale Supérieure des Arts et Industries Textiles (ENSAIT), University of Lille, France; b. The Textile Management Department at the University of Borås, Sweden; and c. The College of Textile and Clothing Engineering at Soochow University, China. The total duration of the project was 48 months with 18 months at each of the two European universities and 12 months at the Chinese university.

Considering the three different departments, the interdisciplinary nature of the research is apparent, and hence this thesis contributes to the engineering and management disciplines. Even though working in these two disciplines simultaneously is challenging, it is also important considering the topic under investigation. Initially, the thesis favored an exploratory research method and started with reviewing the literature to identify various research streams that the research topic touched, and the ones that required the most attention. These streams have been discussed in detail in Chapter 2 of this thesis.

With this knowledge, a preliminary plan for the thesis was devised to be followed at each university. During the first research period at ENSAIT, a systematic literature review was conducted with a focus on the application of AI and big data in research related to the apparel industry, resulting in article A. This article provided further direction to reduce the research scope to the study of opportunities with data in the area of product and customer data, as it was established that little work had been done in this direction. The second and third research periods were focused on exploring these different types of data in the apparel supply chain, collecting the relevant data, exploring distinct tools and techniques to analyze it, and developing models using the different types of data collected. The remaining articles were based on the outcomes derived from the work done in the last two research periods. As has already been discussed, this thesis uses different types of data collected using multiple methods. Hence, articles B and C uses a quantitative method approach to scrutinize product-related data, and article D uses a qualitative method approach to create a conceptual model of providing satisfaction using personalized services with the help of customer data by apparel e-commerce retailers. A brief timeline and the research process followed is shown in Figure 3-1.

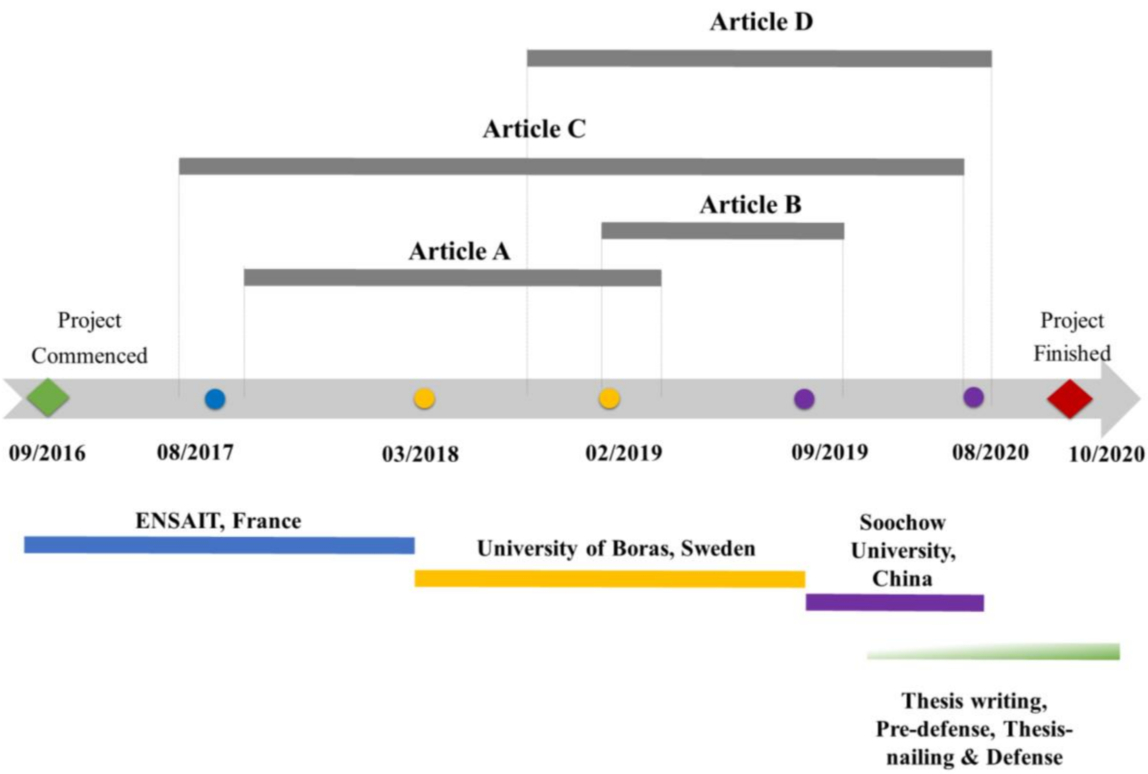

Figure 3-1. The research process

3.2.1. Data Sources

As already mentioned, because of the interdisciplinary nature of this thesis, it has been established on a multiple method approach, using both primary and secondary data sources. In addition, to fully understand the concept and requirement of big data and AI in the apparel industry, various scientific and non-scientific (e.g. white papers, industry reports) data sources were explored and analyzed. Primary data was produced by planning interviews and surveys with experts in the industry and academia, while secondary scientific sources were used for the systematic literature review and to obtain a clear understanding of the key concepts involved.

Considering the aim of the thesis i.e. to investigate whether apparel firms could improve their business operations by employing big data and AI, and in doing so, seek opportunities with big data management using AI solutions. The first appended article presents a systematic literature review to synthesize recent research to form a body of empirical knowledge. Based on this knowledge, the research process was further developed leading to the collection of data from certain primary sources using methods as described in section 3.1. In article B, an online open source database, as shown in Table 3-2, with over 300,000 fashion images was used. This data was important because of the product attributes that the images were tagged with, which were further used for garment categorization. In article C, data was collected from fashion designers, textile designers, and product developers with the help of sensory experiments and interviews. These experiments were designed to gather expert knowledge related to a garment and to establish a knowledge base of design rules that could help in automating the product development process. In article D, interviews from technologically advanced apparel e-commerce retailers were used, where the retailers provided a personalized services by using big data management, information sharing and data analytics. This was done to develop a theoretical framework by proposing satisfaction through personalized services as a middle-range theory to bridge customer perceived value theory and empirical research. The collected data were both qualitative and quantitative in nature as shown in Table 3-3. The results of analyzing the collected data generated knowledge that could be used by the scientific community as well as industry practitioners.

Table 3-2. Data used in article B

Dataset	Initial		Final	
	No. of data points	No. of attributes	No. of data points	No. of attributes
All garments	289222	1000	276253	1000
Upper garments	137770	1000	131620	430
Lower garments	56037	1000	55915	467
Whole-body garments	82446	1000	82202	453

Collecting data from a mixture of collection methods helped in achieving a robust and holistic perspective on the researched phenomenon. The larger part of the collected data was used to produce the appended articles. However, some other data from semi-structured interviews with experts in academia and industry were used to gain a broader understanding of the phenomenon under study and the current thinking of the practitioners.

Table 3-3. Summary of data collection

Data Collection Method	Data Collected
Scientific literature	149 articles with an empirical study conducted using AI techniques (article A)
Open source database	A database containing 300,000 data instances of product attributes, categories, and sub-categories
Participants in sensory evaluation	Discussion with 20 experts from academia and the apparel industry • Responses recorded with the help of a questionnaire
Semi-structured interviews	Seven in-depth interviews (transcribed) with three firms
Additional methods	o Survey responses with five textile and fashion designers o Online survey responses from 67 fashion and apparel designers

3.2.2. Data Analysis

Three of the appended articles in this thesis follow quantitative (articles B and C) or qualitative (article D) methods to analyze data. The reasons for choosing different approaches have been discussed in detail in section 3.1. Article A adopted a systematic literature review approach that used scientific literature published in the field of study as data, and identified the impact of AI in the apparel industry. This contributed to meeting the overall purpose of the thesis i.e. whether apparel firms can improve business operations using big data and AI, and seek opportunities with big data management using AI solutions. With a rigorous review process, relevant articles were filtered and critically analyzed to determine the gaps and future research directions. Furthermore, it provided an indication on which techniques could be used where in the supply chain to automate operations. Article B used machine learning techniques to analyze product attribute data and create a classification model. Article C dealt with the data collected through the sensory evaluation experimental approach and was analyzed using an AI technique and fuzzy logic to create a fuzzy inference system (FIS). These articles provided evidence of managing big data using AI solutions. Article D used the data collected through semi-structured interviews and the concept of middle-range theory to connect the collected empirical evidence with the general theory. Similarly to article A, the findings from this article also contributed to the answering the question on whether apparel firms could improve business operations using big data and AI.

As discussed in section 3.1, the theoretical lens used in this thesis was that of the RBV and the DCV, combining the results of the four articles to not only answer the research questions, but to also fulfill the overall purpose, as discussed in section 2.4. With each article, the aim was to investigate whether by employing big data and AI, apparel firms could improve business operations, and in doing so, identify big data management opportunities using AI solutions. As discussed earlier, article A presents the impact of AI in the apparel industry at various supply chain stages, which shows the support that AI provides in automating various business operations. Articles B and C utilize data available in the supply chain and apply different AI techniques to show how they can be used to improve business operations. Article D presents a framework that suggests increasing customer perceived value by the provision of personalized services by apparel e-commerce retailers and does this by focusing on the customer data collected by them and utilized to enhance customer satisfaction. This corresponds to the idea of the RBV and the DCV that suggests a firm looks for resources internally and uses them to establish capabilities and create sustainable competitive advantage. Moreover, it suggests evaluating the different resources on four aspects, namely value, rarity, inimitability, and organization capability. Even though the firm may have the appropriate data, it has to develop the technical and managerial capabilities to harness the power of that data to sustain it in a competitive business environment. These theories provided a structured tool in the form of the VRIO framework, discussed in section 2.4.3, that can be used for evaluating resources and establishing dynamic capabilities. Using the RBV and the DCV theoretical lens and the results from the four articles, the three research questions along with the overall purpose are answered in detail in Chapter 5.

3.3. Research Quality

This research involves both quantitative and qualitative data obtained from primary as well as secondary sources. Therefore, three conventional criteria, namely internal validity, external validity, and objectivity were used to establish the quality of the research (Guba and Lincoln, 1989).

3.3.1. Internal Validity

Internal validity uses pattern matching and logical models (mostly from the secondary data sources) to explain and build the concept (Rabinovich and Cheon, 2011) and ensures that the research outcomes are replicable by other researchers. Each appended paper in this thesis presents a brief overview of the literature to explore and establish the research gap and work toward filling the gap, and then explains the contribution of the study to the research gap in the results and conclusions section. Moreover, the theoretical framework used in the thesis was established and can be adopted by other researchers to replicate the results of this thesis.

3.3.2. External Validity

External validity addresses the generalizability of the results. To ensure external validity of the research, standard methods with an adequate sample size were used throughout this PhD study. The studies conducted in this thesis are within the context of the apparel industry. However, the results from this thesis can be applied to other domains within consumer goods such as the food industry, cosmetic industry, electronics industry, or automation industry. These areas also have an increased need to match consumer needs with products due to the increasing nature of global competition. Similarly to the apparel industry, big data management and AI can help these industries build data-driven strategies that could assist them in sustaining their competitive advantage.

3.3.3. Objectivity

To ensure that the research inquiry was free of bias and/or prejudice, various standard procedures, as defined in the literature for specific methods, were followed during this research. In article A, to guarantee that all the relevant literature had been covered in the study, two widely used and well-acknowledged citation databases (Scopus and Web of Science) were used. Maximum precautions were taken in formulating the search query to confirm an exhaustive search of the related articles. Moreover, the standard procedure for SLR was followed (Booth et al., 2016; Okoli, 2015). In articles B and C, several evaluation methods including accuracy, precision, recall, and F-score were calculated for each machine learning technique and compared with standards from the literature to ensure the stability and consensus of the results (Ferri et al., 2009; Gupta et al., 2012; Ibrahim, 2016; Jiao and Du, 2016). In addition, in articles C and D, experts for the semi-structured interviews (Drever, 1995; Whiting, 2008) and sensory evaluation (Ruan and Zeng, 2004) were chosen from different backgrounds to include diverse views. Moreover, the methods adopted by each study have been described thoroughly in the articles to ensure transparency and reproducibility.

4. Summary of the appended articles

This chapter presents an overview of the research contribution of the thesis, followed by a summary of the papers appended in this cover essay. For each paper, the purpose, an overview of the research method, the main finding(s), and the contribution to the thesis are outlined.

This thesis is based on four journal articles to address the three research questions. Table 4-1 shows the relationship between the appended papers and the proposed research questions, while Table 3-1 in the previous chapter highlights the focus area of each appended paper.

Table 4-1. Relationship between the research questions and the appended articles.

Article #	**A**	**B**	**C**	**D**
RQ1	X			
RQ2		X	X	
RQ3				X

4.1. Article A

Title: A detailed review of AI applied in the fashion and apparel industry

Purpose: The increasing use of AI in the fashion and apparel industry has made it important to look at the various focus areas and the impact it has had on the different stages of the supply chain. Hence, the purpose of this article was to address three research questions, 1) What has been the impact of AI in the apparel industry? 2) Where have AI methods been applied in the apparel supply chain? 3) To what extent has research addressed the supply chain problems from a B2B and/or B2C perspective?

Methodology: To answer the research questions, an SLR of research articles associated with AI in the fashion and apparel industry was conducted. A total of 1,019 articles were retrieved from two popular scientific databases, Scopus and Web of Science. After performing a rigorous article screening process, 149 articles were reviewed and categorized according to the AI techniques applied and the supply chain stages to which they referred. Moreover, the supply chain stages were classified into business-to-business (B2B) and business-to-consumer (B2C) categories.

Findings: It was found that most of the research relating to the application of AI in the apparel industry was conducted from 2009 to 2019, with machine learning and expert systems being the most popular. The research into the application of deep learning and transfer learning were scant. In addition, very little research discussed big data in the fashion and apparel industry, showing immense potential in the realization of data analytics and AI. Further, the most focused supply chain stages were apparel production, fabric production, and distribution, while design was least covered. Moreover, most of the studies focused on B2B with little focus on B2C business problems.

Practical implications: The implications and future direction discussed in this study could benefit academic and industrial researchers as well as industrial practitioners.

Originality/value: Apparel industry, being one of the largest industries, needs to bring transformation in the traditional way of operating processes by adopting AI techniques at the industrial level.

Contribution to the thesis: This article discusses the various techniques in AI together with its application in the apparel industry. The findings yielded a lack of focus on big data management, the design process, and business-to-customer solutions. Both product design and customer-oriented solutions are central to a business's success. A data-driven design process can help immensely in achieving a customer-oriented product and to generate business value. Hence, this article channels the focus of this research to "product data" and "customer data" in the context of apparel products. The adoption of AI methods at various supply chain stages indicates that there is need for automation of the various supply chain operations, and it is mainly due to the increase in consumer demands and competition that the industry is seeking agility to gain competitive advantage.

4.2. Article B

Title: Garment categorization using data mining techniques

Purpose: There has been rampant use of the term big data in the business world steering the extensive adoption of techniques like data mining, machine learning, and AI. The apparel industry, in particular, can gain many benefits by adopting these techniques as it generates different forms of data at every stage of the supply chain. In research, some of these data types have been employed to generate models targeted at automating specific supply-chain processes. In this research, the focus was on utilizing the data related to the product i.e. the garment to create a classification model that can predict the clothing category (upper, lower, or whole-body garment) and the clothing sub-category (jeans, shirt, dress, etc.) based on product attributes.

The purpose of this article was to use data mining and symmetry-based learning techniques on this product data to create a classification model consisting of two subsystems, the first for predicting the garment category and the second for predicting the garment sub-category.

Methodology: To create the classification model, four machine learning techniques were used to compare and identify the one with better results. The following four techniques—Decision tree, Naïve Bayes, random forest, and Bayesian forest—were applied on an open source dataset "DeepFashion," which contains approximately 300 k data points with three clothing categories, 50 clothing sub-categories, and 1,000 garment attributes. The two subsystems were first trained individually and then integrated using soft classification.

Findings: The classification model thus created consisted of two individual subsystems, one to identify the clothing category and the other to identify the clothing sub-category. It was observed that the performance of the random forest classifier was comparatively better with accuracies of 86%, 73%, 82%, and 90% for the garment category, and sub-categories of upper-body, lower-body, and whole-body garments, respectively.

Practical Implications: Every garment retailer and/or production house collects similar data related to garments i.e. the garment categories and attributes in their archives. In addition, these are also the details present on the product pages of e-commerce websites. Hence, the data can be obtained from these sources and used to create segmentation based on the attributes used for various garments. This segmentation can be used to classify the data based on the methodology described in this article. Such a classification can have various applications such as improving the existing recommendation algorithms by providing words instead of images, enhancing the parsing algorithms, etc. Moreover, as discussed in (Tu et al., 2020), in the internet era there is an availability of massive datasets in various formats, making it essential to design ways in which to handle access to and integration of such data. The presented model can be trained with additional data formats and so incorporate the access and integration of data from multiple resources (especially data from the internet) as it provides a uniform terminology of garment categories, sub-categories, and their attributes.

Contribution to the thesis: In this thesis, it was targeted by using two different types of data: "product data" and "expert knowledge data." This article focused on the former and used an open source product database before employing data mining and machine learning techniques to create a classification model. This model included two subsystems: one for predicting the clothing category and the other for predicting the clothing sub-category. In hindsight, this classification model could be used to improve personalized recommendations or it could be used by supply chain managers to build a common semantic ontology for information exchange between different operators. This is one of the opportunities identified in this thesis with big data management using AI solutions.

4.3. Article C

Title: Mass-customized fashion: Tapping into the mind of an expert in the apparel industry

Purpose: Even though the amount of data is increasing in the fashion and apparel industry and some businesses are using it to a great extent, the industry is far from being free from human intervention. It is important to gather expert knowledge and use it to create models that can be powered by existing data to provide mass-customized or customer-centric products. Therefore, the purpose of this article was to tap into one of the expert categories of the apparel industry, i.e. the product designer's mind, and capture valuable knowledge that could help in creating such a knowledge base. This knowledge was used to realize a data-driven design process, which could assist product designers in the fashion and apparel industry to develop products faster based on various design criteria.

Methodology: As garment design and development is subjective and depends on the perception of the designer, the study adopted a sensory-evaluation-based methodology to acquire expert knowledge. To do this, we first collected real fabric swatches, their technical properties, and four pairs of fabric handle descriptors. Next, we selected nine apparel style descriptors and their representative images to create mood boards. A questionnaire was developed to conduct semi-structured interviews during the sensory evaluation with fashion and apparel experts from industry and academia. To analyze the collected data, the study used a popular AI technique to analyze uncertain data i.e. fuzzy logic.

Findings: The application of fuzzy logic to the collected data led to the creation of a knowledge base containing a set of 51 design rules that could be helpful in conceptualizing products digitally. A graphical user interface was developed based on the fuzzy inference system integrated with the 51 design rules.

Practical Implications: In this study, an intelligent knowledge-based inference system was proposed to support digital product development by automating fabric selection. The proposed DSS has a potential application in digital prototyping and the development of products. The purpose of the system is to assist stakeholders in the supply chain make quick decisions for complex problems.

Contribution to the thesis: The purpose of this article was to connect the technical properties of a fabric with the consumer needs of the garment by conducting sensory experiments with experts in the fashion and apparel industry. The data thus obtained was used to create decision rules using data mining and machine learning, which could be used to further improve the existing design algorithms in designer-oriented recommendation systems. This article presented the utilization of AI techniques on existing data in the industry, and how it could help in making decisions that could create added value. Another opportunity identified in this thesis with big data management using AI solutions was that of a DSS to choose the most suitable fabric in a dynamic product development process that could be used by apparel firms to integrate with existing product configurators or other product development tools to automate fabric selection.

4.4. Article D

Title: Toward a conceptualization of personalized services in apparel e-commerce fulfillment

Purpose: The apparel industry has been a victim of technology proliferation and globalization, which has led to increased competition globally. Apparel firms are constantly working on finding new ways of gaining a competitive advantage by creating more value with their products. Increasingly customers are moving toward shopping through online retail channels. Even so, the challenge of translating a potential sale remains, products and services being two sides of the same coin both of which need to be given equal attention. Today, customers´ perceived value does not only depend on the products, but also on the services provided by a firm. Consequently, it is important to shift the focus beyond the product and discuss the value of personalized services in the context of e-commerce fulfillment. Therefore, the purpose of the article was twofold: 1) to develop a conceptual framework proposing satisfaction through personalized services as a middle-range theory, and 2) to suggest foundational premises to support the framework, which in turn would shape middle-range theory within the context of apparel e-commerce fulfillment.
Methodology: To fulfill the aim of the article, in this theory-driven paper, the authors apply the Scientific Circle of Enquiry (SCE), as it demonstrates the role of theorizing with the help of middle-range theory and empirical evidence and as such provides a methodological scaffolding that connects theory formulation and verification. The authors synthesized existing literature related to customer perceived value and satisfaction customer experiences, followed

by abduction focusing on understanding the empirical domain as it occurred in practice from company cases. The presented case studies were based on semi-structured interviews with three Swedish online retailers within the apparel industry.

Findings: Based on the theoretical foundations and empirical generalizations, three propositions were suggested. The premises regarding satisfaction through personalized service applied in the domain of apparel e-commerce fulfillment are: a) to ensure customer satisfaction require a value co-creation perspective using data during the pre-purchase phase, b) to ensure customer satisfaction and retention require added-value perspective during the post-purchase phase of the shopping journey, and c) to ensure satisfaction and convenience require an added-value perspective at the last mile.

Practical Implications: Apparel firms lose a substantial amount of potential revenue globally due to the poor online customer experience which leads to e-commerce not reaching its full potential. To enhance customer value, apparel e-commerce businesses need to find a resort in advanced technologies and analytics in order to address customer satisfaction, and it is suggested that retailers shift their focus beyond the products and find ways to improve personalized service offerings to gain market advantage, improve fulfillment, drive sales, and increase customer perceived value.

Contribution to the thesis: While reading the existing literature on consumer perceived value, it became apparent that the product as well as the other touchpoints of the customer purchasing journey on an online retail channel were equally important in enhancing the customer's overall experience and benefited from utilizing data during these stages. Thus, providing personalized services could be another way of improving business profitability with big data management in the apparel industry. Big data management using AI could help managers react faster to changing customer demands and market fluctuations. Moreover, it could help to make the online shopping experience slicker for the customer. A supply chain manager who converts the existing data into knowledge and perceives it to be an important capability can gain competitive advantage by providing customers with personalized services. Such a data-driven supply chain can be maintained with the help of AI techniques. Herein lies another opportunity for apparel e-commerce retailers to benefit from big data management.

5. Synthesis of the Results

This chapter presents the analysis of results in consideration of the frame of reference presented in Chapter 2 to address the overall purpose of the thesis and answer the research questions. The purpose of the thesis is to investigate whether apparel firms can improve their business operations by employing big data and AI, and in doing so, seek opportunities with big data management using AI solutions. In this chapter the specific RQs are presented with analysis and answers that correlate to different parts of the purpose. However, the overall purpose needs to be addressed and elaborated on before answering the specific questions, so that together they present new knowledge and fulfill the purpose of the thesis.

5.1. The Overall Purpose

Businesses spend millions on analytics solutions to improve their business value and ultimately make business operations more effective and efficient (Ji-fan Ren et al., 2017). However, the effect of data-driven strategies on the success of a business is not short of obstacles (McAfee and Brynjolfsson, 2012). The appended scientific papers together all put emphasis on the importance of big data management and how to leverage AI solutions to provide personalization, create competitive advantage, and move toward a sustainable supply chain. But what are the specific opportunities with big data management using AI solutions?

Considering the definition of big data management in Chapter 2 (p.39) as collecting, organizing, storing, and utilizing big data using advanced analytics to improve business operations, the specific opportunities with big data management using AI solutions could be presented according to that structure. However, such a presentation would be missing managerial ideas and theory. I chose, instead, to identify the specific opportunities within the conceptual framework based on two management theories: the RBV and the DCV outlined in Chapter 2. It was suggested that the idea of employing the VRIO framework (Barney, 2001) to the field of big data and analytics solutions would contribute to a more precise knowledge on the specific opportunities with big data management using AI solutions (Akter et al., 2016). The RBV theory of a firm helps to overcome the obstacles related to transforming its investment in big data into competitive advantage and find appropriate solutions. The DCV theory supports this by suggesting big data management as a valuable capability of a firm that is already available and can be used to drive effectiveness and efficiency, and deal with uncertain business situations (van Rijmenam et al., 2019).

Table 5-1. Analysis of appended articles using the VRIO framework

Resource	Value	Rarity	Imitability	Organization
Apparel product data and machine learning algorithms (article B)	This data can become a valuable resource when an appropriate AI technique is used. It can help in improving product recommendations thereby creating symbolic value for the customer and business.	This type of data is unique to an organization as it depends on the type of garment collections it offers. Further, algorithms developed can make the analytics capability proprietary.	The possibility of duplicating this solution depends on the complexity and timeliness of the product.	The organization must have the capability of processing and storing a huge amount of data. Moreover, relevant data science capabilities must be present.
Expert Knowledge and decision support system (article C)	Similarly to the above data, this data can be exploited using relevant AI techniques. However, data collection can be difficult as it involves capturing the expert's knowledge.	This data was used to create design rules that are dependent on the experts. Hence, the data is unique to the organization.	The implementation of the DSS is subject to an organization's analytical capability that makes it difficult to imitate.	The organization must have the right analytics capability which must align with its long-term business strategy.
Customer data and data-driven personalized services (article D)	Customer data is one of the most important and valuable resources for an organization's growth and development.	This data may be unique to the organization as it depends on the customer base.	This model will engage organizations in evolving from the exploratory use to a more institutionalized form of use, and	The organization must have the perspective of providing personalized services to its customers in

			hence makes it difficult to imitate.	their business strategy.

As discussed in section 2.3.3, an organization must evaluate the resources under question based on the four aspects of value, rarity, imitability, and organization, to translate the resources into sustainable competitive advantage when looking at the firm from an RBV and a DCV perspective (Barney, 2001). On the basis of the framework shown in Figure 2-5, the different solutions presented in this thesis were evaluated and an analysis is summarized in Table 5-1. The first aspect of the framework was to evaluate if the big data management solution helped in generating value for the firm. The second and third aspects were to establish if the big data management solution was unique to the firm and difficult to replicate. Finally, the fourth aspect was to determine if the firm had the capability of integrating this valuable, rare, and inimitable resource to achieve sustainable competitive advantage.

5.1.1. Concluding the Overall Purpose

Among the several paths through which big data and AI can lead to competitive advantage (Côrte-Real et al., 2017), this thesis shows the effectiveness of data-driven analytical solutions in sustaining competitive advantage via data and knowledge already present within an apparel supply chain. Big data and AI solutions seem to improve the understanding of what customers want, and firms are able to better customize their offerings to increase customers' satisfaction and loyalty (Kitchens et al., 2018; Kumar et al., 2019; Tan et al., 2015) and to decrease customer acquisition costs. Both are key ingredients for enhanced cash flows and more generally for enhanced financial performance (Wamba et al., 2017). More importantly, this thesis also contributes to the field by identifying specific opportunities with big data management using AI solutions. The first is a classification framework to identify different apparel products using AI techniques that can be used by apparel retailers to improve personalized recommendations or by the supply chain managers to build a common semantic ontology for information exchange between different operators. The second is a DSS to choose the most suitable fabric in a dynamic product development process that can be used by apparel firms to integrate with existing product configurators or other product development tools to automate fabric selection. Finally, the third is a theoretical framework based on customer perceived value and empirical evidence that can provide managers in apparel e-commerce firms with ingredients to devise data-drive strategies to deliver personalized experiences. The challenges of using big data management and AI have already been discussed in Chapter 2, but these opportunities can be a starting point for additional research, where the first two solutions can be further developed, and the third solution can be used to verify its applicability in practical scenarios.

After addressing the overall purpose, the next section deals with answering the three research questions shown in Figure 5-1 and their contributions to the purpose.

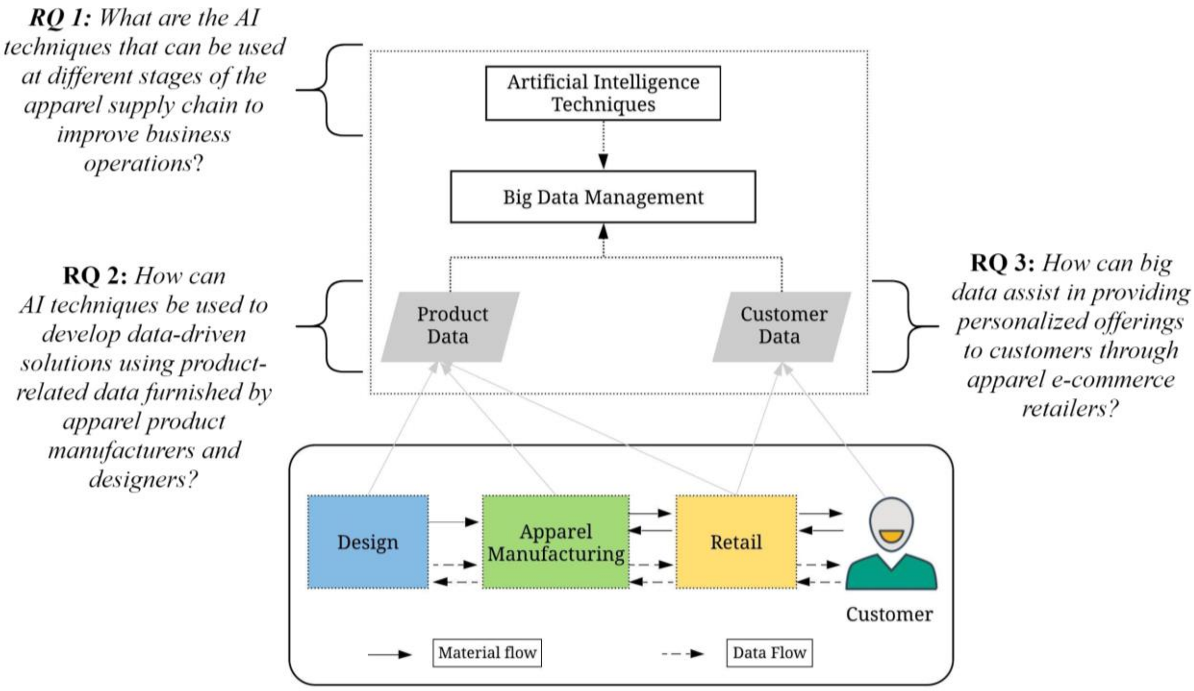

Figure 5-1. Big data and artificial intelligence in the apparel industry.

5.2. Research Question 1

"What are the AI techniques that can be used at different stages of the apparel supply chain to improve business operations?"

The purpose of this RQ is to find the various AI techniques that have been used at different stages of the apparel supply chain. This is in line with the overall purpose as it contributes to finding an answer to 'whether big data and AI can help apparel firms to improve their business operations.' As such this was achieved by finding evidence of the application of AI in the existing literature with the help of a systematic literature review. As per the findings of this review (also discussed in detail in section 2.2.4), it was found that AI does offer some opportunities for improving supply chain operations in the apparel industry (David Kreyenhagen et al., 2014; Li et al., 2017; Martino et al., 2016; Pantano and Vannucci, 2019;

Siegmund et al., 2016; Sodero et al., 2019). It can help in creating platforms for sharing information, automating supply chain operations, and building relationships among customers, suppliers, and retailers in new ways. Apparel firms need to take hold of the various big data flows and manage these new relationships to promote sustainable production and consumption patterns (Ngai et al., 2014). Businesses have perceived big data as a valuable resource and integrated AI to increase revenue, reduce costs, enhance resource utilization, improve the customer experience, all of which is line with the proposed management theories in Chapter 2 (see e.g. Shams and Solima, 2019; Wamba et al., 2017).

Regardless, the realization of these AI techniques in practical scenarios in the apparel supply chain are inadequate (Guo et al., 2011; Nayak and Padhye, 2018). This is due to the numerous challenges that apparel firms face while employing AI techniques such as the lack of labeled data, the high cost and impact of computational time, the dynamic product attributes and cultural resistance (Abd Jelil, 2018). In this context, the appended article A contributed to answering RQ1 by identifying the extent to which AI has been determined to solve various problems at different supply chain stages. It provided the categorization of research articles based on four operational processes in the apparel industry: design, fabric production, apparel production, and distribution (including retailing) and five AI classification techniques: machine learning, expert system, DSS, image recognition and computer vision, and optimization, as discussed in detail in section 2.2.3. An analysis of the findings in answering RQ1 is presented in the following section.

The overall trend of the articles published in three decades from 1989 to 2018 is shown in Figure 5-2. As can be observed, maximum research in the field of AI in apparel supply chain has been carried out in the last decade (2009-2018), which accounts for approximately 56% of the total articles reviewed. While in the first two decades, it was 11% and 33% respectively. Hence, even though AI methods were introduced long back in the 1950s (Stuart and Norvig, 2009) but their capability was realized much later in the last decade. This is possible due to the availability of platforms and higher computational power at lower cost to manage and process big data using AI.

Figure 5-2. Overall trend of AI in fashion and apparel since 1989 (article A)

The detailed trend of articles published per year in journals and conference proceedings is shown in Figure 5-3. As can be seen, the overall importance of this research domain has been similar in both journals and conferences. The only downward slope is visible for conference publications between 2013 and 2016 as highlighted in Figure 5-3. Moreover, the AI class "machine learning" has been used multiple times in journal articles since 1991. There are two peaks visible for journal articles in the years 2007 and 2017, with four and seven articles published, respectively. Whereas for conference articles, the AI class "machine learning" has been used since the year 2000 with three major peaks in the years 2010, 2012, and 2016 with four, three, and seven articles, respectively. On the other hand, the AI class "expert system" has been widely used since 1994 in journal articles while in conference articles there has been no research since 2014. For the AI class "DSS," there has been very little work in conference articles while a gradual increase in presence has been realized in journal articles since 2010. For 'image recognition,' its presence is visible since 2009 in both journal and conference articles, being the least applied AI class. In contrast to other classes, for optimization, there were more conference articles than journal articles. Additionally, it was found that most of the research relating to AI in the apparel supply chain has been carried out in the last decade (2009–2018), accounting for 56% of the total number of publications during the period 1989–2018.

This shows that even though AI methods have existed since 1989, they have only recently gained popularity as a valuable resource to improve business operations. Although AI has left its footprint in research, it is still far from being implemented at the industrial level. In addition to the probable reasons for this provided by Abd Jelil, (2018), another reason could be the lack of expertise of researchers working in AI in the apparel industry and at the same time, the professionals working in the industry itself may lack expertise in AI. Furthermore, industries might be skeptical about the benefits of big data management and AI. Therefore, it is important that they look at the cost-benefit tradeoffs to be able to exploit the full potential of big data management and AI.

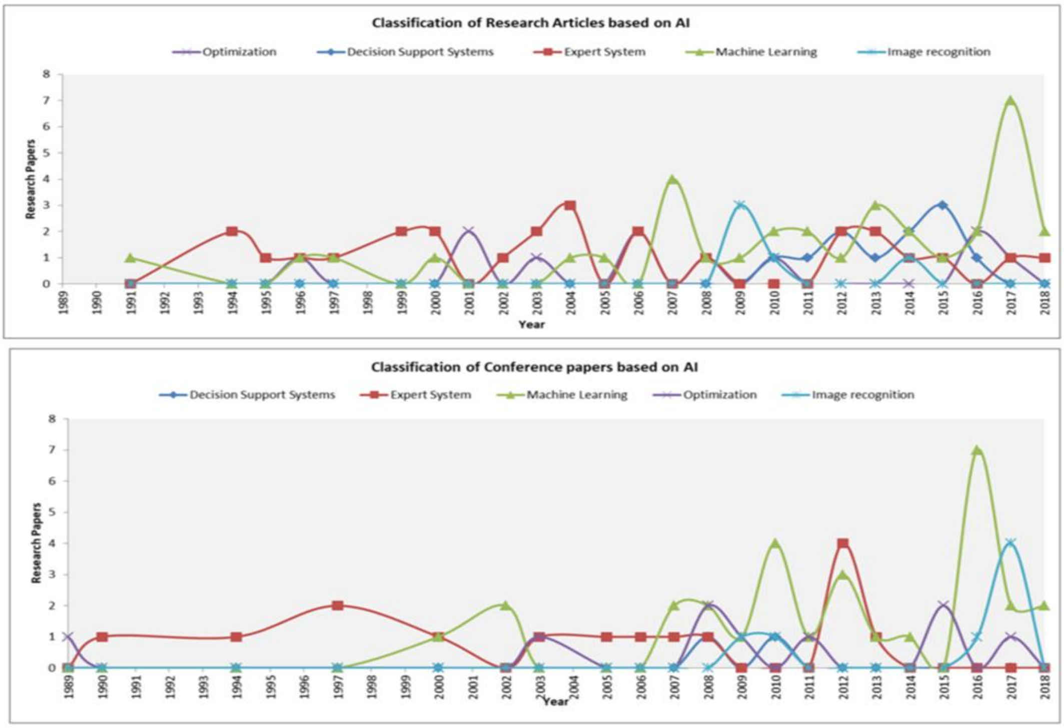

Figure 5-3. Distribution of articles by applied AI over time (article A)

Another important finding was that most of the research studies have focused on B2B business problems, accounting for 81% of the total number of publications. Whereas, little research has been conducted from a B2C perspective, accounting for approximately 8% of the total publications. This clearly illustrates that research needs to focus more on B2C business problems. Therefore, apparel industries need to shift their focus to B2C, considering big data management and AI as resources that could help analyze omnichannel consumer footprints and aid in creating a personalized consumer database or profiles to improve business profitability and provide a competitive advantage.

Additionally, most of the techniques used in the research articles studied fall under the machine learning and expert systems class, which has been extensively applied at the supply chain stages of apparel production, fabric production, and distribution. In this domain, research articles published on DSSs, optimization, and image recognition classes are more or less similar in number. However, the least representation of these algorithms was observed at the design stage. It leaves the impression that there has been little focus on design-related problems and consequently there is huge scope for AI applications at the design stage. For instance, AI methods could be used to create systems that could help fashion and product designers capture consumer needs and preferences more accurately and conveniently. Therefore, the products offered could be more targeted to specific market segments. The AI methods applied in 149 articles can be seen in Tables 5-2 and 5-3.

Table 5-2. AI methods used at various supply chain stages and processes in journal articles (article A)

AI Class	Method/ Technique Used	Supply chain stage	Process	B2B/ B2C	Article Count	Reference
Machine Learning	BP-ANN 9 back propagation artificial neural network; k-means clustering; sequential clustering; fuzzy logic; A two-level clustering method (SOM network+ K-means); Naïve Bayes; Support vector machine; Gene expression programming (GEP); FCM (fuzzy clustering using MSE); Non-parametric regression forecasting; supervised clustering; K-Medoids;CN2-SD; ANN regression; RFM modeling; Association rule; ELM (extreme learning machine); GA; fuzzy constraint logic system, fuzzy rules, fuzzy sets; feed-forward neural network, back-propagation algorithm; decision tree, classification, and regression tree, factor analysis; Treelearner; root mean square; Fuzzy Efficiency based Classifier System; Bucket Brigade Algorithm; neural networks using the error back-propagation mode, e neurofuzzy engine; fuzzy dynamic integratedfiMgment (FDIJ); DIDT technique (Top-Down Induction of Decision Trees ID3); data mining; text mining; semantic data analysis;	Apparel Manufacturing 10, Design 1, Distribution 14, Fabric Production 11	Cutting 2; Dyeing/ Printing/ Finishing/ Inspection 1; Finished Garments 2; Retailing 12; Sewing 4; Spinning 9;	B2B/ B2C 4, B2B 25, B2C 5	34	Available in article A
Decision Support System	Fuzzy logic; fuzzy association rule mining (FARM); classification, regression, clustering and association analysis; Linear optimization with constraints; Fuzzy inference; Fuzzy aggregation; adaptive-network-based fuzzy inference system (ANFIS); analytic hierarchy process (AHP); TOPSIS;	Apparel Manufacturing 4, Distribution 6, Fabric Production 1,	Finished Garments 4; Retailing 6; Spinning 1;	B2B 9, B2C 2	11	Available in article A

Expert System	Association rules; ES named ES-EXITUS has been implemented using the SSM and the DMM; fuzzy association rule mining; fuzzy logic; clustering and probabilistic neural network (PNN); hybrid OLAP-association rule mining; ontology, semantic web, multiple agents; genetic algorithm; gradient descent optimization, fuzzy sets; Chi-square test, correspondence analysis; parametric cubic spline and bicubic surface patch, object-oriented technology for building the knowledge base; linear programming, computer-based heuristic; Semantic network, heuristic rules; Bézier curve models evolutionary model; sensitivity analysis, cognitive mapping technique, cluster analysis; normalization model; programming language used Microsoft Visual C++ version 4.0, rule-based expert system; object-oriented representation technique; t-test, sensory evaluation;	Apparel Manufacturing 5, Design 4, Distribution 8, Fabric Production 9,	Cutting 1; Dyeing, Printing, Finishing, Inspection 5; Fashion Design 2; Finished Garments 1; Retailing 5; Sewing 2; Textile Design 2; Weaving or knitting 1; Wholesaling 1;	B2B/ B2C 3, B2B 21, B2C 2	26	Available in article A
Optimization	Constraint and non-constraint optimization; simulation-based model; fuzzy rule optimization; Tabu-Bees algorithm; linear approximation; evolutionary algorithms; genetic algorithm; Morse function, topological analysis; content-based filtering, wavelet decomposition using Haar transform collaborative filtering, vector correlation using the Pearson correlation coefficient; symbolic regression module; multiple regression analysis, extrapolative forecasting and an adaptive Holt-Winters forecasting;	Apparel Manufacturing 4, Design 2, Distribution 2, Fabric Production 3,	Cutting 2; Fashion Design 1; Finished Garments; Retailing 2; Sewing 1; Spinning 1; Weaving or knitting 1; Wholesaling 1;	B2B 11	11	
Vision	ANN and image processing; K-means clustering, Naïve Bayesian, and a multi-layered perceptron (MLP); NN and GA; back-propagation neural network (NN);	Apparel Manufacturing 2, Fabric Production 3,	Finished Garments 2; Sewing 1; Spinning 1; Textile Design; Weaving or knitting 1;	B2B 5	5	Available in article A

Table 5-3. AI methods used at various supply chain stages and processes in conference articles (article A)

AI Class	Methods/Techniques Used	Supply chain stage	Process	B2B/ B2C	Article count	Reference
Machine Learning	SOA-based data mining framework, classification, ARIMA and KNN models, text mining, naive Bayes classifier, SOM neural network, EM cluster and ELM (extreme learning machine) same prediction, SVM and AdaBoost, artificial neural network, case-based reasoning, supervised learning, self-organizing maps, principal component analysis, type-2 fuzzy sets, clustering, correlation analysis, optimal bandwidth selection in kernel density, ontology, RDF, multilayer perceptron, J48 decision tree, k-nearest neighbor, classifier ripper, C4.5 and PART, neuro-fuzzy with subtractive clustering and genetic algorithm (ANFIS-GA) technique, Java, C/C++, Viswanathan-Bagchi algorithm, correlation, wavelet transform, neural network.	Fabric Production 11, Distribution 7, Apparel Manufacturing 9, Design 1,	Weaving or knitting 3, Retailing 8, Spinning 5, Dyeing, printing and finishing 2, Finished Garments 3, Sewing 3, Cutting 2, Textile Design 1, Fashion Design 1	B2B/B2C 2, B2B 23, B2C 3	**28**	Available in article A

Decision support system	Self-adaptive genetic algorithm, genetic algorithm, top-down and bottom-up analysis, dynamic optimization algorithms, maximum principle of Pontryaguin.	Distribution 1, Fabric Production 1	Finished Garments 1, Retailing 1	B2B 1, B2B/B2C 1	**2**	Available in article A
Expert System	Rule-based, rough set theory, fuzzy, case-based reasoning, fuzzy logic, fuzzy logic sensory evaluation, fuzzy neural network, unsupervised learning, fuzzy clustering, genetic algorithm, approximate reasoning module, rule-based system shell, metric-based fuzzy logic and artificial neural network, If-Then Rules for knowledge base, least-square regression analysis, linear regression, event series.	Distribution 2, Fabric Production 7, Apparel manufacturing 6	Retailing 2, Spinning 3, Dyeing, Printing, Finishing and Inspection 2, Finished garment 1, Yarn to Fabric 1, Cutting 1	B2B 14, B2B/B2C 1	**15**	Available in article A
Optimization	Stochastic descent, list algorithm, evolutionary computing and genetic algorithm, fuzzy set, geometric analysis method, Mirabit algorithm, Apriori algorithm, heuristic methods,	Fabric Production 4, Apparel manufacturing 4, Design 1	Spinning 3, Finished garments 1, Dyeing, printing and finishing 1, Cutting 3	B2B 8, B2B/B2C 1	**9**	Available in article A
Vision	Conditional random fields (CRF), Bayesian classification, CNN based classifier, computer vision, classification, consensus style centralizing auto-encoder (CSCAE), Gabor filter, Gaussian kernel, image processing using IMAQ, median filter, stereovision method.	Fabric Production 4, Distribution 3	Weaving or knitting 1, Spinning 3, Retailing 3	B2B 5, B2C 1, B2B/B2C 1	**7**	Available in article A

5.2.1. Concluding RQ 1

Consequently, with the help of the first RQ, the thesis identifies the extent to which AI has been adopted in research to provide opportunities with big data management and improve business operations in apparel firms. As per the analysis provided above, the most applied AI categories in research related to the apparel industry have been machine learning and expert systems. It was observed that the techniques most used in machine learning were predictive algorithms such as regression and support vector machine, whereas in the case of expert systems the techniques most used were artificial neural networks, genetic algorithm, and fuzzy logic for modeling apparel supply chain problems. Certainly, limited application of algorithms such as deep learning and transfer learning were found. Very few research articles talked about big data in the area of apparel research, which indicated that the industry has not fully realized the potential of big data management. It also indicates that there are challenges and barriers to successful implementation of big data and AI, and both need to be studied in much greater detail. In addition, it was found that apparel supply chain stages—apparel production, fabric production, and distribution—and retailing received the greatest attention when applying AI techniques, whereas product design had the least focus. Additionally, a significant contribution was noted toward B2B problems compared to B2C. Therefore, research needs to adopt a more B2C-centric perspective to be able to offer consumer-oriented solutions to the industry. The adoption of AI methods at various supply chain stages indicates that there is need of automation of the various supply chain operations, as it mainly due to the increase in consumer demands and competition that the industry is seeking agility to gain competitive advanatge (Amed et al., 2017).

5.3. Research Question 2

"How can AI techniques be used to develop data-driven solutions using product-related data furnished by apparel product manufacturers and designers?"

As is evident from the discussion in the previous section, AI techniques can be beneficial at every stage of the apparel supply chain, from the operations related to apparel design and manufacturing to sales and marketing of finished products, but it can have various challenges if employed. The future of the apparel industry is intelligent as it has innumerable sources of data (Nayak and Padhye, 2018). These data can be considered as valuable resources to the firm as they can be used for optimizing supply chain operations and generating competitive advantage. For instance, AI can be used to predict accurate time-to-market by integrating historical data and real-time weather data, agile supply chain practices can be incorporated with the help of instantaneous data on inventory and trend forecasting, and personalized product recommendations can be offered to different customer segments (Darvazeh, 2020; Dash et al., 2019). In this context, the purpose of this research question was to provide specific opportunities to manage this big data using AI. Since it was found that the application of AI was scarce at the design stage, product-related data was used. The product-related data, be it the product attributes, different fabrics used for different styles, the properties of those fabrics, or the various styles, are a valuable source of big data. Other important sources of product-related data are the product development experts. Since apparel is a dynamic industry with human intervention necessary at almost every stage, the expert's product knowledge becomes a rich and valuable resource. The data related to the product is one of the most important data available to apparel firms that to help devise data-driven strategies that are unique and inimitable. Considering this, articles B and C, utilize these product-related data and apply different AI techniques to provide data-driven solutions in an attempt to answer RQ2.

5.3.1. Garment Categorizing Using Product Data

As contemporary customers have shifted their reliance on online retail channels to make purchases, the need arises for powerful and intelligent systems that can recommend, personalize, or help the customers in making purchase decisions. Such models (DSSs) can help the customers in finding the right garment to match their requirements. The first step toward achieving this is to make the models recognize the different garment categories and corresponding garment attributes, which can be done with the help of product-related data available to the retailers. It is important to recommend the right garment to the customer as it directly impacts the customer's shopping experience and their perception of the retailer itself (Manfredi et al., 2014). The stronger the recommendation algorithm, the better the results will. Moreover, classifying products based on their attributes can be beneficial for demand forecasting, and efficient assortment planning and comparison for retailers and producers (Ghani et al., 2006). In this regard, one of the opportunities identified for managing product-related big data available in the apparel industry using one of the AI classes i.e. machine learning techniques, was to support the development of a classification framework. Since, there are many machine learning techniques available, four of them were chosen based on their wide applicability to similar problems. The four techniques chosen were: Naïve Bayes, decision trees, random forest and Bayesian forest. The intelligent classification model learns from an existing training dataset (details provided in section 3.3 Table 3-2) containing garment attributes, categories (upper wear, bottom wear, and whole-body wear garment) and sub-categories (shirt, jeans, dress, blouse, etc.). An instance of the developed classification framework is shown in Figure 5-4.

The mathematical computation of the model developed is provided to ensure repeatability. Managers in apparel firms can use this to customize a solution to maintain dynamic capability. Let us consider that the apparel product dataset X is represented by $X = (x_1, x_2, \dots, x_n)$, where n being the total number of instances in the dataset. Each instance is of the form (F, C), where F is a set of product attributes represented by $F = (f_1, f_2, \dots, f_m)$ and C is a set of target classes represented by $C = (c_1, c_2, \dots, c_w)$. The set of instances X is divided into two sets, train set X_{tr} and test set X_{te}. The instances in X_{tr} i.e. $(F, C)_{tr}$ are used to train the model M_A i.e. the model to classify garment categories (upper, lower, and whole). Similarly, models M_U, M_L, and M_W are trained to classify garment sub-categories belonging to upper, lower, and whole-body garments, respectively. The datasets used for training these models are as explained in article B.

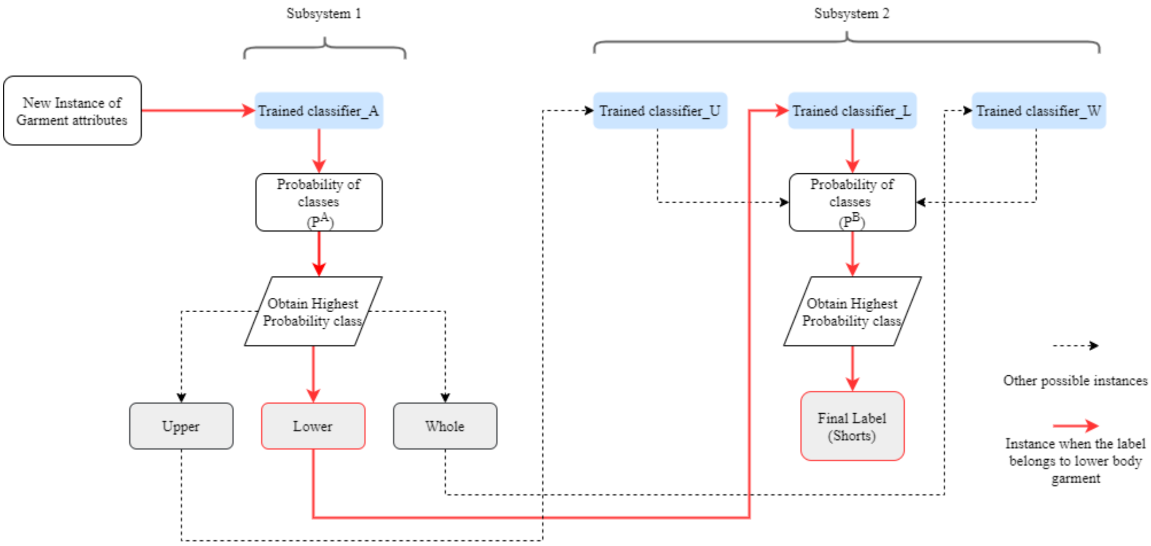

Figure 5 4. Classification framework developed using product data (article B)

Following this, the test set X_{te} was used to integrate the functionality of the trained models. In this case, the set of features F_{te} from $(F, C)_{te}$ was used. When the first instance from F_{te} is given to model M_A, it makes a decision d_i^A among the class probabilities $P^A = (p_1, p_2, \ldots, p_r)$, and the final decision is made using the following formula:

$$d_i^A = j \ni p_j = \max(P^A)$$

Depending on the decision d_i^A, the instance F_{te} passes through one of the classifiers from M_U, M_L, and M_W, where M signifies classifier, subscript indicates the respective dataset U, L, or W. If d_i is lower (L), then $M_L$will be utilized for making further classification of the instance and make a decision $(d_i^B)_L$ from the class probabilities in $(P_k^B)_L = (p_1, p_2, \ldots, p_l)$, where l is the number of target classes in the lower body garment categories, as explained below:

$$(d_i^B)_j = \begin{cases} k \ni p_k^B = \max((d_i^B)_j) & if \ \max_1(d_i^B)_j - \max_2(d_i^B)_j > th \\ \{k, l\} \ni p_k^B = \max_1(d_i^B)_j, p_l^B = \max_2(d_i^B)_j & \text{otherwise} \end{cases}$$

where, $\max_1((d_i^B)_j)$ represents the maximum number in $(d_i^B)_j$, and $\max_2((d_i^B)_j)$ represents the second highest number in $(d_i^B)_j$. The accuracy of the model is calculated by checking whether the final label is same as the class C in the test data set, i.e. if $C \in (d_i^B)_j$. Hence, the resultant class provided by the model is given by $(d_i^B)_j$.

The operation of the developed system is as follows. When subsystem 1 receives a string of garment attributes, it will first try to label the data instance into one of the three target classes: upper, lower, or whole-body garments. The class with the highest probability will be considered to be the resultant label from subsystem 1. If the label of the new set of data was lower-body garment, the string of garment attributes will now pass through the second subsystem. Since it has already been determined that it is a lower-body garment, the classifier trained with dataset *L* will get activated and try to further label the data instance into a specific lower garment sub-category. In this case, the classifier will compute the probabilities of all the lower garment sub-category classes and compare these values to a pre-set threshold value. Based on this value, subsystem 2 will decide the label of the new data instance. For instance, the classifier may label the data instance "trousers" as it had the highest probability. In another case, where two labels have equal or very close probabilities at subsystem 2, then if the classifier delivers the class with the highest probability—even though the difference between the two values may be as low as 0.1—the classification result can be considered to be biased. This would mean that even though the new data instance was close to more than one type of lower garment sub-category, the classifier does not handle this ambiguity well. Consequently, having subsystem 2 provide probabilities of these two classes, instead of a single predicted class, can help reaching an intelligent decision, in turn improving the model accuracy for future data instances.

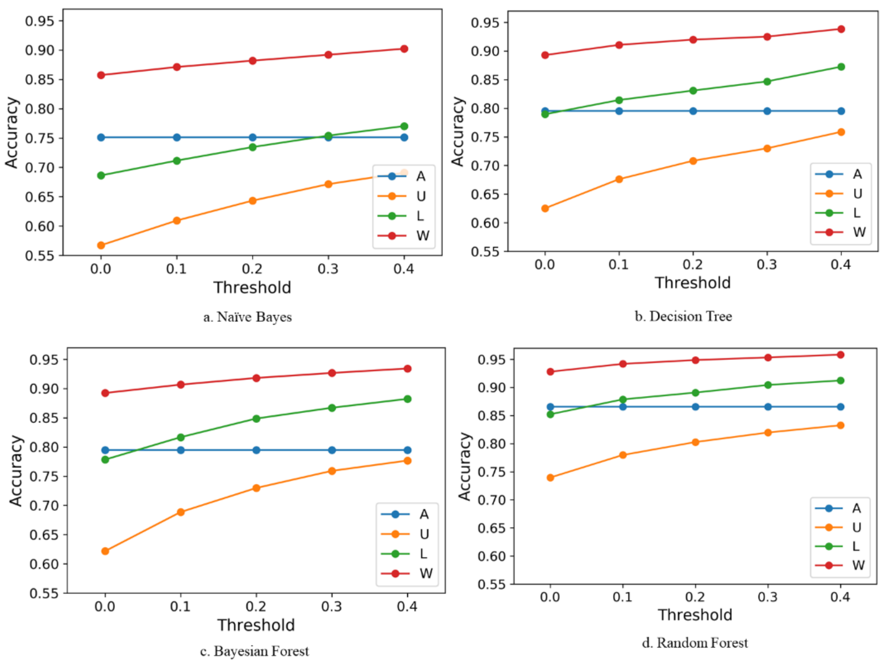

Figure 5-5. Accuracies at different thresholds for a) Naïve Bayes, b) decision tree, c) Bayesian forest, and d) random forest (article B)

In this way, the system becomes equipped to handle ambiguous cases, which can occur frequently in a large dataset, given the complexity of an apparel product. The model accuracy achieved by the four algorithms is shown in Figure 5-5.

5.3.2. Product Design Rules Development Using Expert Knowledge

Utilization of the latest digital technologies to manage and use big data and extract knowledge from industry experts is an important and popular topic of research within the context of the apparel industry (Griva et al., 2018; Wong, W.K., Zeng, X.H. and Au, 2009). With the help of the experts' knowledge, the current supply chain processes can be automated which in turn will help in bringing agility to the supply chain. One such expert's knowledge was captured with the help of sensory evaluation, and this knowledge was modeled using a fuzzy logic AI technique. The relationships between the inputs and outputs information in the fuzzy proposed system are described as linguistic variables, which are more flexible and realistic in reflecting real-world situations. The proposed DSS has a potential application in digital prototyping and the development of products. The purpose of the system is to provide aid to the human resources working in the supply chain in making quick decisions for complex problems. This is also another opportunity with AI for apparel firms to create design rules that can be integrated into the existing recommendation or product development systems.

The basic architecture of the FIS is shown in Figure 5-6. The system helps the product designer to select an appropriate fabric, supporting product conceptualization and development in the apparel industry. Moreover, a graphical user interface was created for easy depiction of the inference system, as shown in Figure 5-7.

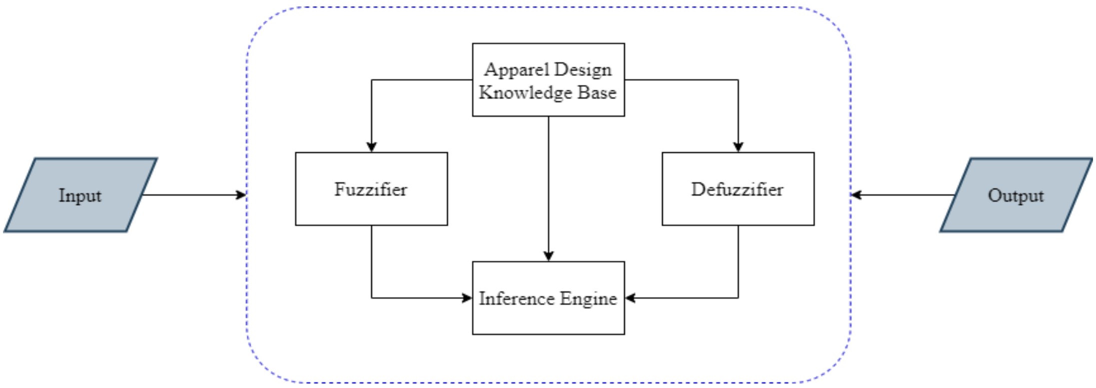

Figure 5-6. Fuzzy inference system using product-related data from the apparel industry (Article C)

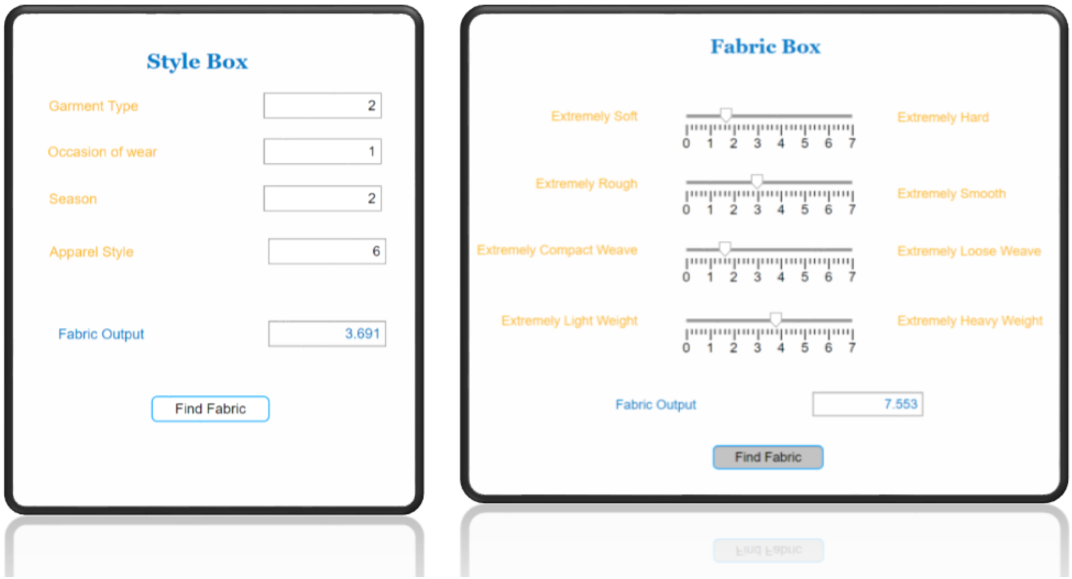

Figure 5-7. Graphical user interface for fabric selection, FIS 1 (left) and FIS 2 (right) (Article C)

For instance, when a user enters the input values as depicted in Table 5-4 and clicks the find fabric button, the system provides a value between 1–8 that corresponds to the fabric closest to the user's requirements.

Table 5-4. Inputs for the graphical user interface or FIS 1 and FIS 2

FIS #	Inputs	Sensory descriptors	Membership function range
1	Type of Garment	Top wear, Bottom wear	0–1
	Occasion of wear	Casual, Work, Sport, Party	0–4
	Season	Spring, Summer, Autumn, Winter	0–4
	Style themes	Trendy, Preppy, Hipster, Feminine, Edgy, Elegant, Casual, Boho, Athletic	0–9
2	Fabric handle: Soft-Hard	Extremely soft, soft, slightly soft, intermediate, slightly hard, hard, extremely hard	0–7
	Fabric handle: Rough-Smooth	Extremely rough, …, Extremely smooth	0–7
	Fabric handle: Compact weave-Loose weave	Extremely compact weave, …, Extremely loose weave	0–7
	Fabric handle: Light weight-Heavy weight	Extremely lightweight, …, Extremely heavy weight	0–7
Output	Fabric	Wool Barathea, Cotton Mousseline, Linen Heavy, Polyester Chiffon, Wool Basketweave, Silk with elastane, Linen Holland, and Polyester Sateen	0–8

5.3.3. *Concluding RQ 2*

The aim of the second RQ was to establish how AI techniques could be used to devise data-driven solutions using product-related data in the apparel supply chain. According to the discussion provided in the last two sections, the thesis identifies two opportunities to manage product-related big data using machine learning and DSSs for the managers in apparel firms. The two articles B and C use these AI techniques to manage and analyze the collected data and provide data-driven solutions. Both approaches contribute toward the automation of supply chain operations that can help provide customers with products that closer meet their needs. This also answers the part regarding the overall purpose, i.e., "seeking opportunities with big data management using AI solutions." With the help of these solutions, apparel firms can automate some operations to instill organizational agility.

5.4. Research Question 3

"How can big data assist in providing personalized offerings to customers through apparel e-commerce retailers?"

As important as AI is for all stages of the apparel supply chain, its importance for online channels is increasing enormously (Pantano et al., 2017; Pantano and Viassone, 2015; Sundström, 2019). With the advent of digitalization and the internet, there has been a rampant increase in purchases through online retail channels (Hagberg et al., 2016). Retail channels, at least in the traditional ready-to-wear sense, are the sole point of interaction with customers. These are the touchpoints that hold the utmost value as the experience the customer has during this interaction decides the future relationship between the customer and the retailer. These interactions are also a rich source of data related to the costumers' preferences and can be used to draw insights helpful in building an agile supply chain and enhancing the customer satisfaction (Cao, L. and Li, 2015). In this context, the purpose of the third RQ was to establish how big data could help apparel e-commerce retailers to provide personalized services, thereby improving the customer satisfaction. The appended article D examined the use of customer data for providing personalized services while holding the argument that the e-retailers need to shift their focus beyond the product and provide personalized services to the customer. The rationale was that since the customer interacts with the product much later during the shopping process i.e. post-delivery, it is important to hold the customer's attention with the help of services during their shopping process through an online retail channel. The effective use of big data management and other organizational resources can assist apparel firms in improving their offerings and maintaining a competitive advantage.

5.4.1. Customer Satisfaction through Personalized Services on e-commerce Platforms

In a digital world, where a customer can make a purchase even through social networking mediums such as Instagram or Facebook, the apparel retailers need to provide customers with more than just a product. Customers seek value in personalized experiences and expect its occurrence much earlier in the shopping process (Bilgihan et al., 2016; Walsh and Godfrey, 2000). To do this, managers need to identify opportunities and challenges to make timely and market-oriented decisions that also favor customers. Moreover, they need to respond to rapid changes in the competitive environment. For this, firms may need to develop flexible strategies grounded in big data management and AI (Akter et al., 2016).

Personalizing services involves knowing how to connect the customer with the product and by extension the firm, as early as the customers' initial search for a product. Providing such a level of personalization is challenging and requires extensive domain experience in product, service, and order management with expert knowledge of digital business to evaluate the existing technical outlook, recognize gaps, and surface opportunities. Using and managing the data collected by businesses on the internet with the help of AI is one possible way of achieving the expected level of personalization. This data can be used to deduce optimal shopping scenarios, create urgency to purchase and deliver the service personalization and convenience that customers' demand and which inherently drives perceived value. The probability of re-purchase is greater if the retailer succeeds in providing something unique and of value to the customer.

In this regard, Figure 5-8 presents a model that portrays the essential ingredients required in providing personalized services using big data during the shopping journey by an apparel e-commerce retailer. The theoretical framework is built on satisfaction through personalized services as the principle of middle-range theory, which bridges the customer perceived value theory with empirical evidence. The empirical evidence suggests that a customer requires that the business should also focus on personalized services in a way that it improves fulfillment. Combining the findings from the empirical evidence and ideas from the theory, three foundational premises are provided (as shown in Figure 5-8). It is suggested that the apparel e-commerce retailers should shift their focus beyond the product to services, where the model presented can be used as a reference. This is in line with the firms competing at a global level, striving to bring a competitive advantage that can sustain increasing customer demands. Adding a personalized service perspective to the e-commerce business strategy will support providing unique experiences and increase overall value to the customer. A fine-tuned and unique shopping experience can go a long way to ensuring customer satisfaction and building loyalty in new and returning customers. Regardless of the various changes in the industry, it remains evident that personalizing customer service in a way that improves fulfillment will always be relevant for a successful customer experience strategy.

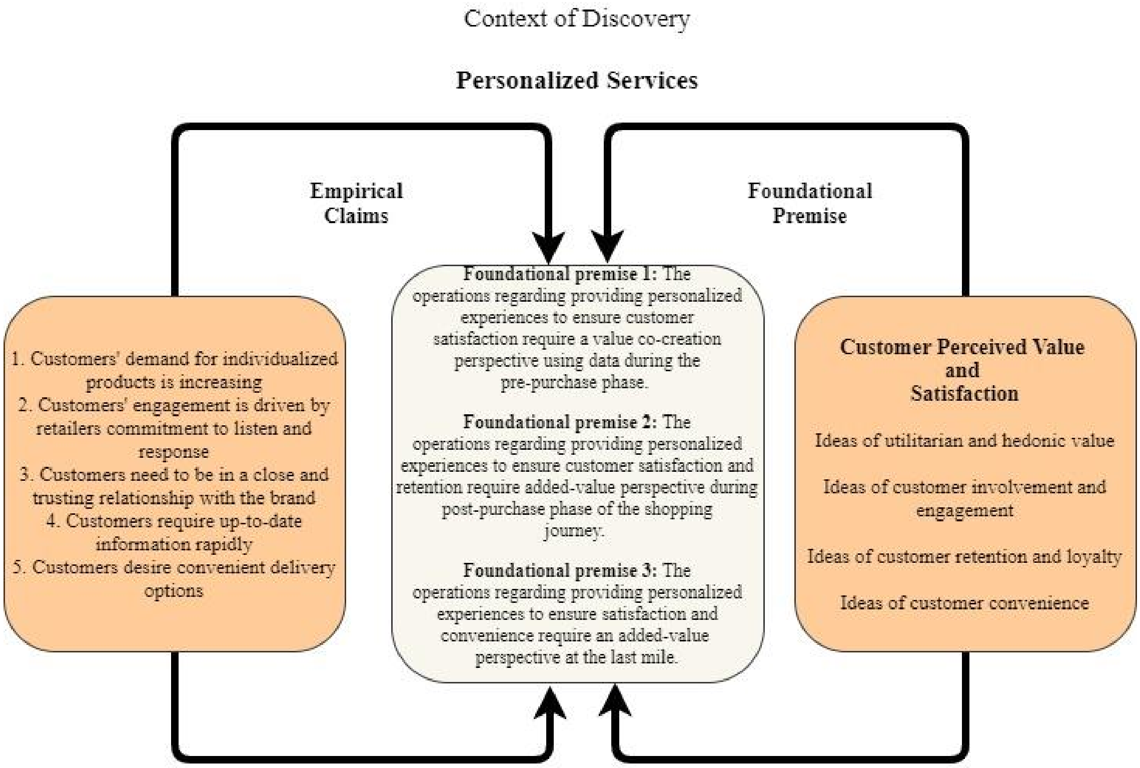

Figure 5-8. A conceptual model for viewing and using personalized services

5.4.2. Concluding RQ3:

The aim of the third research question was to establish how big data could help apparel e-commerce retailers in providing personalized offerings to its customers. According to the discussion provided above, efficiently incorporating big data management in devising business strategies could help in providing personalized services and as such, improve the customer experience. Big data management using AI could help managers react faster to changing customer demands and market fluctuations. Moreover, it could help to make the online shopping experience smoother for the customer. A supply chain manager who converts the existing data into knowledge and perceives it to be an important capability can gain competitive advantage by providing customers with personalized services. Such a data-driven supply chain can be maintained with the help of AI techniques. Herein, another opportunity is provided for apparel e-commerce retailers with big data management.

6. Implications and discussion

In the previous chapter, a synthesis of the findings from the four appended articles is presented as the results of the thesis. In this chapter, building on those findings that address the research questions, diverse implications are provided for the apparel supply chain, and for practitioners who are interested in adopting big data management and AI solutions.

6.1. Implications for Practice

The opportunities presented in this thesis are for those managers who are increasingly interested in big data management using AI solutions and perceive it to be a tool that can be used to provide personalized products and services to customers. With the help of the discussion presented in Chapter 5 for elaborating on the research questions and fulfilling the overall purpose, several implications for practice can be presented:

1. The findings of this thesis point out that big data management can assist apparel firms in creating additional value and support the organizations agility ambitions. It can help firms satisfy their customers with personalized products and services and maintain their competitive edge. To support this, the theoretical framework presented in article D can be used as a reference. However, managers in the firms should not overlook the challenges that accompany big data and AI. It is important to consider both the technical and managerial capabilities required by the firm to create sustainable competitive advantage using big data and AI.
2. The opportunities and gaps identified in article A provides a road map for apparel firms. Using this map, they can find the appropriate AI techniques that they can use at different supply chain stages for tackling various B2B and B2C business problems.
3. The big data management solution presented in article B can be helpful for apparel retailers and producers. Every garment retailer and/or production house collects similar data related to garments i.e. garment categories and attributes. In addition, these is also data that can be collected from the product pages of the e-commerce websites. The data obtained from these sources can be used to create product profiles based on the attributes used in various garments. These profiles can then be used to classify the data based on the methodology described in article B. Such a classification can have various applications such as in improving the existing recommendation algorithms by providing words instead of images and enhancing the parsing algorithms. These applications can further help managers to provide personalized product recommendations to customers.

4. The data-driven fabric selection solution presented in article C can be employed during conceptualization of a garment at the product development stage. Here, the developed solution is built on data extracted from expert knowledge, which is unique to every organization and can be utilized to populate the model for use by a specific firm. The proposed DSS can provide aid to the human resources working in the supply chain in making quick decisions for complex problems. Moreover, it is also an example that can be used by managers to show that big data management and AI solutions are there to support them in performing various operations, which is a challenge that apparel firms often face while making decisions regarding automation (Abd Jelil, 2018).

However, managers should be aware of the fact that some differences may emerge, depending on the particular big data solutions in which they want to invest, and depending on the structure of the particular organization and their specific business problems. There are some open challenges related to identifying and replicating the best big data management solution practices that could enhance financial performance, which still have to be overcome (Ji-fan Ren et al., 2017). Hence, directing managerial attention first toward generating actionable business goals to increase business value and then toward customer satisfaction could be an effective way of channeling the overwhelming amount of data toward operational objectives, without immediately targeting financial performance.

6.2. Discussion

In its aim to investigate whether apparel firms could improve business operations using big data and AI, and provide opportunities with big data management using AI, this thesis commences by accentuating the importance of big data and AI in the apparel supply chain. Further, it goes through the existing literature related to the supply chain, big data, AI with the apparel industry as the central theme and managerial theories applied in the context of big data. Finally, after providing a summary of the appended articles, a synthesis of the findings of these articles is presented to answer the three research questions and the overall purpose.

This thesis provides knowledge on different AI techniques that can be applied at various apparel supply chain stages to automate business operations and achieve agility during rapidly changing market trends and business environments. It founds a general lack of applicability of AI on data related to the product and the customer. Thus, two opportunities were identified to use AI techniques to build data-driven solutions that could help the apparel supply chain provide its customers with products that were closer to their specific needs. The first solution was a classification framework developed using four machine learning techniques (an AI sub-class), Naïve Bayes, decision trees, random forest, and Bayesian forest. To select the best algorithm, the performance was calculated, and it was found that random forest achieved the highest accuracy among all the algorithms. This model can be integrated with existing recommendation systems or used to create a new one to provide personalized recommendations to customers. The second solution is was a DSS developed using fuzzy logic, an AI technique. This solution helps in choosing an appropriate fabric depending on the needs of the user. This type of model can be integrated with product configurators and/or used internally by the product development department to provide customized garments. Finally, the thesis provides a model for apparel retailers to assist them in using big data to deliver personalized services to its customers. This model was built using the evidence found in the industry and in research and provides proposals for apparel retailers aiming to deliver personalized services to its customers.

The big data management solutions presented in this thesis demonstrate the opportunities for apparel firms to look into its supply chain to identify big data resources that are valuable, rare, and inimitable, and use them to create data-driven strategies and establish dynamic capabilities to sustain the organization in an uncertain business environment. With the help of these data-driven strategies, apparel firms can produce garments smartly to provide the customers with a product that is closer to their specific needs, and as such drive sustainable consumption and production practices.

7. Future Research and Recommendations

This chapter highlights the limitations of the present research work, based on which suggestions for future research directions are made.

Recalling the theoretical backdrop of this thesis, it is noteworthy that building dynamic capabilities on existing resources is a complex and iterative process. It requires for the firm to recognize and evaluate its resources thoroughly before using them in establishing capabilities and it is a long process. Similarly, the research conducted in this thesis is only a steppingstone in the direction of making a self-reliant apparel supply chain. The scope of this thesis was limited to big data management and AI, whereas it could be interesting to integrate other upcoming digital technologies including but not limited to virtual reality, augmented reality, the internet of things, and block chain technology. In addition, the thesis focused on the RBV and the DCV by using the VRIO framework to evaluate the different data-driven solutions. However, there are other promising managerial frameworks that might uncover other interesting managerial implications. The thesis did not study several important management issues accompanying big data such as security, surveillance, organizational climate, technological structure, high cost, and variety. These, encapsulated in this thesis, pose a particularly promising future research avenue.

The work done in article B can be extended by incorporating product images and bringing in data from more sources to strengthen the classification framework. The classification framework developed showed promising results with a satisfactory accuracy achieved by the various algorithms. However, considering the availability of other much faster machine learning algorithms and advanced machines, fine-tuning the algorithm could be an area of research to improve accuracy and computational time. Moreover, additional data or a larger dataset could be used to improve the learning of the model. Similarly, the design rules developed in article C could be further developed with the help of additional data. Further investigation could be done to examine the impact on an organization's structure and capabilities with the adoption of these kinds of data-driven strategies.

The conceptual model in article D suggesting personalized services as a middle-range theory to enhance customer perceived value could be tested with empirical data from different businesses, not restricted to the apparel industry. The focus of this article was the development of a conceptual model using theory and empirical evidence. One of the limitations of this study concerns verification from case studies. Even the most detailed narratives are usually a simplification of what was communicated, and even though the transcripts from the cases were rich, I chose to present few quotes and took them of the context of the narratives. It is therefore likely that a revisiting of the data would reveal other issues and aspects of the data. However, as the study focuses on conceptualization and is theory-driven, this limitation was deemed appropriate. One of the future directions would be to undertake more in-depth empirical research supporting the model suggested.

It is evident from the article A that the apparel sector still lacks an integrated platform for data sharing and communication among its stakeholders and consumers. An integrated platform has become a necessity to quickly respond to customers' growing needs and preferences and improving consumer satisfaction and loyalty. AI has a lot of potential to create and maintain such a platform. This platform could help the industry to provide interactive communication, and improved supply chain organization, leading to a digitally connected supply chain. If the apparel industry can successfully adopt the aforementioned AI techniques, it would be easier to integrate B2B and B2C processes, leading to a sustainable business orientation of B2B2C. This will be fully achievable only when the apparel industry embraces the 'FAIR' data principles (Boeckhout et al., 2018) in strategizing their business.

Finally, the data and conceptual models proposed in this thesis can be generalized to be applied in other fast-moving consumer goods such as packaged foods, mobile phones, and similar products. In summary, the work of this thesis meets the scope of its ambitions and expands multiple research horizons.

References

Abd Jelil, R. (2018), “Review of Artificial Intelligence Applications in Garment Manufacturing”, *In: Thomassey S., Zeng X. (Eds) Artificial Intelligence for Fashion Industry in the Big Data Era.*, Springer, Singapore, pp. 97–123.

Abowitz, D.A. and Toole, T.M. (2010), “Fundamental issues of design, validity, and reliability in construction research.”, *Journal of Construction Engineering and Management*, Vol. 136 No. 1, pp. 108–116.

Abrahamson, E. (2011), “The Iron Cage: Ugly, Uncool, and Unfashionable Special Themed Section”, *Organization Studies*, Vol. 32 No. 5, pp. 615–629.

Admuthe, L.S. and Apte, S.D. (2009), “Computational model using anfis and GA : Application for textile spinning process”, *Proceedings - 2009 2nd IEEE International Conference on Computer Science and Information Technology, ICCSIT 2009*, pp. 110–114.

Ahmed, P. and Shepherd, C.D. (2010), *Innovation Management: Context, Strategies, Systems and Processes*, Pearson, available at: https://research.monash.edu/en/publications/innovation-management-context-strategies-systems-and-processes (accessed 27 August 2020).

Akhtar, P., Khan, Z., Tarba, S. and Jayawickrama, U. (2018), “The Internet of Things, dynamic data and information processing capabilities, and operational agility”, *Technological Forecasting and Social Change*, Elsevier Inc., Vol. 136, pp. 307–316.

Aksoy, A., Ozturk, N. and Sucky, E. (2012), “A decision support system for demand forecasting in the clothing industry”, *International Journal of Clothing Science and Technology*, Vol. 24 No. 4, pp. 221–236.

Aktas, E. and Meng, Y. (2017), “An Exploration of Big Data Practices in Retail Sector”, *Logistics*, Vol. 1 No. 2, p. 12.

Akter, S.., Wamba, S.F., Gunasekaran, A.., Dubey, R. and and Childe, S.J. (2016), “How to improve firm performance using big data analytics capability and business strategy alignment?”, *International Journal of Production Economics*, Vol. 182, pp. 113–131.

Akter, S., Gunasekaran, A., Wamba, S.F., Babu, M.M. and Hani, U. (2020), “Reshaping competitive advantages with analytics capabilities in service systems”, *Technological Forecasting and Social Change*, Vol. 159, available at:https://doi.org/10.1016/j.techfore.2020.120180.

Akter, S., Ji, X., Sarker, M.M., Cai, L., Shao, Y., Hasan, M.K., Abir, S.A., et al. (2020), “Clean Manufacturing and Green Practices in the Apparel Supply Chain”, *Open Journal of Business and Management*, Scientific Research Publishing, Inc, Vol. 08 No. 01, pp. 104–113.

Ambrosini, V. and Bowman, C. (2009), “What are dynamic capabilities and are they a useful construct in strategic management?”, *International Journal of Management Reviews*, Vol. 11 No. 1, pp. 29–49.

Amed, I., Berg, A., Kappelmark, S., Hedrich, S., Andersson, J., Drageset, M. and Young, R. (2017), *The State of Fashion 2018*, available at: https://cdn.businessoffashion.com/reports/The_State_of_Fashion_2018_v2.pdf (accessed 30 August 2020).

Amerine, M., Pangborn, R. and Roessler, E. (2013), *Principles of Sensory Evaluation of Food*, Elsevier, available at: https://www.google.com/books?hl=en&lr=&id=kCnLBAAAQBAJ&oi=fnd&pg=PP1&dq=sensory+evaluation&ots=Ar2TYjSaLL&sig=-fQrC7GVDiW1osq6o6DEyQS-9QI (accessed 27 August 2020).

Ariyatum, B. and H.R. (2003), "A strategic approach to new product development in smart clothing. ", *Proceedings of the 6th Asian Design Conference*, Vol. 70, pp. 14–17.

Assunção, M.D., Calheiros, R.N., Bianchi, S., Netto, M.A.S. and Buyya, R. (2015), "Big Data computing and clouds: Trends and future directions", *Journal of Parallel and Distributed Computing*, Academic Press Inc., Vol. 79–80, pp. 3–15.

Ballard, D.H. and Brown, C.M. (1982), *Computer Vision*, *Prentice Hall*, available at: https://trove.nla.gov.au/work/25622561?q&versionId=44901301 (accessed 27 August 2020).

Barnes, L. and Lea-Greenwood, G. (2006), "Fast fashioning the supply chain: shaping the research agenda", *Article in Journal of Fashion Marketing and Management*, Vol. 10 No. 3, pp. 259–271.

Barney, J. (1991), "Firm Resources and Sustained Competitive Advantage", *Journal of Management*, Vol. 17 No. 1, pp. 99–120.

Barney, J., Wright, M. and Ketchen, D.J. (2001), "The resource-based view of the firm: Ten years after 1991", *Journal of Management*, SAGE Publications, Vol. 27 No. 6, pp. 625–641.

Barney, J.B. (2001), "Is the resource-based 'view' a useful perspective for strategic management research? Yes", *Academy of Management Review*, Academy of Management.

Barton, D. and Court, D. (2012), "Making Advanced Analytics Work for You", *Harvard Business Review*, October, available at: https://hbr.org/2012/10/making-advanced-analytics-work-for-you (accessed 18 August 2020).

Becks, A. and Huster, J. (2007), "Trend analysis based on explorative data and text mining: A decision support system for the european home textile industry", *ICEIS 2007 - 9th International Conference on Enterprise Information Systems, Proceedings*, Vol. AIDSS, pp. 253–258.

Beheshti-Kashi, S. and Thoben, K.-D. (2016), "The Usage of Social Media Text Data for the Demand Forecasting in the Fashion Industry", pp. 723–727.

Bertola, P. and Teunissen, J. (2018), "Fashion 4.0. Innovating fashion industry through digital transformation", *Research Journal of Textile and Apparel*, Emerald Group Publishing Ltd., Vol. 22 No. 4, pp. 352–369.

Bhardwaj, V. and Fairhurst, A. (2010a), "Fast fashion: Response to changes in the fashion industry", *International Review of Retail, Distribution and Consumer Research*, Vol. 20 No. 1, pp. 165–173.

Bhardwaj, V. and Fairhurst, A. (2010b), "Fast fashion: Response to changes in the fashion industry", *International Review of Retail, Distribution and Consumer Research*, Vol. 20 No. 1, pp. 165–173.

Biesdorf, S.., David Court and and Paul Willmott. (2013), *Big Data: What's Your Plan?*, available at: https://scholar.google.com/scholar?oi=gsb90&q="Big Data What's Your Plan%3F" McKinsey Quarterly%2C March 2013.↩&lookup=0&hl=en (accessed 30 August 2020).

Bilgihan, A., Kandampully, J. and Zhang, T. (Christina). (2016), "Towards a unified customer experience in online shopping environments: Antecedents and outcomes", *International Journal of Quality and Service Sciences*, Emerald Group Publishing Ltd., Vol. 8 No. 1, pp. 102–119.

Bishop, C. (2006), *Pattern Recognition and Machine Learning*, available at: http://cds.cern.ch/record/998831/files/9780387310732_TOC.pdf (accessed 30 August 2020).

Boeckhout, M., Zielhuis, G.A. and Bredenoord, A.L. (2018), "The FAIR guiding principles for data stewardship: fair enough?", *European Journal of Human Genetics*, Nature Publishing Group, Vol. 26 No. 7, pp. 931–936.

Bonetti, F. and Perry, P. (2017), "A Review of Consumer-Facing Digital Technologies Across Different Types of Fashion Store Formats", available at:https://doi.org/10.4018/978-1-5225-1865-5.ch006.

Booth, A., Sutton, A. and Papaioannou, D. (2016), *Systematic Approaches to a Successful Literature Review*, Sage, available at: https://books.google.com/books?hl=en&lr=&id=JD1DCgAAQBAJ&oi=fnd&pg=PP1&dq=why+systematic+literature+review&ots=IYlNLQbS3B&sig=9FcYNktgIBlVZSKNYcnXsv7n4TA (accessed 10 May 2019).

Bradlow, E., Gangwar, M., Kopalle, P. and Voleti, S. (2017), "The role of big data and predictive analytics in retailing", *Journal of Retailing*, Vol. 93 No. 1, pp. 79–95.

Brahmadeep and Thomassey, S. (2016), "Intelligent demand forecasting systems for fast fashion", *Information Systems for the Fashion and Apparel Industry*, pp. 145–161.

Bruce, M. and Daly, L. (2011), "Adding value: challenges for UK apparel supply chain management – a review", *Production Planning & Control*, Vol. 22 No. 3, pp. 210–220.

Bughin, J.., Hazan, E.., Ramaswamy, S.., Chui, M.., Allas, T.., Dahlström, P.., Henke, N., et al. (2017), "Artificial intelligence: The next digital frontier", *McKinsey Global Institute*, pp. 1–80.

de Camargo Fiorini, P.., Seles, B.M.R.P.., Jabbour, C.J.C.., Mariano, E.B. and and de Sousa Jabbour, A.B.L. (2018), "Management theory and big data literature: From a review to a research agenda", *International Journal of Information Management*, Vol. 43, pp. 112–129.

Cao, L. and Li, L. (2015), "The impact of cross-channel integration on retailers' sales growth", *Journal of Retailing*, Vol. 91 No. 2, pp. 198–216.

Capron, L. and Hulland, J. (1999), "Redeployment of Brands, Sales Forces, and General Marketing Management Expertise following Horizontal Acquisitions: A Resource-Based View", *Journal of Marketing*, SAGE Publications, Vol. 63 No. 2, pp. 41–54.

Cardeal, N. and António, N. (2012), "Valuable, rare, inimitable resources and organization (VRIO) resources or valuable, rare, inimitable resources (VRI) capabilities: What leads to competitive advantage?”, *AFRICAN JOURNAL OF BUSINESS MANAGEMENT*, Academic Journals, Vol. 6 No. 37, pp. 10159–10170.

Carton, F. and Adam, F. (2008), *Studying the Impact of ERP on Collaborative Decision Making- A Case Study*, *Frontiers in Artificial Intelligence and Applications*, Vol. 176.

CBIInsights. (2019), “The Future Of Fashion: From Design To Merchandising, How Tech Is Reshaping The Industry”, *CBI Insights*, available at: https://www.cbinsights.com/research/fashion-tech-future-trends/ (accessed 30 August 2020).

Chen, M.-K., Wang, Y.-H. and Hung, T.-Y. (2014), “Establishing an order allocation decision support system via learning curve model for apparel logistics”, *Journal of Industrial and Production Engineering*, Vol. 31 No. 5, pp. 274–285.

Chen, M., Mao, S. and Liu, Y. (2014), “Big data: A survey”, *Mobile Networks and Applications*, Vol. 19, Kluwer Academic Publishers, pp. 171–209.

Chen, R.-C., Li, S.-S., Lin, C.-C. and Feng, C.-C. (2005), “A GA-based global decision support system for garment production”, *Proceedings of 2005 International Conference on Neural Networks and Brain Proceedings, ICNNB’05*, Vol. 2, pp. 805–809.

Chin, J.., Hagstroem, M., Libarikian, A. and Rifai, K. (2017), *Advanced Analytics: Nine Insights from the C-Suite* , *McKinsey & Company*, New York, available at: https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/advanced-analytics-nine-insights-from-the-c-suite (accessed 30 August 2020).

Civille, G.V. and Oftedal, K.N. (2012), “Sensory evaluation techniques - Make ‘good for you’ taste ‘good’”, *Physiology and Behavior*, Elsevier, Vol. 107 No. 4, pp. 598–605.

Conca, J. (2015), “Making Climate Change Fashionable - The Garment Industry Takes On Global Warming”, available at: https://www.forbes.com/sites/jamesconca/2015/12/03/making-climate-change-fashionable-the-garment-industry-takes-on-global-warming/#72b408b979e4 (accessed 30 August 2020).

Côrte-Real, N.., Oliveira, T. and Ruivo, P. (2017), “Assessing business value of Big Data Analytics in European firms”, *Journal of Business Research*, Vol. 70, pp. 379–390.

Della Corte, V., Del Gaudio, G. and Sepe, F. (2020), “Leadership in the Digital Realm: What Are the Main Challenges?”, *Digital Leadership - A New Leadership Style for the 21st Century*, IntechOpen, available at:https://doi.org/10.5772/intechopen.89856.

Craparotta, G., … S.T.-I. and 2019, undefined. (n.d.). “A Siamese Neural Network Application for Sales Forecasting of New Fashion Products Using Heterogeneous Data”, *Download.Atlantis-Press.Com*, available at: https://download.atlantis-press.com/journals/ijcis/125924347/view (accessed 30 August 2020).

Darvazeh, S.S.. V.I.R. and M.F.M. (2020), “Big Data Analytics and Its Applications in Supply Chain Management”, *In New Trends in the Use of Artificial Intelligence for the Industry 4.0.* , IntechOpen., available at: https://www.intechopen.com/books/new-trends-in-the-use-of-artificial-intelligence-for-the-industry-4-0/big-data-analytics-and-its-applications-in-supply-chain-management (accessed 7 June 2020).

Darwish, S.M. (2013), "Soft computing applied to the build of textile defects inspection system", *IET Computer Vision*, Vol. 7 No. 5, pp. 373–381.

Dash, R., Mcmurtrey, M., Rebman, C. and Kar, U.K. (2019), *Application of Artificial Intelligence in Automation of Supply Chain Management*, *Journal of Strategic Innovation and Sustainability*, Vol. 14, available at: https://www.articlegateway.com/index.php/JSIS/article/view/2105 (accessed 30 August 2020).

David Kreyenhagen, C., Aleshin, T.I., Bouchard, J.E., Wise, A.M.I. and Zalegowski, R.K. (2014), "Using supervised learning to classify clothing brand styles", *2014 IEEE Systems and Information Engineering Design Symposium, SIEDS 2014*, IEEE Computer Society, pp. 239–243.

Dhar, V. (2013), "Data science and prediction", *Communications of the ACM*, Vol. 56 No. 12, pp. 64–73.

DiCicco-Bloom, B. and Crabtree, B.F. (2006), "The qualitative research interview", *Medical Education*, Vol. 40 No. 4, pp. 314–321.

Dong, M., Zeng, X., Koehl, L. and Zhang, J. (2020), "An interactive knowledge-based recommender system for fashion product design in the big data environment", *Information Sciences*, Vol. 540, pp. 469–488.

Drever, E. (1995), *Using Semi-Structured Interviews in Small-Scale Research. A Teacher's Guide.*, available at: https://eric.ed.gov/?id=ED394990 (accessed 25 August 2020).

Dubey, R., Gunasekaran, A. and Childe, S.J. (2019), "Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility", *Management Decision*, Vol. 57 No. 8, pp. 2092–2112.

Eisenhardt, K.M. and and Martin, J.. (2000), "Dynamic capabilities: what are they?", *Strategic Management Journal*, Vol. 21 No. 10–11, pp. 1105–1121.

Emani, C.K.., Cullot, N. and and Nicolle, C. (2015), "Understandable big data: a survey", *Computer Science Review*, Vol. 17, pp. 70–81.

Ericsson, D. and Sundström, M. (2015), "Demand chain management and consumer insight: keys to success in retailing", *Nordic Retail and Wholesale Conference, Lund, Sweden, 7-8 Nov*, available at: http://www.diva-portal.org/smash/record.jsf?pid=diva2:887551 (accessed 30 August 2020).

Ericsson, D. (2011), "Demand chain management- The evolution", *Orion*, Vol. 27 No. 1, available at: https://www.ajol.info/index.php/orion/article/view/67800 (accessed 30 August 2020).

Ericsson, D. and Sundström, M. (2012), "Value Innovation and Demand Chain Management-keys to future success in the fashion industry", *Nordic Textile Journal*, Vol. 1, pp. 83–90.

Ferreira, K.J., Lee, B.H.A. and Simchi-Levi, D. (2016), "Analytics for an online retailer: Demand forecasting and price optimization", *Manufacturing and Service Operations Management*, Vol. 18 No. 1, pp. 69–88.

Ferri, C., Hernández-Orallo, J. and Modroiu, R. (2009), "An experimental comparison of performance measures for classification", *Pattern Recognition Letters*, Elsevier BV, Vol. 30 No. 1, pp. 27–38.

Fiarni, C., Maharani, H. and Pratama R. (2016), "Sentiment analysis system for Indonesia online retail shop review using hierarchy Naive Bayes technique", *Information and Communication Technology (ICoICT), 2019 4th International Conference*, pp. 1–6.

Fischer, F. (2018), *Artificial Intelligence in Companies: Strategies, Governance and Challenges of Data Intelligence* , available at: www.cigref.fr (accessed 30 August 2020).

Fisher, M. and Raman, A. (2018), "Using Data and Big Data in Retailing", *Production and Operations Management*, Wiley-Blackwell, Vol. 27 No. 9, pp. 1665–1669.

Forsyth, D. and Ponce, J. (2003), "Computer vision: a modern approach", *Prentice Hall*, available at: http://catalogue.pearsoned.ca/assets/hip/ca/hip_ca_pearsonhighered/preface/013608592X.pdf (accessed 30 August 2020).

Fosso Wamba, S. and Akter, S. (2019), "Understanding supply chain analytics capabilities and agility for data-rich environments", *International Journal of Operations and Production Management*, Vol. 39, pp. 887–912.

Fox, R., Goldrick, M., Peng, A. and Whittington, K. (2018), "Geek meets chic: Four actions to jump-start advanced analytics in apparel", *McKinsey & Company*, 30 October, available at: https://www.mckinsey.com/industries/retail/our-insights/geek-meets-chic-four-actions-to-jump-start-advanced-analytics-in-apparel (accessed 30 August 2020).

Freno, A. (2017), "Practical lessons from developing a large-scale recommender system at Zalando", *Proceedings of the Eleventh ACM Conference on Recommender Systems*, Association for Computing Machinery, Inc, pp. 251–259.

Gandomi, A. and and Haider, M. (2015), "Beyond the hype: Big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35 No. 2, pp. 137–144.

Gereffi, G. and Frederick, S. (2010), *The Global Apparel Value Chain, Trade And The Crisis : Challenges And Opportunities For Developing Countries*, The World Bank, available at:https://doi.org/10.1596/1813-9450-5281.

Gereffi, G. and Memedovic, O. (2003), *The Global Apparel Value Chain: What Prospects for Upgrading by Developing Countries. Vienna: United Nations Industrial Development Organization.*, available at: https://www.researchgate.net/profile/Gary_Gereffi/publication/228150738_The_Global_Apparel_Value_Chain_What_Prospects_for_Upgrading_by_Developing_Countries/links/02bfe50d85b7e37517000000.pdf?disableCoverPage=true (accessed 30 August 2020).

Ghani, R., Probst, K., Liu, Y., Krema, M. and Fano, A. (2006), "Text mining for product attribute extraction", *ACM SIGKDD Explorations Newsletter*, Association for Computing Machinery (ACM), Vol. 8 No. 1, pp. 41–48.

Ghosh, A., Guha, T., Bhar, R.B. and Das, S. (2011), "Pattern classification of fabric defects using support vector machines", *International Journal of Clothing Science and Technology*, Vol. 23 No. 2, pp. 142–151.

Giri, C., Harale, N., Thomassey, S. and Zeng, X. (2018), "Analysis of consumer emotions about fashion brands:

An exploratory study", *Data Science and Knowledge Engineering for Sensing Decision Support*, world scientific, pp. 1567–1574.

Giri, C., Jain, S., Zeng, X. and Bruniaux, P. (2019), "A Detailed Review of Artificial Intelligence Applied in the Fashion and Apparel Industry", *IEEE Access*, Vol. 7, pp. 95364–95384.

Giri, C., Thomassey, S. and Zeng, X. (2019), "Exploitation of Social Network Data for forecasting Garment Sales", *International Journal of Computational Intelligence Systems*, Atlantis Press, available at:https://doi.org/10.2991/ijcis.d.191109.001.

Glaser, B. and Strauss, A. (2017), *Discovery of Grounded Theory: Strategies for Qualitative Research*, Routledge., available at: https://books.google.com/books?hl=en&lr=&id=GTMrDwAAQBAJ&oi=fnd&pg=PP1&dq=Glaser,+B.+G.,+%26+Strauss,+A.+L.+(2009).+Discovery+of+grounded+theory:+Strategies+for+qualitative+research.+Transaction+Publishers.&ots=Js1gFuytkZ&sig=F4AQHnaTslOQf4N9aFwTjEKoPzk (accessed 30 July 2020).

Glock, R. and Kunz, G. (2005), *Apparel Manufacturing: Sewn Product Analysis*, Pearson/Prentice Hall, Upper Saddle River, NJ, available at: https://pdfs.semanticscholar.org/8703/16d02be478333369a117187fb034a1d977dc.pdf (accessed 29 July 2020).

Glynis, S. (2015), "It's the second dirtiest thing in the world—and you're wearing it", *Alternet*, p. Web.

Godley, A. (1997), "The Development of the Clothing Industry: Technology and Fashion", *Textile History*, Andrew Godley, Vol. 28 No. 1, pp. 3–10.

Goworek, H. (2010), "An investigation into product development processes for UK fashion retailers: A multiple case study", *Journal of Fashion Marketing and Management*, Emerald Group Publishing Limited, Vol. 14 No. 4, pp. 648–662.

Grewal, D., Roggeveen, A.L. and Nordfält, J. (2017), "The Future of Retailing", *Journal of Retailing*, New York University, Vol. 93 No. 5, pp. 1–6.

Gries, T., Lutz, V., Niebel, V., Saggiomo, M. and Simonis, K. (2017), "Automation in quality monitoring of fabrics and garment seams", *Automation in Garment Manufacturing*, Elsevier Inc., pp. 353–376.

Griva, A., Bardaki, C., Pramatari, K. and Papakiriakopoulos, D. (2018), "Retail business analytics: Customer visit segmentation using market basket data", *Expert Systems with Applications*, Elsevier Ltd, Vol. 100, pp. 1–16.

Guan, C., Qin, S., Ling, W. and Ding, G. (2016), "Apparel Recommendation System Evolution: An empirical review", *International Journal of Clothing Science and Technology*, Vol. 28 No. 6, pp. 854–879.

Guemes-Castorena, D. and Ruiz, B. (2017), "Balancing Supply Chain Archetypes and Ambidexterity in the Apparel Industry.", *In 2017 Portland International Conference on Management of Engineering and Technology (PICMET)*, IEEE, pp. 1–13.

Günther, W.A.., Mehrizi, M.H.R.., Huysman, M. and Feldberg, F. (2017), “Debating big data: A literature review on realizing value from big data”, *The Journal of Strategic Information Systems*, Vol. 26 No. 3, pp. 191–209.

Guo, Z.X., Wong, W.K., Leung, S.Y.S. and Li, M. (2011), “Applications of artificial intelligence in the apparel industry: A review”, *Textile Research Journal*, Vol. 81 No. 18, pp. 1871–1892.

Gupta, D.L., Malviya, A.K. and Singh, S. (2012), “Performance analysis of classification tree learning algorithms”, *International Journal of Computer Applications*, Vol. 55 No. 6, available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.244.9217&rep=rep1&type=pdf (accessed 18 December 2019).

Gupta, U.G. and Gupta, A. (2016), “Vision: a missing key dimension in the 5V Big Data framework”, *Journal of International Business Research and Marketing*, Vol. 1 No. 3, pp. 50–56.

Gwilt, A. (2012), *Integrating Sustainable Strategies in the Fashion Design Process: A Conceptual Model of the Fashion Designer in Haute Couture.*, Doctoral dissertation, RMIT University, available at: https://researchbank.rmit.edu.au/view/rmit:160826 (accessed 30 August 2020).

Ha, Y.Y.-I., Kwon, S., Cha, M. and Joo, J. (2017), “Fashion conversation data on instagram”, *Proceedings of the 11th International Conference on Web and Social Media, ICWSM 2017*, pp. 418–427.

Hagberg, J., Sundström, M. and Nicklas, E.Z. (2016), “The digitalization of retailing: an exploratory framework”, *International Journal of Retail & Distribution Management*, Vol. 44 No. 7, pp. 694–712.

Halcomb, E.J. and Davidson, P.M. (2006), “Is verbatim transcription of interview data always necessary?”, *Applied Nursing Research*, W.B. Saunders, Vol. 19 No. 1, pp. 38–42.

Hammar, K.. J.S.. D.N. and M.M. (2018), “Deep Text Mining of Instagram Data Without Strong Supervision 4 th Mihhail Matskin”, *N 2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI)* , IEEE, pp. 158–165.

Hammond, J. and Kohler, K. (2000), “E-Commerce in the Textile and Apparel Industries”, *The E-Business Transformation: Sector Developments and Policy Implications*.

Henke, N.., Bughin, J.., Chui, M.., Manyika, J.., Saleh, T.., Wiseman, B. and and Sethupathy, G. (2016), “The age of analytics: Competing in a data-driven world”, *McKinsey Global Institute*, Vol. 4.

Holbrook, M.B. and Hulbert, J.M. (2002), “Elegy on the death of marketing”, *European Journal of Marketing*, Emerald, Vol. 36 No. 5/6, pp. 706–732.

Holland, J. (1975), “Adaptation in natural and artificial systems: an introductory analysis with application to biology”, *Control and Artificial Intelligence.*, available at: https://ci.nii.ac.jp/naid/10019844035/ (accessed 30 August 2020).

Holland, J.H., Langton, C., Wilson, S.W., Varela, F.J., Bourgine, P., Koza, J.R. and Book, A.B. (1992), *Genetic Programming Complex Adaptive Systems Genetic Programming On the Programming of Computers by*

Means of Natural Selection, MIT Press edition John H. Holland Toward a Practice of Autonomous Systems, available at: https://doc.lagout.org/science/Artificial Intelligence/Evolutionary computation/Genetic programming Complex adaptive systems - Koza J.R..pdf (accessed 30 August 2020).

Hoopes, D.G., Madsen, T.L. and Walker, G. (2003), "Guest editors' introduction to the special issue: Why is there a resource-based view? Toward a theory of competitive heterogeneity", *Strategic Management Journal*, Vol. 24 No. 10 SPEC ISS., pp. 889–902.

Hsiao, S.-W., Lee, C.-H., Chen, R.-Q. and Yen, C.-H. (2017), "An intelligent system for fashion colour prediction based on fuzzy C-means and gray theory", *Color Research & Application*, Vol. 42 No. 2, pp. 273–285.

Hu, H.., Wen, Y.., Chua, T.S. and and Li, X. (2014), "Toward scalable systems for big data analytics: A technology tutorial", *IEEE Access*, No. 2, pp. 652–687.

Hu, Z.-H. and Yu, X.-K. (2014), "Optimization of fast-fashion apparel transshipment among retailers", *Textile Research Journal*, Vol. 84 No. 20, pp. 2127–2139.

Hui, P.C.L., Chan, K.C.C., Yeung, K.W. and Ng, F.S.F. (2007), "Application of artificial neural networks to the prediction of sewing performance of fabrics", *International Journal of Clothing Science and Technology*, Vol. 19 No. 5, pp. 291–318.

Hutter, M. (2012), "One Decade of Universal Artificial Intelligence", *Theoretical Foundations of Artificial General Intelligence*, pp. 67–88.

Ibrahim, D. (2016), "An Overview of Soft Computing", *Procedia Computer Science*, Vol. 102, Elsevier B.V., pp. 34–38.

J Gantz, D.R. (2011), *Extracting Value from Chaos*, *IDC Iview*, Vol. 1142.

Jackson, P. (1999), *Introduction to Expert Systems*, Third edit., available at: https://www.worldcat.org/title/introduction-to-expert-systems/oclc/40267520 (accessed 30 August 2020).

Jahne, B. (2000), *Computer Vision and Applications: A Guide for Students and Practitioners*, Elsevier, available at: https://books.google.com/books?hl=en&lr=&id=lcSccjdqmpkC&oi=fnd&pg=PP2&dq=Bernd+Jähne%3B+Horst+Haußecker+(2000).+Computer+Vision+and+Applications,+A+Guide+for+Students+and+Practitioners.+Academic+Press.+ISBN+978-0-13-085198-7.&ots=xNK5v7QDxK&sig (accessed 30 August 2020).

Jain, G., Rakesh, S., Kamalun Nabi, M. and Chaturvedi, K.R. (2018), "Hyper-personalization – fashion sustainability through digital clienteling", *Research Journal of Textile and Apparel*, Vol. 22 No. 4, pp. 320–334.

Jain, S., Bruniaux, J., Zeng, X. and Bruniaux, P. (2017), "Big data in fashion industry", *IOP Conference Series: Materials Science and Engineering*, IOP Publishing, Vol. 254 No. 15, p. 152005.

Jeble, S., Dubey, R., Childe, S.J., Papadopoulos, T., Roubaud, D. and Prakash, A. (2018), "Impact of big data and predictive analytics capability on supply chain sustainability", *International Journal of Logistics*

Management, Vol. 29 No. 2, pp. 513–538.

Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R. and Childe, S.J. (2017), "Modelling quality dynamics, business value and firm performance in a big data analytics environment", *International Journal of Production Research ISSN:*, Taylor and Francis Ltd., Vol. 55 No. 17, pp. 5011–5026.

Jiao, Y. and Du, P. (2016), "Performance measures in evaluating machine learning based bioinformatics predictors for classifications", *Quantitative Biology*, Vol. 4 No. 4, pp. 320–330.

Joy, A., Sherry, J.F., Venkatesh, A., Wang, J. and Chan, R. (2012), "Fast fashion, sustainability, and the ethical appeal of luxury brands", *Fashion Theory - Journal of Dress Body and Culture*, Vol. 16 No. 3, pp. 273–295.

Kache, F. and Seuring, S. (2017), "Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management", *International Journal of Operations and Production Management*, Emerald Group Publishing Ltd., Vol. 37 No. 1, pp. 10–36.

Kaufmann, M. (2019), "Big Data Management Canvas: A Reference Model for Value Creation from Data", *Big Data Cogn. Comput*, Vol. 3 No. 1, p. 19.

Keen, P.G. (1980), "Decision support systems: a research perspective", *Decision Support Systems: Issues and Challenges: Proceedings of an International Task Force Meeting*, pp. 23–44.

Kersting, K. and Meyer, U. (2018), "From Big Data to Big Artificial Intelligence?", *KI - Künstliche Intelligenz*, Springer Nature, Vol. 32 No. 1, pp. 3–8.

Khalifa, N.A., Darwish, S.M. and El-Iskandarani, M.A. (2012), "Automated textile defects recognition system using computer vision and interval type-2 fuzzy logic", *Proceedings of the 2012 1st International Conference on Innovative Engineering Systems, ICIES 2012*, pp. 148–153.

Kim, C.E. and Lee, J.H. (2018), "Trends of big data and artificial intelligence in the fashion industry", *Journal of the Korean Society of Clothing and Textiles*, Dept. of Clothing and Textiles, College of Human Ecology, Pusan National University, South Korea, Vol. 42 No. 1, pp. 148–158.

Kim, H.S. and Cho, S.B. (2000), "Application of interactive genetic algorithm to fashion design", *Engineering Applications of Artificial Intelligence*, Vol. 13 No. 6, pp. 635–644.

Kitchens, B., Dobolyi, D., Li, J. and Abbasi, A. (2018), "Advanced Customer Analytics: Strategic Value Through Integration of Relationship-Oriented Big Data", *Journal of Management Information Systems*, Routledge, Vol. 35 No. 2, pp. 540–574.

Koustoumpardis, P.N., Fourkiotis, J.S. and Aspragathos, N.A. (2007), "Intelligent evaluation of fabrics' extensibility from robotized tensile test", *International Journal of Clothing Science and Technology*, Vol. 19 No. 2, pp. 80–98.

Kumar, S.V. and Poonkuzhali, S. (2018), "Improvising the Sales of Garments by Forecasting Market Trends using Data Mining Techniques", *International Journal of Pure and Applied Mathematics*, Vol. 119 No. 7, pp. 797–805.

Kumar, V., Rajan, B., Venkatesan, R. and Lecinski, J. (2019), "Understanding the Role of Artificial Intelligence in Personalized Engagement Marketing", *California Management Review*, SAGE Publications Ltd, Vol. 61 No. 4, pp. 135–155.

Kwon, O., Lee, N. and Shin, B. (2014), "Data quality management, data usage experience and acquisition intention of big data analytics", *International Journal of Information Management*, Elsevier Ltd, Vol. 34 No. 3, pp. 387–394.

Labrinidis, A. and Jagadish, H. V. (2012), "Challenges and opportunities with big data", *Proceedings of the VLDB Endowment*, Association for Computing Machinery, Vol. 5 No. 12, pp. 2032–2033.

Laenen, K., Zoghbi, S. and Moens, M.-F. (2017), "Cross-modal Search for Fashion Attributes", *Proceedings of the KDD 2017 Workshop on Machine Learning Meets Fashion*, No. Figure 1, available at:https://doi.org/10.475/123.

Lakshen, G.A.., Vraneš, S. and and Janev, V. (2016), "Big data and quality: A literature review", *2016 24th Telecommunications Forum (TELFOR)* , IEEE, pp. 1–4.

Lam, J.K.C. and Postle, R. (2006), "Textile and apparel supply chain management in Hong Kong", *International Journal of Clothing Science and Technology*, Vol. 18 No. 4, pp. 265–277.

Laney, D. (2001), "3D data management: Controlling data volume, velocity and variety", *META Group Research Note*, Vol. 6 No. 70, p. 1.

LaValle, S.., Lesser, E.., Shockley, R.., Hopkins, M.S. and Kruschwitz, N.. (2011), "Big data, analytics and the path from insights to value", *MIT Sloan Management Review*, Vol. 52 No. 2, pp. 21–32.

Lee, C.K.H., Choy, K.L., Ho, G.T.S., Chin, K.S., Law, K.M.Y. and Tse, Y.K. (2013), "A hybrid OLAP-association rule mining based quality management system for extracting defect patterns in the garment industry", *Expert Systems with Applications*, Vol. 40 No. 7, pp. 2435–2446.

Lee, C.K.H., Choy, K.L., Ho, G.T.S. and Lam, C.H.Y. (2016), "A slippery genetic algorithm-based process mining system for achieving better quality assurance in the garment industry", *Expert Systems with Applications*, Vol. 46, pp. 236–248.

Lee, C.K.H., Choy, K.L., Law, K.M.Y. and Ho, G.T.S. (2012), "An intelligent system for production resources planning in Hong Kong garment industry", *IEEE International Conference on Industrial Engineering and Engineering Management*, pp. 889–893.

Leondes, C.T. (2002), *Expert Systems : The Technology of Knowledge Management and Decision Making for the 21st Century*, Academic Press.

Li, B.-R., Wang, Y. and Wang, K.-S. (2017), "A novel method for the evaluation of fashion product design based on data mining", *Advances in Manufacturing*, Vol. 5 No. 4, pp. 370–376.

Li, P.F., Wang, J., Zhang, H.H. and Jing, J.F. (2012), "Automatic woven fabric classification based on support vector machine", *IET Conference Publications*, Vol. 2012, pp. 581–584.

Li, Y., Kuzmichev, V.E., Luo, Y. and Wang, X. (2010), "Garment industry oriented clothes shape classifying by cluster", *ICIMA 2010 - 2010 2nd International Conference on Industrial Mechatronics and Automation*, Vol. 2, pp. 472–475.

Lin, J.J. (2007), "Intelligent Decision Making Based on GA for Creative Apparel Styling", *Journal of Information Science and Engineering*, Vol. 23 No. 6, pp. 1923–1937.

Liu, K., Wang, J., Kamalha, E., Li, V. and Zeng, X. (2017), "Construction of a prediction model for body dimensions used in garment pattern making based on anthropometric data learning", *The Journal of The Textile Institute*, Vol. 108 No. 12, pp. 2107–2114.

Liu, K., Zeng, X., Bruniaux, P., Wang, J., Kamalha, E. and Tao, X. (2017), "Fit evaluation of virtual garment try-on by learning from digital pressure data", *Knowledge-Based Systems*, Elsevier B.V., Vol. 133, pp. 174–182.

Luger, G.F. and Stubblefield, W.A. (1993), *Artificial Intelligence : Structures and Strategies for Complex Problem Solving*, Benjamin/Cummings Pub. Co.

Luo, J.., Fan, M. and and Zhang, H. (2015), "Information Technology, Cross-Channel Capabilities, and Managerial Actions: Evidence from the Apparel Industry", *Journal of the Association for Information Systems*, pp. 2016–056.

Mallett, R., Hagen-Zanker, J., Slater, R. and Duvendack, M. (2012), "The benefits and challenges of using systematic reviews in international development research", *Journal of Development Effectiveness*, Taylor & Francis , Vol. 4 No. 3, pp. 445–455.

Manfredi, M., Grana, C., Calderara, S. and Cucchiara, R. (2014), "A complete system for garment segmentation and color classification", *Machine Vision and Applications*, Springer Verlag, Vol. 25 No. 4, pp. 955–969.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R. and McKinsey & Company. (2011), "Big data: The next frontier for innovation, competition, and productivity", *McKinsey Global Institute*, No. June, p. 156.

Martino, G., Iannone, R., Fera, M., Miranda, S. and Riemma, S. (2017), "Fashion retailing: A framework for supply chain optimization", *Uncertain Supply Chain Management*, Vol. 5 No. 3, pp. 243–272.

Martino, G., Yuce, B., Iannone, R. and Packianather, M.S. (2016), "Optimisation of the replenishment problem in the Fashion Retail Industry using Tabu-Bees algorithm", *IFAC-PapersOnLine*, Vol. 49 No. 12, pp. 1685–1690.

Martins, A., Bruniaux, P. and Thomassey, S. (2016), "Cluster-Based Sales Forecasting of Fast Fashion using Linguistic Variables and ELM", *Uncertainty Modelling in Knowledge Engineering and Decision Making: Proceedings of the 12th International FLINS Conference*, world scientific, pp. 978–983.

Matthias, O., Fouweather, I., Gregory, I. and Vernon, A. (2017), "Making sense of Big Data – can it transform operations management?", *International Journal of Operations and Production Management*, Emerald Group Publishing Ltd., Vol. 37 No. 1, pp. 37–55.

De Mauro, A., Greco, M. and Grimaldi, M. (2016), "A formal definition of Big Data based on its essential features", *Library Review*, Emerald Group Publishing Ltd., 4 April.

Mazzei, M.J. and Noble, D. (2017), "Big data dreams: A framework for corporate strategy", *Business Horizons*, pp. 405–414.

McAfee, A. and Brynjolfsson, E. (2012), "Big Data. The management revolution", *Harvard Buiness Review*, Vol. 90 No. 10, pp. 61–68.

McCormick, H., Cartwright, J., Perry, P., Barnes, L., Lynch, S. and Ball, G. (2014), "Fashion retailing - Past, present and future", *Textile Progress*, Taylor & Francis, Vol. 46 No. 3, pp. 227–321.

McNeill, L. and Moore, R. (2015), "Sustainable fashion consumption and the fast fashion conundrum: fashionable consumers and attitudes to sustainability in clothing choice", *International Journal of Consumer Studies*, Vol. 39 No. 3, pp. 212–222.

Mehrjoo, M. and Pasek, Z.J. (2016), "Risk assessment for the supply chain of fast fashion apparel industry: a system dynamics framework", *International Journal of Production Research*, Vol. 54 No. 1, pp. 28–48.

Meso, P. and Smith, R. (2000), "A resource-based view of organizational knowledge management systems", *Journal of Knowledge Management*, Vol. 4 No. 3, pp. 224–234.

Metaxiotis, K. (2004), "RECOT: An expert system for the reduction of environmental cost in the textile industry", *Information Management and Computer Security*, Vol. 12 No. 3, pp. 218–227.

Min, M. (2013), "A rule based expert system for analysis of mobile sales data on fashion market", *2013 International Conference on Information Science and Applications, ICISA 2013*, available at:https://doi.org/10.1109/ICISA.2013.6579450.

Mohri, M., Rostamizadeh, A. and Talwalkar, A. (2012), *Foundations of Machine Learning*, MIT Press, available at: https://mitpress.mit.edu/books/foundations-machine-learning (accessed 30 August 2020).

Mok, P.Y., Cheung, · T Y, Wong, · W K, Leung, · S Y S and Fan, · J T. (2013), "Intelligent production planning for complex garment manufacturing", *J Intell Manuf*, Vol. 24 No. 1, pp. 133–145.

Moon, K.L.K., Lee, J.Y. and Lai, S. yeung C. (2017), "Key drivers of an agile, collaborative fast fashion supply chain: Dongdaemun fashion market", *Journal of Fashion Marketing and Management*, Emerald Group Publishing Ltd., Vol. 21 No. 3, pp. 278–297.

Morris, K.D. (2011), *Collaborative Product Development: Examining the Development of a Nursing Sports Bra*, Colorado State University, Fort Collins.

Nakandala, D., Samaranayake, P. and Lau, H.C.W. (2013), "A fuzzy-based decision support model for monitoring on-time delivery performance: A textile industry case study", *European Journal of Operational Research*, Vol. 225 No. 3, pp. 507–517.

Nasira, G.M. and Banumathi, P. (2014), "An intelligent system for automatic fabric inspection", *Asian Journal of Information Technology*, Vol. 13 No. 6, pp. 308–312.

Nayak, R. and Padhye, R. (2015), *Garment Manufacturing Technology*, available at: https://books.google.com/books?hl=en&lr=&id=7kadBAAAQBAJ&oi=fnd&pg=PP1&ots=cpQgHWeZT7&sig=Hl_uUVIGBd4W_nWDhnNGZzVeEzk (accessed 30 August 2020).

Nayak, R. and Padhye, R. (2018), "Artificial intelligence and its application in the apparel industry", *Automation in Garment Manufacturing*, Woodhead Publishing, pp. 109–138.

Ngai, E.W.T., Peng, S., Alexander, P. and Moon, K.K.L. (2014), "Decision support and intelligent systems in the textile and apparel supply chain: An academic review of research articles", *Expert Systems with Applications*, Vol. 41 No. 1, pp. 81–91.

Nikolina, S. (2019), *Environmental Impact of Textile and Clothes Industry*, available at: http://www.europarl.europa.eu/RegData/etudes/BRIE/2019/633143/EPRS_BRI(2019)633143_EN.pdf (accessed 30 August 2020).

Nilsson, N.J. (1998), *Artificial Intelligence : A New Synthesis*, Morgan Kaufmann Publishers.

Nogry, S. and Varly, P. (2018), "Everyday Laptop Use by Children in a Southern Country: A Mixed-Method Approach", *Journal of Research on Technology in Education*, Taylor and Francis Inc., Vol. 50 No. 1, pp. 18–33.

O'Leary, D.E. (2013), "Artificial intelligence and big data", *IEEE Intelligent Systems*, Vol. 28 No. 2, pp. 96–99.

Ofek, E., Katona, Z. and Sarvary, M. (2011), "'Bricks and clicks': The impact of product returns on the strategies of multichannel retailers", *Marketing Science*, Vol. 30 No. 1, pp. 42–60.

Okoli, C. (2015), "A guide to conducting a standalone systematic literature review", *Communications of the Association for Information Systems*, Vol. 37, available at: https://hal.archives-ouvertes.fr/hal-01574600/ (accessed 30 August 2020).

Oliver, K. (2019), "How to overcome the top 3 AI challenges using data management", *IBM Big Data & Analytics Hub*, 9 September, available at: https://www.ibmbigdatahub.com/blog/how-overcome-top-3-ai-challenges-using-data-management (accessed 30 August 2020).

Oussous, A., Benjelloun, F.Z., Ait Lahcen, A. and Belfkih, S. (2018), "Big Data technologies: A survey", *Journal of King Saud University - Computer and Information Sciences*, King Saud bin Abdulaziz University, 1 October.

Palinkas, L.A., Aarons, G.A., Horwitz, S., Chamberlain, P., Hurlburt, M. and Landsverk, J. (2011), "Mixed Method Designs in Implementation Research", *Administration and Policy in Mental Health and Mental Health Services Research,* Vol. 38 No. 1, pp. 44–53.

Pantano, E.., Priporas, C.V.., Sorace, S. and Iazzolino, G. (2017), "Does innovation-orientation lead to retail industry growth? Empirical evidence from patent analysis", *Journal of Retailing and Consumer Services*, Vol. 34, pp. 88–94.

Pantano, E. and Vannucci, V. (2019), "Who is innovating? An exploratory research of digital technologies diffusion in retail industry", *Journal of Retailing and Consumer Services*, Vol. 49, pp. 297–304.

Pantano, E. and Viassone, M. (2015), "Engaging consumers on new integrated multichannel retail settings: Challenges for retailers", *Journal of Retailing and Consumer Services*, Elsevier, Vol. 25, pp. 106–114.

Park, J., Ciampaglia, G.L. and Ferrara, E. (2016), "Style in the age of instagram : Predicting success within the fashion industry using social media", *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW*, Vol. 27, pp. 64–73.

Pavlinić, D.Z. and Geršak, J. (2004), "Design of the system for prediction of fabric behaviour in garment manufacturing processes", *International Journal of Clothing Science and Technology*, Vol. 16 No. 1–2, pp. 252–261.

Peteraf, M.A. (1993), "The cornerstones of competitive advantage: A resource-based view", *Strategic Management Journal*, Vol. 14 No. 3, pp. 179–191.

Peterson, J. (2016), "The Co-design Process in Mass Customization of Complete Garment Knitted Fashion Products", *Journal of Textile Science & Engineering*, Vol. 6 No. 4, pp. 1–8.

Pfahl, L. and Moxham, C. (2014), "Achieving sustained competitive advantage by integrating ECR, RFID and visibility in retail supply chains: a conceptual framework.", *Production Planning & Control*, Taylor and Francis Ltd., Vol. 25 No. 7, pp. 548–571.

Pînzaru, F.., Zbuchea, A. and and Vidu, C. (2016), "Exploring Challenges for Managers in the Digital Economy", *In Proceedings of The12th European Conference on Management, Leadership and Governance ECMLG 2016*, Bucharest, pp. 328–333.

Plummer, L. (2017), "This is how Netflix's top-secret recommendation system works | WIRED UK", available at: https://www.wired.co.uk/article/how-do-netflixs-algorithms-work-machine-learning-helps-to-predict-what-viewers-will-like (accessed 30 August 2020).

Poland, B.D. (1995), "Transcription Quality as an Aspect of Rigor in Qualitative Research", *Qualitative Inquiry*, Sage Publications, Inc, Vol. 1 No. 3, pp. 290–310.

Poole, D., Mackworth, A. and Goebel, R. (1998), "Computational intelligence: a logical approach", available at: https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Poole%2C+David%3B+Mackworth%2C+Alan%3B+Goebel%2C+Randy+%281998%29.+Computational+Intelligence%3A+A+Logical+Approach.+New+York%3A+Oxford+University+Press.+ISBN+978-0-19-510270-3.&btnG= (accessed 30 August 2020).

Rabenasolo, B. and Zeng, X. (2012), "A Risk-Based Multi-criteria Decision Support System for Sustainable Development in the Textile Supply Chain", *Intelligent Systems Reference Library*.

Raguseo, E. and Vitari, C. (2018), "Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects", *International Journal of Production Research*, Vol. 56 No. 15, pp. 5206–5221.

Ram, J.., Zhang, C. and and Koronios, A. (2016), "The implications of Big Data analytics on Business Intelligence: A qualitative study in China", *Procedia Computer Science*, Vol. 87, pp. 221–226.

Rasmussen, P. (2010), *Skräddaren, Sömmerskan Och Modet: Arbetsmetoder Och Arbetsdelning i Tillverkningen Av Kvinnlig Dräkt 1770-1830*, Nordiska museets förlag, available at: http://lup.lub.lu.se/record/4646778 (accessed 30 August 2020).

Reagan, C. (2016), "A $260 billion 'ticking time bomb': The costly business of retail returns", *CNBC*, available at: https://www.cnbc.com/2016/12/16/a-260-billion-ticking-time-bomb-the-costly-business-of-retail-returns.html (accessed 30 August 2020).

Reinartz, W., Wiegand, N. and Imschloss, M. (2019), "The impact of digital transformation on the retailing value chain", *International Journal of Research in Marketing*, Elsevier B.V., Vol. 36 No. 3, pp. 350–366.

Ren, S., Chan, H.L. and Siqin, T. (2019), "Demand forecasting in retail operations for fashionable products: methods, practices, and real case study", *Annals of Operations Research*, Springer New York LLC.

van Rijmenam, M., Erekhinskaya, T., Schweitzer, J. and Williams, M.-A. (2019), "Avoid being the Turkey: How big data analytics changes the game of strategy in times of ambiguity and uncertainty", *Long Range Planning*, Vol. 52 No. 5, available at:https://doi.org/10.1016/j.lrp.2018.05.007.

Rodríguez-Torrico, P., San José Cabezudo, R. and San-Martín, S. (2017), "Tell me what they are like and I will tell you where they buy. An analysis of omnichannel consumer behavior", *Computers in Human Behavior*, Vol. 68, pp. 465–471.

Rossi, R. and Hirama, K. (2015), "Characterizing Big Data Management", *Issues in Informing Science and Information Technology*, Vol. 12, pp. 165–180.

Roßmann, B., Canzaniello, A., von der Gracht, H. and Hartmann, E. (2018), "The future and social impact of Big Data Analytics in Supply Chain Management: Results from a Delphi study", *Technological Forecasting and Social Change*, Vol. 130, pp. 135–149.

Rowley, J. (2012), "Conducting research interviews", *Management Research Review*, Vol. 35 No. 3–4, pp. 260–271.

Ruan, D. and Zeng, X. (2004), "Intelligent Sensory Evaluation: An Introduction", *Intelligent Sensory Evaluation*, Springer Berlin Heidelberg, pp. 1–9.

Rumsfeld, J.S.., Joynt, K.E. and Maddox, T.M. (2016), "Big data analytics to improve cardiovascular care: promise and challenges", *Nature Reviews Cardiology*, Vol. 13 No. 6, p. 350.

Russom, P. (2011), "Big data analytics", *TDWI Best Practices Report, Fourth Quarter*, Vol. 19 No. 4, pp. 1–34.

Saaty, T. and Alexander, J. (1981), *Thinking with Models: Mathematical Models in the Physical, Biological, and Social Sciences*, RWS Publications, available at: https://books.google.com/books?hl=en&lr=&id=RoVoBgAAQBAJ&oi=fnd&pg=PT10&dq=It+involves+creating+physical,+conceptual,+or+mathematical+models+that+help+scientists+to+replicate+the+reality+u

nder+investigation+through+simplification.&ots=pEbdom_whv&sig=S2aHhwQn9kydHbUBpTaRDR8hz1U (accessed 30 August 2020).

Saleem, H., LI, Y., Ali, Z., Mehreen, A. and Mansoor, M.S. (2020), "An empirical investigation on how big data analytics influence China SMEs performance: do product and process innovation matter?", *Asia Pacific Business Review*, available at:https://doi.org/10.1080/13602381.2020.1759300.

Sambamurthy, V.., Bharadwaj, A. and and Grover, V. (2003), "Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms", *MIS Quarterly*, pp. 237–263.

Shams, S.M.R. and Solima, L. (2019), "Big data management: implications of dynamic capabilities and data incubator", *Management Decision*, Vol. 57 No. 8, pp. 2113–2123.

Shang, X., Liu, X., X., G., C., C., Ma, Y. and and Nyberg, T.R. (2013), "Social manufacturing cloud service platform for the mass customization in apparel industry", *Proceedings of 2013 IEEE International Conference on Service Operations and Logistics, and Informatics*, Ieee, pp. 220–224.

Shang, X., Wang, F.-Y., Xiong, G., Nyberg, T.R., Yuan, Y., Liu, S., Guo, C., et al. (2018), "Social manufacturing for high-end apparel customization", *IEEE/CAA Journal of Automatica Sinica*, State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, 100190, China, Vol. 5 No. 2, pp. 489–500.

Siegmund, D., Kuijper, A. and Braun, A. (2016), "Stereo-image normalization of voluminous objects improves textile defect recognition", *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*.

Silva, M.J., Herrero, C., Menegassi, M., Nunes, N., Junior, T., José Da Silva, M., Sartori, R., et al. (2018), "Knowledge management within the fashion and clothing industry: an investigation into the purchase processes within a company", *International Journal of Development Research*, Vol. 08 No. 03, pp. 19739–19743.

Singh Adhikari, S., Singh, S., Rajagopal, A. and Rajan, A. (2019), "Progressive Fashion Attribute Extraction", *ArXiv Preprint ArXiv:1907.00157*, available at:https://doi.org/10.1145/1122445.1122456.

Sivarajah, U.., Kamal, M.M.., Irani, Z. and Weerakkody, V. (2017), "Critical analysis of Big Data challenges and analytical methods", *Journal of Business Research*, Vol. 70, pp. 263–286.

Sodero, A., Jin, Y.H. and Barratt, M. (2019), "The social process of Big Data and predictive analytics use for logistics and supply chain management", *International Journal of Physical Distribution and Logistics Management*, Vol. 49 No. 7, pp. 706–726.

Sonka, M., Hlavac, V. and Boyle, R. (2008), *Image Processing, Analysis, and Machine Vision*, Thompson Learning.

Soufflet, I., Calonnier, M. and Dacremont, C. (2004), "A comparison between industrial experts' and novices' haptic perceptual organization: A tool to identify descriptors of the handle of fabrics", *Food Quality and Preference*, Vol. 15 No. 7-8 SPEC.ISS., pp. 689–699.

Sprague, R.H. (1980), *A Framework for the Development of Decision Support Systems*, *Management Information Systems Research Center, University of Minnesota*, Vol. 4, available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.476.4750&rep=rep1&type=pdf (accessed 30 August 2020).

Srimarut, T. and Mekhum, W. (2020), "From supply chain connectivity (SCC) to supply chain agility (SCA), adaptability and alignment: Mediating role of big data analytics capability", *International Journal of Supply Chain Management*, Vol. 9 No. 1, pp. 183–189.

Statista. (2019), "Textile & clothing EU household consumption 2009-2017 | Statistics", *Statista*, available at: https://www.statista.com/statistics/417674/eu-european-union-textile-clothing-household-consumption/ (accessed 30 August 2020).

Stella, N. and Chuks, A.. (2011), "Expert System : A Catalyst in Educational Development in Nigeria", *School of Science Education*.

Stuart, J.R. and Norvig, P. (2009), "Artificial intelligence: A modern approach", *Prentice Hall*.

Sugumaran, P. and Sukumaran, V. (2019), "Recommendations to improve dead stock management in garment industry using data analytics", *MBE*, Vol. 16 No. 6, pp. 8121–8133.

Sull, D. and Turconi, S. (2008), "Fast fashion lessons", *Business Strategy Review*, Vol. 19 No. 2, pp. 4–11.

Sundström, M. (2019), "Data-driven Innovation Within E-Business: An Introduction", *FIIB Business Review*, SAGE Publications, Vol. 8 No. 2, pp. 79–87.

Sutton, A. (2018), "Distinguishing between authenticity and personality consistency in predicting well-being: A mixed method approach", *European Review of Applied Psychology*, Vol. 68 No. 3, pp. 117–130.

Syed, A.R., Gillela, K. and Venugopal, C. (2013), "The Future Revolution on Big Data", *International Journal of Advanced Research in Computer and Communication Engineering*, Vol. 2 No. 6, pp. 2446–2451.

Tan, K.H.., Zhan, Y.., Ji, G.., Ye, F. and Chang, C. (2015), "Harvesting big data to enhance supply chain innovation capabilities: An analytic infrastructure based on deduction graph", *International Journal of Production Economics*, Vol. 165, pp. 223–233.

Tecuci, G. (2012), "Artificial intelligence", *Wiley Interdisciplinary Reviews: Computational Statistics*, John Wiley & Sons, Ltd, Vol. 4 No. 2, pp. 168–180.

Teece, D. and Pisano, G. (2003), "The Dynamic Capabilities of Firms", *Handbook on Knowledge Management*, Springer Berlin Heidelberg, pp. 195–213.

Teece, D.J.., Pisano, G. and and Shuen, A. (1997), "Dynamic capabilities and strategic management", *Strategic Management Journal*, Vol. 18 No. 7, pp. 509–533.

Tehrani, A.F. and Ahrens, D. (2016), "Supervised regression clustering: A case study for fashion products", *International Journal of Business Analytics*, Vol. 3 No. 4, pp. 21–40.

Tim Morris. (2004), "Computer Vision and Image Processing - Tim Morris - Macmillan International Higher Education", *Palgrave Macmillan*.

Tokatli, N. (2008), "Global sourcing: insights from the global clothing industry—the case of Zara, a fast fashion retailer", *Journal of Economic Geography*, Vol. 1, pp. 12–38.

Tokatli, N. and Kizilgün, Ö. (2009), "From manufacturing garments for ready-to-wear to designing collections for fast fashion: Evidence from Turkey", *Environment and Planning A*, Vol. 41 No. 1, pp. 146–162.

Tu, D.Q., Kayes, A.S.M., Rahayu, W. and Nguyen, K. (2020), "ISDI: A New Window-Based Framework for Integrating IoT Streaming Data from Multiple Sources", *Advances in Intelligent Systems and Computing*, Vol. 926, Springer Verlag, pp. 498–511.

Vaccaro, K., Agarwalla, T., Shivakumar, S. and Kumar, R. (2018), "Designing the Future of Personal Fashion", *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems - CHI '18*, ACM Press, New York, New York, USA, pp. 1–11.

Vorasitchai, S. and Madarasmi, S. (2003), "Improvements on layout of garment patterns for efficient fabric consumption", *Proceedings - IEEE International Symposium on Circuits and Systems*, Vol. 4, pp. IV552–IV555.

Waller, M.A. and Fawcett, S.E. (2013), "Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management", *Journal of Business Logistics*, Council of Supply Chain Management Professionals, Vol. 34 No. 2, pp. 77–84.

Walsh, J. and Godfrey, S. (2000), "The internet: A new era in customer service", *European Management Journal*, Elsevier Ltd, Vol. 18 No. 1, pp. 85–92.

Wamba, S.F.., Gunasekaran, A.., Akter, S.., Ren, S.J.F.., Dubey, R. and Childe, S.J. (2017), "Big data analytics and firm performance: Effects of dynamic capabilities", *Journal of Business Research*, Vol. 70, pp. 356–365.

Wang, G., Gunasekaran, A., Ngai, E.W.T. and Papadopoulos, T. (2016), "Big data analytics in logistics and supply chain management: Certain investigations for research and applications", *International Journal of Production Economics*, Elsevier B.V., 1 June.

Wang, X.G., Li, X.Z. and Li, Y. (2011), "Application of cluster algorithm in clothes shape classifying", *Applied Mechanics and Materials*.

Ward, J.S. and Barker, A. (2013), "Undefined By Data: A Survey of Big Data Definitions", *ArXiv Preprint ArXiv:1309.5821*, available at: http://arxiv.org/abs/1309.5821 (accessed 4 February 2020).

Weill, P.., Subramani, M. and and Broadbent, M. (2002), "Building IT infrastructure for strategic agility", *MIT Sloan Management Review*, Vol. 44 No. 1, pp. 57–66.

Whiting, L.S. (2008), "Semi-structured interviews: Guidance for novice researchers.", *Nursing Standard*, Vol. 22 No. 23, available at:

http://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=00296570&AN=30051376&h=xI%2BY3QMLlgvqHJ2VPIjnTGVw9IcjUWZf8AKvntTC%2BPLMD3asFr0Noc5Dn70gmNJqge1RRxewNejj37Fy5SCa5Q%3D%3D&crl=c (accessed 25 August 2020).

Wong, W.K., Zeng, X.H. and Au, W.M.. (2009), "A decision support tool for apparel coordination through integrating the knowledge-based attribute evaluation expert system and the T–S fuzzy neural network", *Expert Systems with Applications*, Vol. 36 No. 2, pp. 2377–2390.

Wong, W.K. and Leung, S.Y.S. (2008), "Genetic optimization of fabric utilization in apparel manufacturing", *International Journal of Production Economics*, Vol. 114 No. 1, pp. 376–387.

Wong, W.K., Leung, S.Y.S., Guo, Z.X., Zeng, X.H. and Mok, P.Y. (2012), "Intelligent product cross-selling system with radio frequency identification technology for retailing", *International Journal of Production Economics*, Vol. 135 No. 1, pp. 308–319.

Wong, W.K., Yuen, C.W.M., Fan, D.D., Chan, L.K. and Fung, E.H.K. (2009), "Stitching defect detection and classification using wavelet transform and BP neural network", *Expert Systems with Applications*, Pergamon, Vol. 36 No. 2, pp. 3845–3856.

X. Wu, G. Fang and Z. Wu. (2006), "The dynamic IT capabilities and firm agility: A resource-based perspective ", *2006 International Technology and Innovation Conference (ITIC 2006)*, Hangzhou, pp. 666–671.

Yang, C., Huang, Q., Li, Z., Liu, K. and Hu, F. (2017), "Big Data and cloud computing: innovation opportunities and challenges", *International Journal of Digital Earth*, Taylor and Francis Ltd., Vol. 10 No. 1, pp. 13–53.

Yang, J., Xie, H., Yu, G. and Liu, M. (2021), "Achieving a just–in–time supply chain: The role of supply chain intelligence", *International Journal of Production Economics*, Elsevier, Vol. 231, p. 107878.

Yang, S.J. and Jang, S. (2019), "Fashion trend forecasting using ARIMA and RNN: Application of tensorflow to retailers' websites", *Asia Life Sciences*, Department of Consumer Science & Living Culture Industry, Sungshin University, 55 Dobong-ro 76ga-gil, Gangbuk-gu, Seoul, 01133, South Korea, No. 1, pp. 407–418.

Yesil, E., Kaya, M. and Siradag, S. (2012), "Fuzzy forecast combiner design for fast fashion demand forecasting", *INISTA 2012 - International Symposium on Innovations in Intelligent SysTems and Applications*, available at:https://doi.org/10.1109/INISTA.2012.6247034.

Yin, S. and Kaynak, O. (2015), "Big data for modern industry: challenges and trends", *Proceedings of the IEEE*, Vol. 103 No. 2, pp. 143–146.

Yu, Y., Choi, T.-M. and Hui, C.-L. (2011), "An intelligent fast sales forecasting model for fashion products", *Expert Systems with Applications*, Vol. 38 No. 6, pp. 7373–7379.

Yu, Y., Hui, C.-L. and Choi, T.-M. (2012), "An empirical study of intelligent expert systems on forecasting of fashion color trend", *Expert Systems with Applications*, Vol. 39 No. 4, pp. 4383–4389.

Yuan, M., Khan, I.R., Farbiz, F., Yao, S., Niswar, A. and and Foo, M.H. (2013), "A mixed reality virtual clothes try-on system", *IEEE Transactions on Multimedia*, Vol. 15 No. 8, pp. 1958–1968.

Yuen, C.W.M., Wong, W.K., Qian, S.Q., Chan, L.K. and Fung, E.H.K. (2009), "A hybrid model using genetic algorithm and neural network for classifying garment defects", *Expert Systems with Applications*, Vol. 36 No. 2 PART 1, pp. 2037–2047.

Yuen, C.W.M., Wong, W.K., Qian, S.Q., Fan, D.D., Chan, L.K. and Fung, E.H.K. (2009), "Fabric Stitching Inspection Using Segmented Window Technique and BP Neural Network", *Textile Research Journal*, Vol. 79 No. 1, pp. 24–35.

Zeng, J. and Glaister, K.W. (2018), "Value creation from big data: Looking inside the black box", *Strategic Organization*, Vol. 16 No. 2, pp. 105–140.

Zeng, X., Koehl, L., Wang, L. and Chen, Y. (2013), "An intelligent recommender system for personalized fashion design", *Proceedings of the 2013 Joint IFSA World Congress and NAFIPS Annual Meeting, IFSA/NAFIPS 2013*, pp. 760–765.

Zielnicki, K. (2019), "Simulacra and Selection: Clothing Set Recommendation at Stitch Fix", Association for Computing Machinery (ACM), Paris, pp. 1379–1380.

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A Detailed Review of Artificial Intelligence Applied in the Fashion and Apparel Industry

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ABSTRACT The enormous impact of artificial intelligence has been realized in transforming the fashion and apparel industry in the past decades. However, the research in this domain is scattered and mainly focuses on one of the stages of the supply chain. Due to this, it is difficult to comprehend the work conducted in the distinct domain of the fashion and apparel industry. Therefore, this paper aims to study the impact and the significance of artificial intelligence in the fashion and apparel industry in the last decades throughout the supply chain. Following this objective, we performed a systematic literature review of research articles (journal and conference) associated with artificial intelligence in the fashion and apparel industry. Articles were retrieved from two popular databases ‘‘Scopus’’ and ‘‘Web of Science’’ and the article screening was completed in five phases resulting in 149 articles. This was followed by article categorization which was grounded on the proposed taxonomy and was completed in two steps. First, the research articles were categorized according to the artificial intelligence methods applied such as machine learning, expert systems, decision support system, optimization, and image recognition and computer vision. Second, the articles were categorized based on supply chain stages targeted such as design, fabric production, apparel production, and distribution. In addition, the supply chain stages were further classified based on business-to-business (B2B) and business-to-consumer (B2C) to give a broader outlook of the industry. As a result of the categorizations, research gaps were identified in the applications of AI techniques, at the supply chain stages and from a business (B2B/B2C) perspective. Based on these gaps, the future prospects of the AI in this domain are discussed. These can benefit the researchers in academics and industrial practitioners working in the domain of the fashion and apparel industry.

INDEX TERMS Artificial intelligence, big data analytics, machine learning, expert systems, fashion and apparel industry.

I. INTRODUCTION

Fashion and apparel (F&A) industry is one of the largest economies contributing 38% to the Asia Pacific, 26% to Europe and 22% to North America [1]. According to Business of Fashion, (2019), F&A sales are projected to grow by 7.5% and 5.5% in the Asia Pacific and Europe respectively. F&A is also one of the largest waste producers globally [3] because of problems like overproduction and product returns. The principal reason behind this is the consumer's dissatisfaction with the products offered by the industry in terms of size, color, and style. Hence, it is essential for the industry to become customer-centric for successfully regulating environment-friendly manufacturing practices. Consequently, it is important that the industry adopt sustainable production practices to alleviate waste production and management. One of the ways of achieving this can be by taking advantage of emerging Artificial Intelligence (AI) techniques for creating a sustainable digital supply chain [4].

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In the past decades, AI has transformed many industries like health, transportation, and manufacturing due to its capability to solve problems using conventional mathematical models [5]–[7]. The application of AI has been recognized in the F&A industry at various stages such as apparel design, pattern making, forecasting sales production, supply chain management [8], [9].

With the emergence of globalization and digitalization, AI has gained attention to connect businesses globally. In the last decade, the F&A industry has utilized AI to a certain extent for improving supply chain processes like apparel production [10], fabric inspection [11], distribution [12]. This was important as the F&A industry is volatile and it is always challenging to quickly respond to change in trends and continuously evolving consumer's demands.

An additional impact of digitalization is noticed in consumer behavior in the F&A industry. The increase in awareness and advent of new offline and online mediums has changed the contemporary consumer's decision-making pattern, influenced by the various online and offline mediums [13]. It is, therefore, important to create digital platforms for efficient requirements elicitation and collection. This can be attained by utilizing the benefits accompanied by Information technology (IT), Artificial intelligence (AI) techniques, big data analytical tools and other current technologies [14].

Evidently, the F&A industry is one of the most dynamic industries with new data being generated every time a new garment is designed, produced and sold [15]. However, the industry still lacks the extensive adoption of AI methods. The industry is still using computational tools based on classical algorithms and modern AI techniques are confined to academic research. Hence, it is a requisite for the industry to adopt new AI techniques to have a competitive advantage and improve business profitability. To do this, it is indispensable to have a consolidated description of different AI techniques used in research to target various business problems in the F&A supply chain.

After scrutinizing the extant literature in this domain, we encountered a few review articles, where the focus was on either AI or supply chain in F&A. For instance, the review conducted in [8] shows categorization of research articles on the basis of four operation processes in the apparel industry: apparel design, manufacturing, retailing, and supply chain management. This study presented the limitations of academic research that hinders the application of AI methods at an industrial level and also found that the F&A industry received less recognition from AI research groups. The work represented in [16] was restricted to AI algorithms, ''Decision support systems'' and ''Intelligent systems'' in the textile and apparel supply chain. In addition, this study only considered journal articles for the review. In contrast to these two reviews, the review carried out in [17] focuses on ''Data mining and Machine learning models'' implemented in the textile industry. According to this study, classification techniques were applied more frequently as compared to clustering techniques.

Despite valuable contributions to the previous literature reviews, when observed, none of the reviews studied the overall impact of AI in the F&A industry. In addition, there is a need to have a broader outlook of AI techniques employed for improving business operations at different supply chain stages. Furthermore, no study emphasized on defining the F&A supply chain stages according to the business perspective. Every business is composed of Business-to-Business (B2B) and Business-to-Consumer (B2C) transactions. In a traditional business setting, every personnel involved in business operations has knowledge confined to a specific domain. However, with the proliferation of AI technology, the complexity of business operations has risen, making it important for individuals (industrial researchers, academic researchers, managers) to have interdisciplinary knowledge.

By segregating the supply chain operations into B2B and B2C, the purpose is to provide a roadmap for individuals who are willing to expand the horizon of their expertise to help the F&A industry in improving their business models and profitability.

The objectives of this study are threefold. First, to do an in-depth analysis of the ongoing trend of AI in the F&A industry over the last decades. For this, no time constraint was introduced while retrieving the articles from scientific databases. Second, to understand the exploitation of AI techniques employed at various F&A chain stages. This is to examine the industrial transformation from a technical perspective. Third, to comprehend the utilization of AI techniques with a business perspective in F&A supply chain. Hence, this paper addresses the following research questions:

RQ1. What is the impact of Artificial Intelligence on F&A Industry over the past decades?

RQ2. Where have the AI methods been applied in F&A supply chain?

RQ3. To what extent has research addressed the supply chain problems from a B2B and/or B2C perspective?

In this direction, this research aims to conduct a systematic and comprehensive literature review of AI methods applied in the F&A industry in the past decades. This study is viable for an independent researcher to understand AI trend in F&A irrespective of their domain. Another important attribute of this work is the consideration of all journal and conference publications, which is rarely found in other review studies.

The remaining article is organized as follows: Section II outlines the research framework for conducting the systematic literature review. Section III describes the steps involved in the article screening process. Section IV represents the taxonomy proposed for the classification of AI methods and F&A supply chain. This is followed by section V that discusses the analysis and findings of the review process. Section VI and VII present the research gaps identified, future implications, conclusion, and limitations.

II. RESEARCH FRAMEWORK

In an attempt to answer the research questions, this study presents a systematic literature review (SLR) focusing on

FIGURE 1. Systematic literature review: Research framework.

TABLE 1. Competencies of researchers.

Researcher	Competencies	
	Major	Minor
First Researcher	Artificial Intelligence, Data Science, Expert Systems, Machine Learning	Fashion, Textile, Supply Chain, Management
Second Researcher	Fashion and Apparel Supply Chain, Fashion Technology, Information Technology, Data analysis	Machine Learning, Artificial Intelligence
Expert Researcher	Significant Knowledge of Both Domains (AI and F&A)	NA

artificial intelligence methods applied in the F&A industry. An SLR methodology was chosen to make the research more rational, transparent and reproducible [18].

Based on the research focus, the methodology adopted is shown in Figure 1. The review process commenced with collecting and preparing data from scientific databases. Subsequently, articles were selected in five phases (depicted in Figure 2), strictly adhering to the inclusion and exclusion criteria defined in table 4 and 5. Finally, the selected articles were considered for classification (described in section IV) and further analysis complying with the research questions. There were two researchers involved in the entire review process and one expert researcher for the validation of the classification process. The competencies of each researcher can be seen in the following Table 1.

III. ARTICLE SCREENING PROCESS

The article screening process is presented in Figure 2. It is comprised of three steps, namely article retrieval, article selection, and information extraction.

TABLE 2. Synonyms of the targeted search keywords.

Artificial Intelligence (AI)	Fashion and Apparel (F&A)
Machine Learning	Fashion Industry
Deep Learning	Garment Industry
Data Mining	Apparel Industry
Artificial Intelligence	Clothing Industry
Data Analytics	Textile Industry
Expert Systems	
Knowledge Systems	
Intelligent Systems	
Decision Support Systems	
Data Management	

A. ARTICLE RETRIEVAL

This section discusses the steps involved in article retrieval, which is the initial part of the article selection process. The first step was to choose the databases to conduct the SLR. Two popular scientific databases, Scopus and Web of Science, were selected because of their popularity in academia. In addition, these databases index most of the journals and conference proceedings. Especially, most of the work in this research's domain is also indexed in these two databases [19], [20].

This was followed by formulating the search string, which included all the synonyms related to artificial intelligence and the F&A industry (shown in Table 2). The final search string defined for both the databases are as follows:

1) SEARCH STRING FOR SCOPUS

TITLE-ABS-KEY ((''Machine learning'' OR''deep learning'' OR ''data mining'' OR ''artificial intelligence'' OR ''data analytics'' OR ''expert system''OR ''knowledge system'' OR ''intelligent system'' OR''decision support system'') AND ((fashion OR garment∗ OR apparel∗ OR cloth∗ OR textile∗) industry∗)) AND (LIMIT-TO (LANGUAGE, ''ENGLISH'')))

2) SEARCH STRING FOR WEB OF SCIENCE

TS = (((''Machine learning″ OR ''deep learning'' OR ''data mining'' OR ''artificial intelligence'' OR ''data analytics'' OR ''expert system'' OR ''knowledge system'' OR ''intelligent system'' OR ''decision support system'') AND ((fashion OR garment∗ OR apparel∗ OR cloth∗ OR textile∗) industr∗)))

Refined By: **LANGUAGES:** (ENGLISH)

where,
TITLE-ABS-KEY/ TS = Title, Abstract, and Keywords
AND/ OR = Boolean operators to connect different keywords

∗ = used for loose/approximate phrase
'' = used for exact phrase

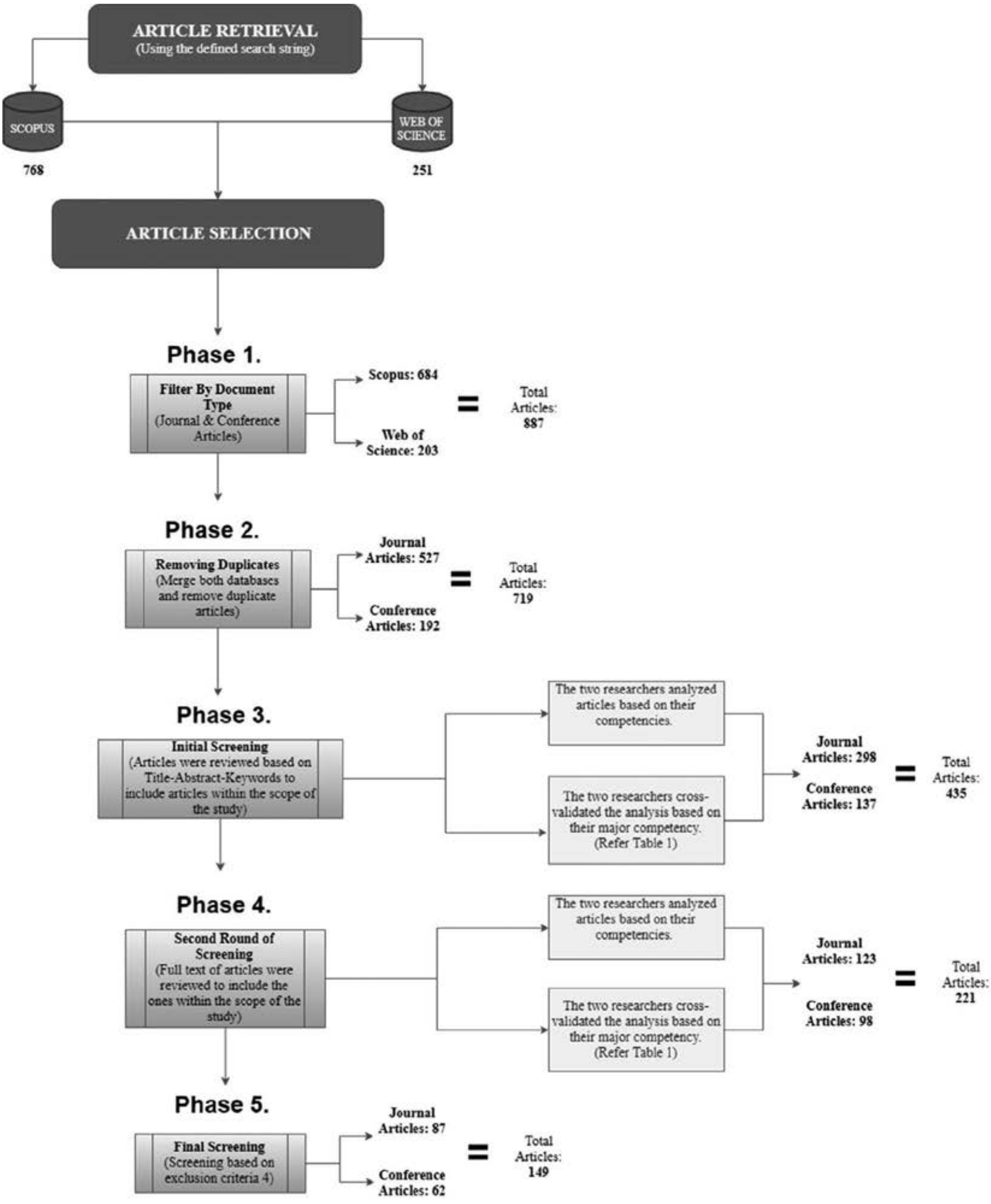

FIGURE 2. Article screening process.

TABLE 3. Extracted documents.

Scopus		Web of Science	
Document Type	Number of Articles	Document Type	Number of Articles
Conference Paper	319	Articles	138
Article	352	Conference Paper	65
Conference Review	44	Book and Book Chapter	48
Book and Book Chapter	32		
Review	13		
Article in Press	6		
Editorial	1		
Note	1		
Total	**768**		**251**

TABLE 4. Inclusion criteria.

Number	Criteria	Reason for Inclusion
1	No time Constraint	To understand the overall trend of AI in the F&A domain to answer RQ1
2	All Journal Articles and Conference Proceedings indexed in Scopus and Web of Science Databases	These databases index most of the journals and conference proceedings in the research field; To make sure that all articles relevant for addressing our three RQs are fetched
3	All countries and markets	To prevent biases while investigating the literature
4	All researches that applied AI techniques in F&A domain	To recognize all the stages in F&A supply chain where the implementation and execution of AI has been realized (to answer RQ2)
5	All researches conducted with a perspective of B2B, B2C or Both in F&A domain	To examine the extent with which business problems have been acknowledged using AI (to answer RQ3)

TABLE 5. Exclusion criteria.

Number	Criteria	Reason for Exclusion
1	Grey literature	To maintain the scientific reliability of the literature review
2	Non-English articles	To eliminate the misapprehension while scrutinizing the articles and avoid language barrier
3	Indutries that are not F&A industry	As the study concentrated on Fashion and Apparel industry
4	Research discussing theoretical and/or conceptual frameworks	To ensure the empirical validation of the AI models that can be applied in F&A industry

The execution of these search strings on Scopus and Web of Science yielded 768 and 251 articles (total articles 1019) respectively. The different document types are shown in Table 3. In Scopus, the research articles were found from a time-period of 33 years (1989-2018). Whereas on Web of Science, the time period was of 18 years (1991-2017). It should be noted that no time constraint was applied while searching for articles as the aim was to study all the work done in the research domain, fulfilling the goal of RQ1. The article selection process was carried out using certain inclusion and exclusion criteria enumerated in Table 4 and 5.

B. ARTICLE SELECTION

This section describes the rigorous screening process employed by the two researchers involved in order to select the articles relevant to address the research questions. The screening included five phases as shown in Figure 2. In the 'Phase 1', the articles were filtered by document type in accordance with inclusion criteria 2 and exclusion criteria 1, resulting into 684 articles in Scopus and 203 articles in Web of Science (total articles 887). In the 'Phase 2', the articles from both data sets were merged into one and redundant articles were eliminated, reducing the articles to 527 from journals and 192 from conference proceedings (total articles 719). In the 'Phase 3', initial screening was carried out by analyzing the "Title-Abstract-Keywords", conforming to inclusion criteria 3 & 4 and exclusion criteria 3. The initial screening was conducted in two sub-phases. First, the two researchers analyzed articles according to their competencies. Second, the two researchers cross-validated the analysis based on their major competencies (refer to Table 1). At this stage, the number of articles decreased to 298 from journals and 137 from conference proceedings (total articles 435).

Similarly, considering the same inclusion and exclusion criteria in the 'Phase 4', the two researchers first studied and analyzed the "Full text" of the articles, and then cross-validated the analysis based on their major competencies (refer Table 1). While accessing the full texts, a few conference articles were encountered having published only abstracts. Such abstracts were excluded from the study. At this point, the number of remaining articles were 123 from journals and 98 from conference proceedings (total articles 221).

Lastly, in the 'Phase 5', the articles were scanned based on the exclusion criteria 4. The rationale was to include studies where the conceptual AI model was implemented and empirically validated. The final count of the articles was 87 from journals and 62 from conference proceedings (total articles 149). In all the phases, the articles were excluded based on the consensus between the two researchers.

The final 149 articles were considered for the classification based on supply chain stages, applied artificial intelligence techniques, and business perspective: B2B and B2C. To accomplish this, different stages in F&A supply chain and classes in AI (explained in detail in section IV) were defined. Further, the F&A supply chain stages were categorized into Business-to-Business (B2B) and Business-to-Customer (B2C). This classification was important to get a clear outlook of the different AI classes applied at the F&A supply chain stages to address the research questions as this would help to identify opportunities with AI to accomplish business-related problems in F&A industry.

C. INFORMATION EXTRACTION

This section discusses the process followed for extracting information and classifying the selected articles based on supply chain stages, artificial intelligence classes, B2B and B2C to address our research questions RQ1, RQ2, and RQ3. The 149 articles were thoroughly examined to extract the following information:

1) *Applied AI class and algorithm*
2) *Supply chain stage under study*
3) *Business perspective: B2B and B2C*
4) *Research gaps Identified*

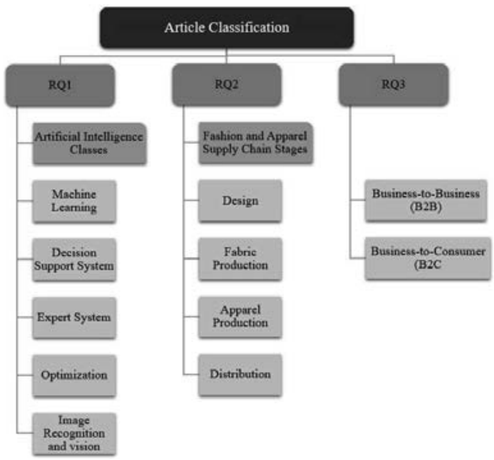

FIGURE 3. Article classification based on research questions.

The article classification conforming to the research questions is represented in Figure 3. As it can be seen, RQ1 is focused on understanding the overall trend of AI in the F&A industry. Hence, the focus of the screening process was limited to those articles discussing the implementation and execution of AI techniques in the F&A industry. To acknowledge RQ1, AI techniques were divided into five categories: Machine Learning, Decision Support System, Expert System, Optimization, and Image Recognition & Vision. The algorithms considered under each class are discussed in section IV.B. While extracting information, these classes were assigned to the articles.

RQ2 is aimed at identifying the various stages in the supply chain at which the AI method was employed. Hence, during the information extraction stage, the supply chain stage under study was recorded. To acknowledge RQ2, the supply chain stages were classified as Design, Fabric Production, Apparel Production, and Distribution. The processes considered under these stages are shown in Figure 4. While extracting information, the articles were assigned these supply chain stages.

RQ3 aims to understand the extent of business problems being a focus of research studies. To do this, the supply chain stages identified were further categorized from a business perspective into B2B and B2C (discussed in detail in section IV.A and Table 6). These classes were allocated to the research articles during information extraction.

This classification of research articles was verified with the help of an expert researcher actively involved in research related to artificial intelligence and F&A industry from the past two decades. The competency of the expert researcher is also mentioned in Table 1.

TABLE 6. B2B and B2C activities in the F&A industry.

B2B	B2C
Fashion Design	Fashion Design
Textile Design	Textile Design
Spinning	Dyeing & Printing
Weaving or Knitting	Cutting
Dyeing, Printing, Finishing & Inspection	Sewing & Assembly
Cutting	Finished Garment
Sewing & Assembly	Retailing
Finished Textile	E-commerce
Wholesaling	
Retailing	

IV. ADOPTED STRUCTURE FOR CLASSIFICATION OF ARTICLES

This section elucidates the structure of the fashion and apparel supply chain and attempts to cluster different supply chain stages into B2B and B2C. This is discussed in sub-section IV.A, which proposes a taxonomy to address RQ 2 and RQ 3 respectively. Similarly, AI techniques were assembled into five classes as explained in the sub-section IV.B to propose a taxonomy to address RQ 1.

A. PROPOSED TAXONOMY OF FASHION & APPAREL SUPPLY CHAIN STAGES

The fashion and apparel supply chain is a complex network of various actors designated worldwide. It deals with a diversity of raw materials: fiber, yarn, fabric, dyestuff, and other chemicals, and the related processes are broadly classified into four stages: design, fabric production, apparel production, and distribution as shown in figure 4. Traditionally, the supply chain follows a push system [21], where the brand owners or retailers (buyer) provide the manufacturers with information like the design or technical specification of the fabric and garment to be produced, the volume of the products, sizes in which the garment is to be produced. The fabric and garment producers follow the instructions to create samples, which upon approval by the buyer are converted into finished fabric and garment respectively. Usually, the finished fabrics are the raw material for the apparel production process. Finally, the finished garments are transported to a wholesaler or retailer. In the case of the wholesaler, there is another actor, which acts as a distributor between the consumer and the wholesaler. On the other hand, in the case of the retailer, the garments are sold through one or more channels, for instance, brick & mortar stores, web-shops (e-commerce), departmental stores, multi-brand retailers.

The designers employed by retailers are responsible for creating collections based on the current market and trend analysis. In most scenarios, retailers do not own any production house and play an important role to bring the products into the market. Hence, in the conventional supply chain, all the actors from design up to retailers/brand owners are

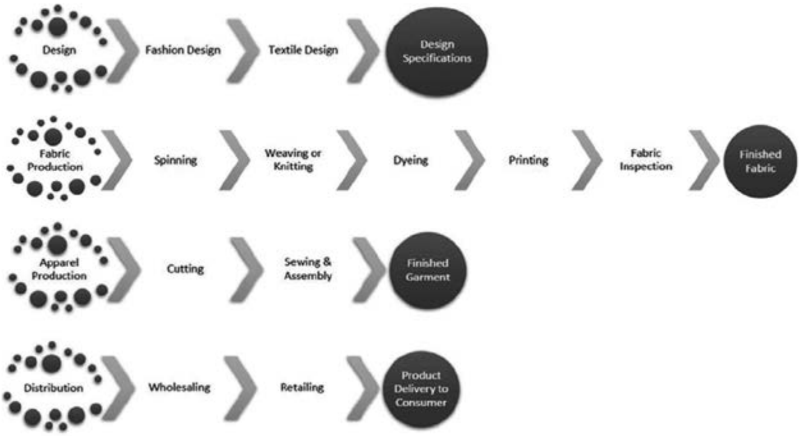

FIGURE 4. **Stages in F&A supply chain.**

considered as Business to business (B2B) as their primary customers are other businesses, while retailers are considered as business to consumer (B2C) as their primary customers are the end-users or consumers. However, in the past decade, with the advent of e-commerce, the definition of B2B and B2C has evolved [22]. Therefore, it has become important for the industry to adapt to this change and create new business strategies. It has also become vital to give a comprehensive demarcation between B2B and B2C, and how AI can help in combating problems at these segments.

1) B2B (BUSINESS-TO-BUSINESS)

The F&A industry has a convoluted supply chain due to diverse product categories and their short lifecycle. The contemporary consumer has increased awareness and information related to the latest styles and designs [23]. Therefore, consumer buying behavior and engagement has changed. This is highly influenced by the proliferation of social media and internet [24], which is a widespread medium for dissemination of information related to the latest fashion trends, upcoming fashion weeks and popular celebrities. Due to this, the F&A supply chain has to rapidly change the collections to fulfill the growing consumer demand [25]. Hence, it is driven by a combination of business-to-business (B2B) and business-to-consumer (B2C) transactions. In any business, the number of B2B transactions is higher in comparison to that of B2C transactions [26], [27]. The main reason for this is that for every product there can be as many B2B transactions as there are sub-components or raw materials involved, while there will be only one B2C transaction.

Business to business (B2B) in the F&A industry is referred to as the commerce between two or more businesses. A B2B transaction, thus, will occur when a business demands raw material for the production process to manufacture the product (e.g. garment manufacturer buying yarn), needs services for operational reasons (e.g. employing a third-party logistics service provider), re-sells goods and services produced by other businesses (e.g. a retailer buying products from manufacturer). The goal of a B2B transaction is to help their business stay profitable, competitive and successful. Table 2 shows the classification of the supply chain into B2B.

2) B2C (BUSINESS-TO-CONSUMER)

B2C refers to the transactions conducted directly between a business and consumers who are the end-users of its product and/or services [28]. Behind a B2C transaction is a well-researched consumer regarding their options in order to find the best price and quality tradeoff. Traditionally, B2C referred to outlet shopping, however, with the rise of internet, smartphones and other mobile technology, a set of completely new B2C business channels have developed in the form of e-commerce, m-commerce, social media commerce or selling products and services over the internet [29]. It has become important for B2C companies to be omnipresent because of uncertainty in consumer behavior over different retail channels [30]. The success of a B2C model depends on the capacity of a business to evolve based on new technologies that are widely used by the consumers. Businesses that rely on B2C sales must maintain good relations with consumers to ensure their retention and loyalty.

In addition to this, another set of B2C transactions have evolved with the adoption of mass customization (MC) to fulfill growing consumer needs. In this, consumer interactions with the business increases and can even occur at the product development stage. Hence, fashion or textile design, dyeing, printing, cutting, sewing & assembly can all have customer involvement. Table 2 shows the classification of the supply chain into B2B and B2C.

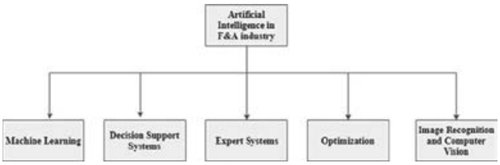

FIGURE 5. Classification of AI in the F&A industry.

B. PROPOSED TAXONOMY OF APPLIED AI METHODS IN F&A SUPPLY CHAIN

Artificial intelligence has already proved its capability to solve the real world problems due to its heuristic characteristics of generalizing data. In the last three decades, the F&A industry has undergone a number of changes and AI has played a key role in this transformation. Currently, the F&A industry is equipped with advanced machines required at the various stages of apparel production, which has improved the overall efficiency of the industrial processes [9]. Application of AI is well explained and categorized by operating processes at a managerial level in the F&A [8]. However, these researches lack the categorization of the applied AI in the F&A supply chain. The study in [8] explains the research issues in the operating process of the apparel industry. This study found that AI research has 45% contribution to apparel manufacturing issues, approximately 9% to apparel forecasting and 4.2% to fashion recommendation.

Research in [17] is a comprehensive review of classification and clustering techniques utilized in the F&A industry and shows that classification algorithms have been used more than clustering. On the contrary, this research work does not talk about linear and non-linear predictive models. Moreover, this research does not convey about the current applications of computer vision and deep learning [31], customer analytics [32], optimization techniques [33], and big data analytics for digital manufacturing and customization [15], [34]. Taking into account the recent research conducted in the area of AI in F&A, this study categorizes the AI into five broad classes as shown in Figure 5.

1) MACHINE LEARNING

Machine Learning is a technical process by which the computers are trained to perform the assigned task without human intervention and learns from the patterns of the data itself. Mathematical models are built on historical data to predict and find hidden patterns to make a future decision [35]. Machine Learning can be classified as Supervised or Unsupervised learning.

Supervised Learning- is a parametric model and it has input (independent variables) and target variable (dependent variable) [36]. Supervised model performance can be improved by optimizing the model parameters through iterative processes [37]. Based on the research problem, it could be a classification or regression task and this relies on dependent variable whether it is categorical or numerical.

Unsupervised Learning- models have only input attributes or independent variables with the main task of grouping similar data points. This grouping the similar pattern data points is called clustering and this process creates their own labels [35].

Machine learning has been implemented in the F&A industry for sales prediction [38], trend analysis, color prediction [39], demand forecasting [40], fabric defect detection [41], predicting fabric behavior using mechanical properties [42].

2) DECISION SUPPORT SYSTEMS

The decision support system (DSS) is used in an organization at the commercial level for taking mid-level or high-level managerial decisions. It can be automatized or regulated by a human or blend of both. Few authors considered the decision support systems as a software tool whereas others considered it as a system that can be integrated with the business to make intelligent decisions [43]. Research in [44] states that DSS combines the mathematical model with conventional data retrieval methods; it is flexible and adapts to the organizational environment as per defined strategy. In the F&A industry, it is widely used to industrialize innumerable tasks by optimizing decision making process in the supply chain [45] Decision support systems help the various actors in apparel manufacturing and production to choose appropriate process and resources to decrease the overall cost and enhance the performance of the apparel supply chain [46].

3) EXPERT SYSTEMS

In artificial intelligence, 'Expert system' is a system that makes a decision without human intervention [47]. It uses a reasoning approach to solve the complex problem, characterized by "if-then" rules. The first system was found around the 1970s and then gained popularity by 1980s [48]. They were considered the first popular software in the field of AI [36]. Expert systems are classified as Inference engine and knowledge base. 'Knowledge base' works on the principle of facts and rules, while 'inference engine' uses the rules to learn the facts and derive new facts [49]. In the F&A industry, it is applied in apparel manufacturing and production to select appropriate processes and equipment in order to generate minimal environmental pollution [50]. Furthermore, it has been applied for creating a recommendation engine in fashion retailing to improve the overall satisfaction of customers [51].

4) OPTIMIZATION

Artificial intelligence has the ability to solve complex problems and find numerous solutions by intelligent searching [36], [52]. Classical search algorithm starts with some random guess and this is improved using the iterative process. 'Hill climbing', 'Beam search' and 'Random optimization' are some of these methods [53]. Machine learning algorithms use 'search algorithms', which are based on optimization techniques. Simple exhaustive searches [52], [54] are too slow and therefore 'Heuristics' approach is adapted to serve as a technique to find a solution. The limitation of the heuristics search approach is that it fails to work with smaller datasets [55]. An evolutionary algorithm is another form of optimization search, which starts with the initial guesses of the population permitting them to mutate, recombine and select the best one while discarding others. Popular Evolutionary algorithms are genetic algorithms (GA), gene expression programming and genetic programming [56], [57]. Distributed search method could be done using 'swarm intelligent' algorithms. GA is extensively used in the F&A industry to overcome the problems of scheduling and design layout of the apparel production [58], [59]. GA has the ability to respond to quick changes in the fashion industry. This algorithm has been used to improve the fitting services as well [60].

5) IMAGE RECOGNITION AND VISION

In Artificial intelligence, Computer vision is a scientific area, which trains a machine to achieve high-level interpretation of the images or videos. These images or videos can come from many sources such as the medical field, global sensing position, cameras [61], [62]. The principal tasks of computer vision algorithms are extraction, pre-processing, exploring the high dimensional data and creating supervised or unsupervised models [63]. Models use the concept of geometry, statistics, physics, and machine learning theory to get insights into the image understanding [64]. Object recognition, video tracking, motion estimation are some of the sub-areas in the field of computer vision [65]. Machine vision is applied in F&A to automate many industrial applications like inspection and process control [66]. Image recognition and vision is also popular for content-based image retrieval systems, virtual try-on and augmented reality in the F&A industry [67]–[69].

V. ANALYSIS AND FINDINGS

According to our research framework, we selected 149 articles, which includes articles from both journals and conference proceedings. The articles were classified based on the taxonomy discussed in the previous section (refer section IV). This section discusses the result of our review addressing the three research questions in the form of distribution of articles. Section V.A and V.B correspond to RQ 1 by presenting the overall trend of AI in the F&A industry. Section V.C supports RQ 2 by showing articles that applied AI methods at various F&A supply chain stages. Section V.D correlates to RQ 3 by exhibiting articles by B2B and B2C. All the extracted information from the articles a) AI class, b) Methods, c) Supply chain stages and processes, d) B2B/B2C and the corresponding count of articles are consolidated in the form of Table 8 and 9 for journals and conferences respectively.

A. THE OVERALL DISTRIBUTION OF ARTICLES OVER TIME

The overall trend of the articles published in three decades (1989 to 2018) is shown in figure 6. As can be observed, maximum research in the field of AI in F&A has been carried out in the last decade (2009-2018), which accounts for approximately 56% of the total articles reviewed. While in the first two decades, it was 11% and 33% respectively. Hence, even though AI methods were introduced long back in the 1950s [36] but their capability was realized much later in the last decade.

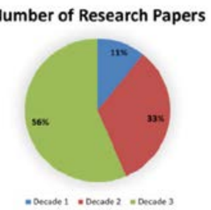

FIGURE 6. Decade-wise article representation of AI in F&A.

The detailed trend per year of articles published in journals and conference proceedings is depicted in Figure 7. As can be seen, the overall importance of this research domain has been equal in both journals and conferences. The only downward slope is visible for conference publications between the year 2013 and 2016 as highlighted in Figure 7. Apart from this, figure 8 shows the top 10 authors and institutions contributing to the literature of AI in the F&A industry.

B. DISTRIBUTION OF ARTICLES BY APPLIED AI OVER TIME

In this section, a comprehensive result of the review in terms of the number of articles classified based on the AI classes defined in section IV.B is shown in figure 9. The maximum number of articles are published in the field of machine learning with a total contribution of 42%, followed by expert systems with 28%, and the least contribution of the other three AI classes.

The distribution of articles in journals and conferences since 1989 has been shown in figure 10. The AI class 'Machine learning' has been applied multiple times in journal articles since 1991. There are two peaks visible for journal articles in the year 2007 and 2017 with 4 and 7 articles published respectively. Whereas for conference articles, it has been applied since the year 2000 with three major peaks in the year 2010, 2012 and 2016 with 4, 3, and 7 articles respectively. On the other hand, the AI class 'Expert system' was widely used since 1994 in journal articles while in conference articles there has been no research after 2014. For AI class 'decision support system', there has been very little work in conference articles, while a gradual increase in presence is realized in journal articles since 2010. For 'image recognition', its presence is visible since 2009 in both journal and conference articles, being the least applied AI class (also shown in figure 10). In addition, it can be noticed that since the year 2017, its application has increased in journal articles. In contrast to other classes, for optimization, there were more articles in the conference as compared to journals.

FIGURE 7. Overall trend of AI in F&A since 1989.

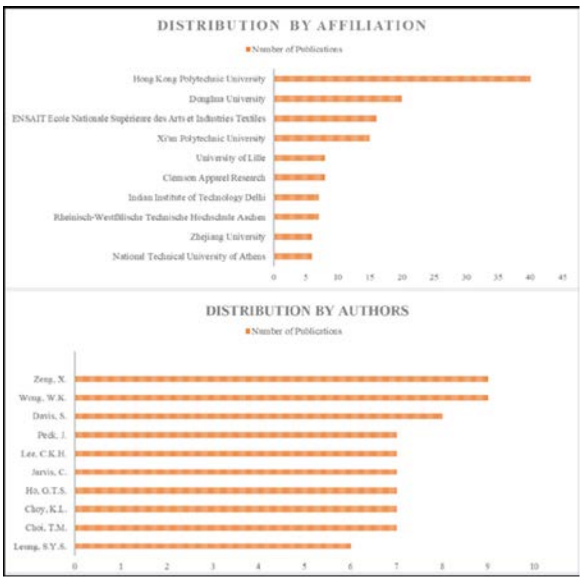

FIGURE 8. Top 10 affiliations and authors.

C. DISTRIBUTION OF ARTICLES BY APPLICATION OF AI IN F&A SUPPLY CHAIN

As shown in table 7, machine learning and expert systems have been applied widely at the four F&A supply chain stages, with least research in design. This is followed by optimization that has been applied with the least focus at the distribution stage.

The classification of articles by applied AI methods in F&A supply chain is shown in figure 11. In apparel production, all AI classes are applied in journal articles, while in conference articles image recognition and decision support system has been not used. In design, research has focused on three AI classes: optimization, machine learning, and expert systems for journal articles, whereas the expert system is not applied in conference articles. In distribution, majorly used AI classes are machine learning, decision support systems, and expert systems in journal articles, while the focus has been on machine learning and image recognition in conference articles. In fabric production, all AI classes have been widely used with a major focus on machine learning and Expert systems. Additionally, there has been growing use of image recognition in fabric inspection, which is a process under fabric production (described in section IV.A).

D. DISTRIBUTION OF ARTICLES BY B2B AND B2C OVER TIME

As discussed in the previous sections the importance of B2B and B2C in F&A, we classified the articles based on their business focus. As can be seen in figure 12, research is focused on solving the issues related to B2B and there is

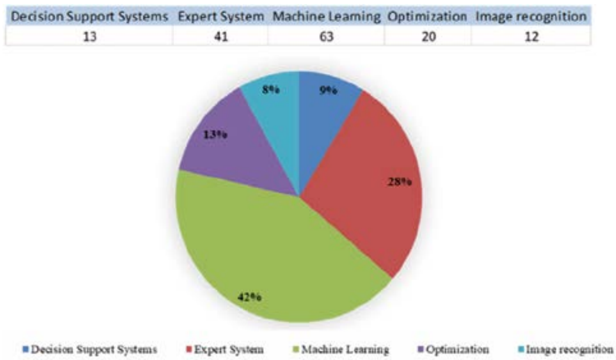

FIGURE 9. Total distribution of articles by AI methods applied.

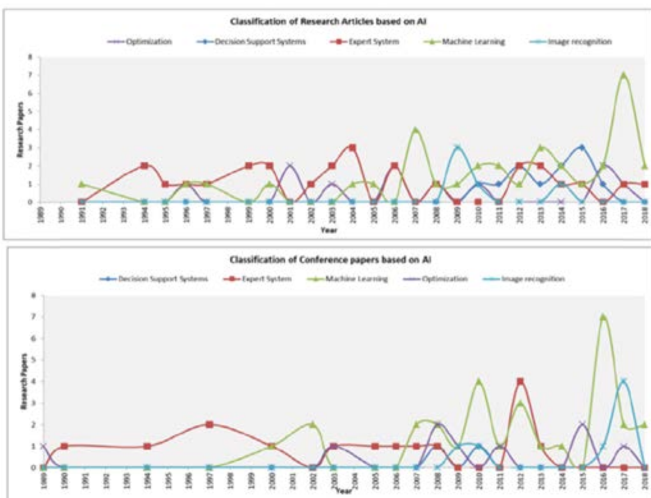

FIGURE 10. Distribution of articles by applied AI over time.

TABLE 7. Count of applied artificial articles in F&A supply chain.

	Decision support systems	Expert System	Machine Learning	Optimization	Image recognition	
Apparel Production	4	11	19	8	2	44
Design	0	4	2	3	0	9
Distribution	7	10	20	2	3	42
Fabric Production	2	16	22	7	7	54
	13	41	63	20	12	Total=149

little attention on B2C both in journal and conference articles. To get a clear picture, figure 13 shows the distribution of articles in three decades separately for B2B, B2C and both.

There were total 149 articles reviewed, out of which 122, 13 and 14 belonged to B2B, B2C and both (B2B/B2C) respectively. If we consider B2B, as shown in figure 13, substantial research has been carried out in all three decades as compared to B2C. In the case of B2C, the total number of articles published in itself is low i.e. 13. Out of this, only two were published in the second decade and rest were

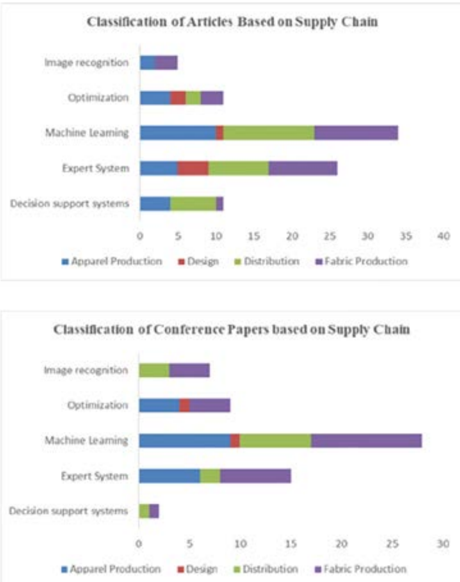

FIGURE 11. Distribution by supply chain processes.

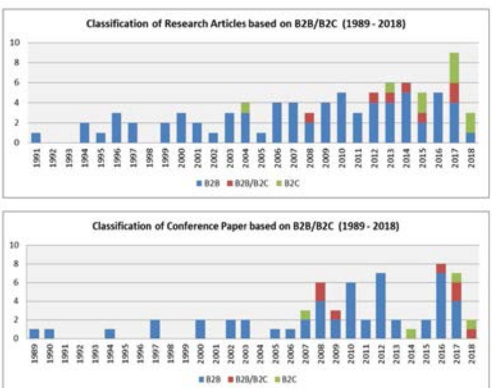

FIGURE 12. Distribution of articles by B2B and B2C.

published in decade 3. There were no articles published in decade 1. By both, it is meant that the focus of the study is both B2B and B2C. The total number of articles, in this case, is 14, out of which ten were published in the third decade and four in the second decade. There were no articles published in decade 1 for this as well. As a conclusion, we can say that little work has been done with the perspective of B2C and there is a need to attend to this gap.

VI. DISCUSSION AND IMPLICATIONS

Based on the review conducted following the proposed research framework and addressing the three research questions, this study recognized a number of gaps with respect to applied AI in the F&A industry. These gaps in research provide the foundation to recommend future research direction in the F&A and AI domain.

A. GAPS AND IMPLICATIONS

As discussed in section IV.A, most of the research related to AI in F&A industry has been carried out in the last decade (2009 to 2018), accounting to 56% of the total number of publications in the year 1989-2018. This shows that even though the AI methods existed since 1989, they have recently gained popularity in research related to F&A industrial problems. Although AI has left its footprint in research, it is still far from being implemented at the industrial level. One of the reasons for this is that researchers working in AI may lack expertise in F&A and at the same time, the professionals working in the industry may lack expertise in AI. In addition, industries are skeptical about the benefits of AI and big data analytics. Therefore, it is important that they look at the cost and benefit tradeoff to be able to exploit the full potential of AI.

In section V.B, we classified the articles based on their focus on B2B and B2C. The result demonstrates that most of the research work has been carried to target B2B business problems, accounting to 81% of the total number of publications. Whereas, little research has been conducted with a B2C perspective, accounting to approximately 8% of the total publications. This clearly illustrates that research needs to focus on B2C business problems. According to the State of Fashion (2019), two of the major industrial challenges faced will be rapidly changing consumer preferences and competition from online and omnichannel. Therefore, research related to the F&A industry needs to shift their focus to B2C, taking into account the importance of AI. AI can help to analyze consumer footprint omnichannel, which can help in creating personalized consumer database or profiles helping to improve business profitability and providing a competitive advantage.

In section V.C and V.D, we classified the articles based on applied AI method in the F&A supply chain. Most of the research articles fall under machine learning and expert systems class, which has been extensively applied at the supply chain stages: apparel production, fabric production, and distribution. Decision support systems, optimization and image recognition class have a more or less similar number of research articles published in this domain. Their application was seen to some extent at all three stages. However, least representation of these algorithms was observed at the design stage. It gives an impression that little focus has been given to design-related problems and hence, there is a huge scope of AI applications at this stage. For instance, AI methods can be used to create systems that can help fashion and product designers to capture consumer needs and preferences more

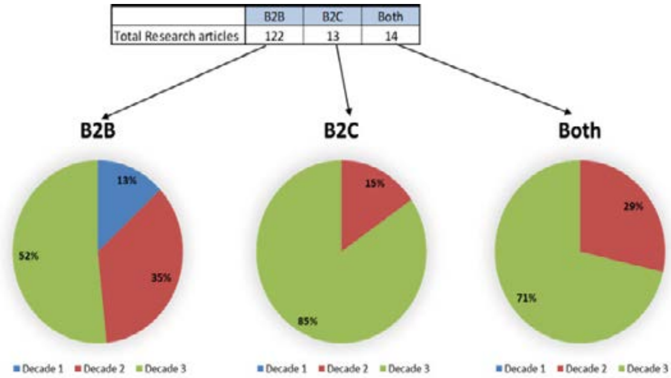

FIGURE 13. Decade-wise article representation of B2B, B2C and both.

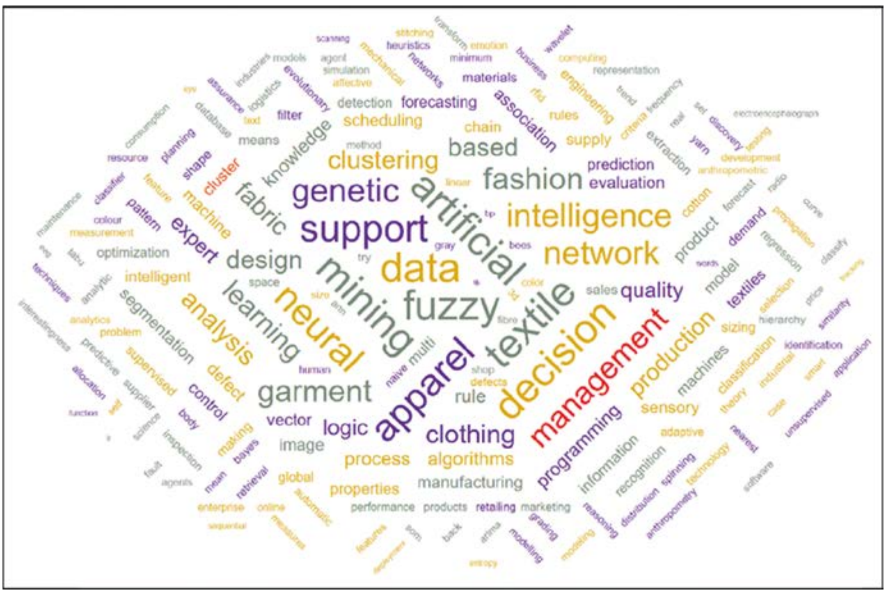

FIGURE 14. Word cloud using text mining on abstracts.

accurately and conveniently. Hence, the products offered can be more targeted to the market segments. In addition, predictive tools that use consumer's historical (past transactions) and social media (real-time demand) data can facilitate the product development/designing process. The AI methods applied in 149 articles can be seen in Table 8 and 9.

To get an outlook of the most popular AI methods used and their applications in F&A, we applied text mining on the abstracts of the selected 149 articles. Accordingly, a word cloud was created shown in figure 14. As a result, it was observed that genetic algorithm, artificial neural network, and fuzzy logic are the most popular methods applied for prediction (yarn, fabric properties, color), evaluation (quality inspection, defect detection), forecasting (trend analysis, supplier selection, demand forecasting).

B. FUTURE RESEARCH AREAS

Based on the analysis and gaps identified, we suggest some future directions of AI methods in the F&A supply chain. Machine learning techniques could be beneficial for fashion

TABLE 8. AI methods used at various supply chain stages and processes in journal articles.

AI Class	Method/ Technique used	Department Targeted	Process Targeted	B2B/B2C	Journal Articles Count	Reference
Machine Learning	BP-ANN 9 back propagation artificial neural network; k-means clustering; sequential clustering; fuzzy logic; A two-level clustering method (SOM network+ K-means); Naïve Bayes; Support vector machine; Gene expression programming (GEP); FCM (fuzzy clustering using MSE); Non parametric regression forecasting; supervised clustering; K-Medoids ;CN2-SD; ANN regression; RFM modeling; Association rule; ELM (extreme learning machine); GA; fuzzy constraint logic system, fuzzy rules, fuzzy sets; feed-forward neural network, back-propagation algorithm; decision tree, classification, and regression tree, factor analysis; Regression; Treelearner; root mean square; Fuzzy Efficiency based Classifier System; Logistic regression; Bucket Brigade Algorithm; neural networks using the error back propagation mode, e-neuro fuzzy engine; DIDT technique (Top-Down Induction of Decision Trees ID3; data mining; text mining; semantic data analysis;	Apparel Manufacturing 10, Design 1, Distribution 14, Fabric Production 11	Cutting 2; Dyeing/ Printing/ Finishing/ Inspection 1; Finished Garments 2; Retailing 12; Sewing 4; Spinning 9;	B2B/B2C 4, B2B 25, B2C 5	34	[70] [38] [71] [72] [73] [74] [75] [76] [39] [77] [78] [79] [80] [81] [82] [83] [84] [85] [86] [41] [87] [87] [88] [89] [90] [91] [92] [93] [42] [94] [95] [96]
Decision support system	Fuzzy logic; fuzzy association rule mining (FARM); classification, regression, clustering and association analysis; Linear optimization with constraints; Fuzzy inference; Fuzzy aggregation; adaptive-network-based fuzzy inference system (ANFIS); analytic hierarchy process (AHP); TOPSIS;	Apparel Manufacturing 4, Distribution 6, Fabric Production 1,	Finished Garments 4; Retailing 6; Spinning 1;	B2B 9, B2C 2	11	[97] [98] [99] [100] [101] [12] [102] [103] [104] [105] [106]
Expert System	Association rules; ES named ES-EXITUS has been implemented using the SSM and the DMM; Fuzzy association rule mining; Fuzzy logic; clustering and probabilistic neural network (PNN); hybrid OLAP-association rule mining; Ontology, semantic web, multiple agents; Genetic Algorithm; gradient descent optimization, fuzzy sets; Chi-square test, Correspondence analysis; parametric cubic spline and bi-cubic surface patch, object-oriented technology for building the knowledge base; Linear programming, computer-based heuristic; Semantic network, heuristic rules; Bézier curve models evolutionary model; Sensitivity analysis, Cognitive mapping technique, cluster analysis; Normalization model; Programming language used Microsoft Visual C++ version 4.0, Rule-based expert system; Object-oriented representation technique; t-test, sensory evaluation;	Apparel Manufacturing 5, Design 4, Distribution 8, Fabric Production 9,	Cutting 1; Dyeing, Printing, Finishing, Inspection 5; Fashion Design 2; Finished Garments 1; Retailing 5; Sewing 2; Textile Design 2; Weaving or knitting 1; Wholesaling 1;	B2B/B2C 3, B2B 21, B2C 2	26	[107] [108] [109] [110] [111] [112] [113] [114] [115] [116] [117] [50] [118] [119] [120] [121] [122] [123] [124] [125] [126] [127] [128]
Optimization	Constraint and non-constraint optimization; simulation-based model; fuzzy rule optimization; Tabu-Bees algorithm; linear approximation; Evolutionary algorithms; Genetic algorithm; Morse function, topological analysis; Content-based filtering, wavelet decomposition using Haar transform collaborative filtering, vector correlation using the Pearson correlation coefficient; symbolic regression module; Multiple regression analysis, extrapolative forecasting and an adaptive Holt-Winters forecasting;	Apparel Manufacturing 4, Design 2, Distribution 2, Fabric Production 3,	Cutting 2; Fashion Design 1; Finished Garments; Retailing 2; Sewing 1; Spinning 1; Weaving or knitting 1; Wholesaling 1;	B2B 11	11	[129] [130] [131] [132] [46] [133] [134] [94] [135] [136]
Vision	ANN and image processing; K-means clustering, Naïve Bayesian, and a multi-layered perceptron (MLP); NN and GA; Back propagation neural network (NN);	Apparel Manufacturing 2, Fabric Production 3,	Finished Garments 2; Sewing 1; Spinning 1; Textile Design; Weaving or knitting 1;	B2B 5	5	[11] [137] [138] [139] [140]

TABLE 9. AI methods used at various supply chain stages and processes in conference articles.

AI Class	Methods/ Techniques used	Department Targeted	Process Targeted	B2B/B2C	Conference paper count	Reference
Machine Learning	SOA-based data mining framework, classification, ARIMA and KNN models, text mining, naive Bayes classifier, SOM neural network, EM cluster and ELM (extreme learning machine) same prediction, SVM and AdaBoost, artificial neural network, case-based reasoning, supervised learning, self-organizing maps, principal component analysis, type-2 fuzzy sets, clustering, correlation analysis, optimal bandwidth selection in kernel density, ontology, RDF, Multilayer Perceptron, J48 decision tree, k-nearest neighbor, classifier ripper, C4.5 and PART, neuro-fuzzy with subtractive clustering and genetic algorithm (ANFIS-GA) technique, Java, C/C++, Viswanathan-Bagchi algorithm, correlation, wavelet transform, neural network.	Fabric Production 11, Distribution 7, Apparel Manufacturing 9, Design 1,	Weaving or knitting 3, Retailing 8, Spinning 5, Dyeing, printing and finishing 2, Finished Garments 3, Sewing 3, Cutting 2, Textile Design 1, Fashion Design 1	B2B/B2C 2, B2B 23, B2C 3	**28**	[141] [142] [143] [144] [145] [146] [147] [148] [149] [150] [151] [152] [153] [154] [155] [156] [157] [158] [159] [160] [161] [162] [163] [164] [165] [166] [167] [168]
Decision support system	Self-adaptive genetic algorithm, genetic algorithm, top-down and bottom-up analysis, dynamic optimization algorithms, Maximum Principle of Pontryaguin.	Distribution 1, Fabric Production 1	Finished Garments 1, Retailing 1	B2B 1, B2B/B2C 1	**2**	[169] [170]
Expert System	Rule-based, rough set theory, fuzzy, case-based reasoning, fuzzy logic, fuzzy logic sensory evaluation, Fuzzy neural network, Unsupervised learning, fuzzy clustering, genetic algorithm, approximate reasoning module, Rule-based System Shell , Metric-based Fuzzy Logic and artificial neural network, If-Then Rules for knowledge base, least-square regression analysis, linear regression, event series	Distribution 2, Fabric Production 7, Apparel manufacturing 6	Retailing 2, Spinning 3, Dyeing, Printing, Finishing and Inspection 2, Finished garment 1, Yarn to Fabric 1, Cutting 1	B2B 14, B2B/B2C 1	**15**	[171] [172] [173] [174] [10] [175] [176] [177] [178] [179] [180] [181] [182] [183] [184]
Optimization	Stochastic descent, list algorithm, Evolutionary computing and genetic algorithm, Fuzzy set, geometric analysis method, Mirabit algorithm, apriori algorithm, Heuristic methods,	Fabric Production 4, Apparel manufacturing 4, Design 1	Spinning 3, Finished garments 1, Dyeing, printing and finishing 1, Cutting 3	B2B 8, B2B/B2C 1	**9**	[185] [59] [186] [187] [188] [189] [190] [191] [192]
Vision	Conditional Random Fields (CRF), Bayesian classification, CNN based classifier, computer vision, classification, consensus style centralizing auto-encoder (CSCAE), Gabor filter, Gaussian kernel, image processing using IMAQ, median filter, stereovision method	Fabric Production 4, Distribution 3	Weaving or knitting 1, Spinning 3, Retailing 3	B2B 5, B2C 1, B2B/B2C 1	**7**	[193] [194] [195] [196] [197] [198] [199]

and product designers. They can take its advantage in predictive analysis of future trends based on historical and real-time data. This can also prove promising in improving the existing recommendation engines, which currently rely on collaborative or content-based filtering. These engines can be improved by integrating with consumer data from social media and real-time trends from fashion blogs, magazines and other social networks like Pinterest, Instagram. Additionally, the performance of existing predictive models can be enhanced with the help of advanced techniques like ensemble learning and transfer learning. An instance is the use of random forest instead of decision trees, the use of which has outperformed the classical model in terms of computational time [201], [202].

Another application area in F&A is mass customization, where machine learning can be used to reduce the lead times by creating a classifier that could be trained on the existing style database, enabling the product designers to prepare the raw material inventory in advance. Pre-trained deep learning models using a library like Keras [203], inception model [204] along with big data analytics can be used to create co-design platforms with style recommendations helping consumers in co-designing garments.

One of the important application of image recognition and computer vision is to target the key consumer pain point of not having an appropriate size of the garment. This problem has been addressed with the help of virtual fitting tools. However, these tools are still at a nascent stage and can be highly improved with the help of these techniques.

As we have noticed that fuzzy techniques and genetic algorithms are exhaustively used for expert systems, decision support systems and optimization. These techniques can be combined with advanced AI techniques to enhance the computational ability of a machine learning algorithm. Similarly, if the classical forecasting model is combined with AI it can lead to better forecasting in terms of seasonality and trends.

It is evident from the review that the F&A industry still lacks an integrated platform for data sharing and communication amongst its stakeholders and consumers. An integrated platform has become a necessity to quickly respond to customer's growing needs and preferences and improving consumer satisfaction and loyalty. AI has a lot of potentials to create and maintain such a platform. This platform can help the industry to provide interactive communication, improved supply chain organization, hence, leading to a digitally connected supply chain. Another possibility is by merging AI techniques with blockchain technology, which can ensure security and transparency between consumers and various supply chain actors. The industry can be benefitted by integrating their business with cloud-based technologies like Microsoft Azure, Amazon web services, IBM Watson, etc., and parallel computing tools for big data analytics like Hadoop and Hive. If the fashion industry can successfully adopt the aforementioned AI techniques, it will be easier to integrate B2B and B2C leading to a sustainable business orientation of B2B2C. This will be fully achievable only when the F&A industry equip 'FAIR' data principle [205] in strategizing their business.

VII. CONCLUSION

The aim of the study was to conduct a systematic literature review to address the three defined research questions (RQ1, RQ2, and RQ3). In line with the research framework, we retrieved 1019 articles published between 1989 and 2018, from two popular academic databases: Scopus and Web of Science. The article screening process was carried out in five phases (shown in figure 2), which resulted in 149 articles. To extract information from these articles and address our research questions, a taxonomy was proposed considering AI methods and F&A supply chain stages acknowledging RQ1 and RQ2 respectively. To acknowledge RQ3, F&A supply chain was further classified into B2B and B2C.

The research analysis says that most of the work in the field of F&A was carried out in the last decade (2009-2018) with the most applied AI categories being ''Machine Learning'' and ''Expert Systems''. It was observed that the techniques most used in Machine Learning were predictive algorithms like regression and SVM, and whereas in the case of Expert Systems were ''Artificial Neural Network'', ''Genetic Algorithm'' and ''Fuzzy Logic'' for modeling F&A supply chain problems. Certainly, no application of algorithms like ''deep learning'' and ''transfer learning'' was realized. Further, very few research articles talked about ''Big Data'' in the field of F&A, which clearly states that the industry has not fully realized the potential of data analytics and AI.

This research found that F&A supply chain stages: ''Apparel Production'', ''Fabric Production'' and ''Distribution'' received maximum attention when applying AI techniques, whereas ''Design'' was the least focused. Additionally, a significant contribution was noted towards B2B problems compared to B2C. Hence, research needs to adopt a B2C perspective to be able to offer consumer-oriented solutions to the industry.

A comprehensive review reveals the research gap and implication presented in section VI stating that F&A needs a transformation in their supply chain by using AI techniques at the industrial level. With this, the industry can move towards a digital and sustainable supply chain. The implications and future directions proposed in this study can be beneficial for academic and industrial researchers, and industrial practitioners, who are willing to provide a substantial contribution to the subject area.

Regardless of this valuable work, there are some limitations to this study. First, the articles were searched in two databases, while there could be other databases that are relevant. Second, the publications apart from English were excluded. There could be valuable research available in other languages. Third, even though the review process was completed rigorously, it could still be prone to human error. Fourth, this study was restricted to researches with an empirical validation of the proposed AI models. There could be beneficial theoretical and conceptual frameworks in research, which were missed because of the exclusion criterion. Fifth, even though the synonyms considered for article retrieval were carefully decided, the study could have missed some articles due to different terminology being used. Seventh, grey literature was excluded from the review process, which also includes industrial reports. These reports can provide helpful insights and contribution in this domain.

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REFERENCES

[1] Lenzing, Statista. *Demand Share of Apparel Market Worldwide From 2005 to 2020, by Region*. Accessed: May 10, 2019. [Online]. Available: https://www.statista.com/statistics/821457/demand-share-of-global-apparel-market-by-region/

[2] Statista. *Worldwide Forecasted Sales Growth in the Fashion Industry in 2019, by Region*. Accessed: May 10, 2019. [Online]. Available: https://www.statista.com/statistics/802943/fashion-industry-sales-growth-worldwide-by-region/

[3] G. Sweeny, "It's the second dirtiest thing in the world—And you're wearing it," *AlterNet*, Aug. 2015.

[4] X. Shang, X. Liu, G. Xiong, C. Cheng, Y. Ma, and T. R. Nyberg, "Social manufacturing cloud service platform for the mass customization in apparel industry," in *Proc. IEEE Int. Conf. Service Oper. Logistics, Informat.*, Jul. 2013, pp. 220–224.

[5] J. H. Thrall, X. Li, Q. Li, C. Cruz, S. Do, K. Dreyer, and J. Brink, "Artificial intelligence and machine learning in radiology: Opportunities, challenges, pitfalls, and criteria for success," *J. Amer. College Radiol.*, vol. 15, no. 3, pp. 504–508, 2018.

[6] G. Xiong, F. Zhu, X. Liu, X. Dong, W. Huang, S. Chen, and K. Zhao, "Cyber-physical-social system in intelligent transportation," *IEEE/CAA J. Autom. Sinica*, vol. 2, no. 3, pp. 320–333, Jul. 2015.

[7] X. Xu and Q. Hua, "Industrial big data analysis in smart factory: Current status and research strategies," *IEEE Access*, vol. 5, pp. 17543–17551, 2017.

[8] Z. X. Guo, W. K. Wong, S. Y. S. Leung, and M. Li, "Applications of artificial intelligence in the apparel industry: A review," *Text. Res. J.*, vol. 81, no. 18, pp. 1871–1892, 2011.

[9] R. Nayak and R. Padhye, "Artificial intelligence and its application in the apparel industry," in *Automation in Garment Manufacturing*. Amsterdam, The Netherlands: Elsevier, 2018, pp. 109–138.

[10] C. K. H. Lee, K. L. Choy, K. M. Y. Law, and G. T. S. Ho, "An intelligent system for production resources planning in Hong Kong garment industry," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage.*, Dec. 2012, pp. 889–893.

[11] G. M. Nasira and P. Banumathi, "An intelligent system for automatic fabric inspection," *Asian J. Inf. Technol.*, vol. 13, no. 6, pp. 308–312, 2014.

[12] M.-K. Chen, Y.-H. Wang, and T.-Y. Hung, "Establishing an order allocation decision support system via learning curve model for apparel logistics," *J. Ind. Prod. Eng.*, vol. 31, no. 5, pp. 274–285, 2014.

[13] C. Giri, N. Harale, S. Thomassey, and X. Zeng, "Analysis of consumer emotions about fashion brands: An exploratory study," in *Proc. Data Sci. Knowl. Eng. Sens. Decis. Support*, 2018, pp. 1567–1574.

[14] A. Acharya, S. K. Singh, V. Pereira, and P. Singh, "Big data, knowledge co-creation and decision making in fashion industry," *Int. J. Inf. Manage.*, vol. 42, pp. 90–101, Oct. 2018.

[15] S. Jain, J. Bruniaux, X. Zeng, and P. Bruniaux, "Big data in fashion industry," *IOP Conf., Mater. Sci. Eng.*, vol. 254, no. 15, Oct. 2017, Art. no. 152005.

[16] E. W. T. Ngai, S. Peng, P. Alexander, and K. K. L. Moon, "Decision support and intelligent systems in the textile and apparel supply chain: An academic review of research articles," *Expert Syst. Appl.*, vol. 41, no. 1, pp. 81–91, 2014.

[17] P. Yildirim, D. Birant, and T. Alpyildiz, "Data mining and machine learning in textile industry," *Wiley Interdiscip. Rev. Data Mining Knowl. Discovery*, vol. 8, no. 1, p. e1228, Jan. 2018.

[18] A. Booth, A. Sutton, and D. Papaioannou, *Systematic Approaches to a Successful Literature Review*. Newbury Park, CA, USA: Sage, 2016.

[19] S. A. AlRyalat, L. W. Malkawi, and S. M. Momani, "Comparing bibliometric analysis using pubmed, scopus, and Web of science databases," *J. Vis. Express*, to be published.

[20] A. Martín-Martín, E. Orduna-Malea, M. Thelwall, and E. D. López-Cózar, "Google scholar, Web of science, and scopus: A systematic comparison of citations in 252 subject categories," *J. Informetrics*, vol. 12, no. 4, pp. 1160–1177, Nov. 2018.

[21] B. Mihm, "Fast fashion in a flat world: Global sourcing strategies," *IBER*, vol. 9, no. 6, Jun. 2010.

[22] P. Sen, *B2B Marketing Evolution: Customers Demand B2C Experiences*. Accessed: May 10, 2019. [Online]. Available: https://www.the-future-of-commerce.com/2019/03/14/b2b-marketing-evolution/

[23] J. M. Kozar and K. Y. H. Connell, "Barriers to socially responsible apparel purchasing behavior: Are consumers right?" in *Marketing Orientations in a Dynamic Business World*. Cham, Switzerland: Springer, 2017, pp. 79–85.

[24] J. Manyika, M. Chui, B. Brown, J. Bughin, and R. Dobbs, *Big Data: The Next Frontier for Innovation, Competition, and Productivity*. McKinsey Global Institute, 2011.

[25] V. Bhardwaj and A. Fairhurst, "Fast fashion: Response to changes in the fashion industry," *Int. Rev. Retail, Distrib. Consum. Res.*, vol. 20, no. 1, pp. 165–173, Feb. 2010.

[26] R. L. Sandhusen, *Marketing*. Hauppauge, NY, USA: B.E.S. Publishing, 2008.

[27] G. B. Shelly and H. J. Rosenblatt, *Systems Analysis and Design*. Borton, MA, USA: Course Technology, 2011.

[28] M. Singh, "E-services and their role in B2C e-commerce," *Manag. Service Qual. Int. J.*, vol. 12, no. 6, pp. 434–446, Dec. 2002.

[29] L. J. Anderson-Connell, P. V. Ulrich, and E. L. Brannon, "A consumer-driven model for mass customization in the apparel market," *J. Fashion Marketing Manag. Int. J.*, vol. 6, no. 3, pp. 240–258, Sep. 2002.

[30] E. Brynjolfsson, Y. J. Hu, and M. S. Rahman, *Competing in the Age of Omnichannel Retailing*, vol. 54, no. 4. Cambridge, MA, USA: MIT, 2013.

[31] L. B. Hales, M. L. Hales, and D. T. Collins, "Improving real-time expert control systems through deep data mining of plant data and global plant-wide energy monitoring and analysis," in *Proc. SME Annu. Meeting Exhib., SME, Meeting Preprints*, 2012, pp. 414–417.

[32] C. Murray, "Retailers' disconnect with shoppers is costing them," A Forrester Consulting Thought Leadership Paper Commissioned By Cognizant, Tech. Rep., 2017. [Online]. Available: https://www.cognizant.com/whitepapers/retailers-disconnect-with-shoppers-is-costing-them-codex2693.pdf

[33] Z.-H. Hu and X.-K. Yu, "Optimization of fast-fashion apparel transshipment among retailers," *Text. Res. J.*, vol. 84, no. 20, pp. 2127–2139, 2014.

[34] M. Y. Wong, Y. Zhou, and H. Xu, "Big data in fashion industry: Color cycle mining from runway data," in *Proc. AMCIS, Surfing IT Innov. Wave-22nd Amer. Conf. Inf. Syst.*, 2016, pp. 1–10.

[35] C. Bishop, *Pattern Recognition and Machine Learning*. Springer, 2006.

[36] R. Stuart and P. Norvig, *Artificial Intelligence: A Modern Approach*. Upper Saddle River, NJ, USA: Prentice-Hall, 2009.

[37] M. Mohri, A. Rostamizadeh, and A. Talwalkar, *Foundations of Machine Learning*. Cambridge, MA, USA: MIT Press, 2012.

[38] S. V. Kumar and S. Poonkuzhali, "Improvising the sales of garments by forecasting market trends using data mining techniques," *Int. J. Pure Appl. Math.*, vol. 119, no. 7, pp. 797–805, 2018.

[39] S.-W. Hsiao, C.-H. Lee, R.-Q. Chen, and C.-H. Yen, "An intelligent system for fashion colour prediction based on fuzzy C-means and gray theory," *Color Res. Appl.*, vol. 42, no. 2, pp. 273–285, Apr. 2017.

[40] Brahmadeep and S. Thomassey, "Intelligent demand forecasting systems for fast fashion," in *Information Systems for the Fashion and Apparel Industry*. Woodhead Publishing, 2016, pp. 145–161. [Online]. Available: https://www.researchgate.net/publication/301345185_Intelligent_demand_forecasting_systems_for_fast_fashion

[41] A. Ghosh, T. Guha, R. B. Bhar, and S. Das, "Pattern classification of fabric defects using support vector machines," *Int. J. Clothing Sci. Technol.*, vol. 23, nos. 2–3, pp. 142–151, 2011.

[42] D. Z. Pavlinić and J. Geršak, "Design of the system for prediction of fabric behaviour in garment manufacturing processes," *Int. J. Cloth. Sci. Technol.*, vol. 16, nos. 1–2, pp. 252–261, 2004.

[43] P. G. Keen, "Decision support systems: A research perspective," in *Decision Support Systems: Issues and Challenges: Proceedings of an International Task Force Meeting*, 1980, pp. 23–44.

[44] R. H. Sprague, Jr., "A framework for the development of decision support systems," *MIS Quart.*, vol. 4, no. 4, pp. 1–26, 1980.

[45] Y. Tu and E. H. H. Yeung, "Integrated maintenance management system in a textile company," *Int. J. Adv. Manuf. Technol.*, vol. 13, no. 6, pp. 453–462, 1997.

[46] W. K. Wong and S. Y. S. Leung, "Genetic optimization of fabric utilization in apparel manufacturing," *Int. J. Prod. Econ.*, vol. 114, no. 1, pp. 376–387, 2008.

[47] P. Jackson, *Introduction to Expert Systems*, vol. 2. Reading, MA, USA: Addison-Wesley, 1990.

[48] C. T. Leondes, *Expert Systems: The Technology of Knowledge Management and Decision Making for the 21st Century*. New York, NY, USA: Academic, 2002.

[49] N. N. Stella and A. O. Chuks, "Expert system: A catalyst in educational development in Nigeria," 2011. [Online]. Available: http://hrmars.com/admin/pics/261.pdf

[50] K. Metaxiotis, "RECOT: An expert system for the reduction of environmental cost in the textile industry," *Inf. Manage. Comput. Secur.*, vol. 12, no. 3, pp. 218–227, 2004.

[51] W. K. Wong, X. H. Zeng, and W. M. R. Au, "A decision support tool for apparel coordination through integrating the knowledge-based attribute evaluation expert system and the T-S fuzzy neural network," *Expert Syst. Appl.*, vol. 36, no. 2, pp. 2377–2390, 2009.

[52] G. F. Luger and W. A. Stubblefield, *Artificial Intelligence: Structures and Strategies for Complex Problem Solving*. San Francisco, CA, USA: Benjamin Cummings, 1993.

[53] D. Poole, A. Mackworth, and R. Goebel, *Computational Intelligence: A Logical Approach*. New York, NY, USA: Oxford Univ. Press, 1998.

[54] N. J. Nilsson, *Artificial Intelligence: A New Synthesis*. San Mateo, CA, USA: Morgan Kaufmann, 1998.

[55] G. Tecuci, "Artificial intelligence," *Wiley Interdiscip. Rev. Comput. Statist.*, vol. 4, no. 2, pp. 168–180, Mar./Apr. 2012.

[56] J. H. Holland, *Adaptation in Natural and Artificial Systems: An Introductory Analysis With Applications to Biology, Control, and Artificial Intelligence*. Cambridge, MA, USA: MIT Press, 1992.

[57] J. H. Holland, *Genetic Programming Complex Adaptive Systems Genetic Programming On the Programming of Computers by Means of Natural Selection*. Cambridge, MA, USA: MIT Press, 1992.

[58] R. Guruprasad and B. K. Behera, "Genetic algorithms and its application to textiles," *Textile Asia*, vol. 40, nos. 4–5, pp. 35–38, 2009.

[59] Z.-J. Lu, Q. Xiang, Y.-M. Wu, and J. Gu, "Application of support vector machine and genetic algorithm optimization for quality prediction within complex industrial process," in *Proc. IEEE Int. Conf. Ind. Inform. (INDIN)*, Jul. 2015, pp. 98–103.

[60] P. C. L. Hui, K. C. C. Chan, K. W. Yeung, and F. S. F. Ng, "Application of artificial neural networks to the prediction of sewing performance of fabrics," *Int. J. Cloth. Sci. Technol.*, vol. 19, no. 5, pp. 291–318, Oct. 2007.

[61] D. H. Ballard and C. M. Brown, *Computer Vision*. Upper Saddle River, NJ, USA: Prentice-Hall, 1982.

[62] M. Sonka, V. Hlavac, and R. Boyle, *Image Processing: Analysis and Machine Vision*. Boston, MA, USA: Thompson Learning, 2008.

[63] B. Jahne, *Computer Vision and Applications: A Guide for Students and Practitioners*. Amsterdam, The Netherlands: Elsevier, 2000.

[64] D. Forsyth and J. Ponce, *Computer Vision: A Modern Approach*. Upper Saddle River, NJ, USA: Prentice-Hall, 2003.

[65] T. Morris, Computer Vision and Image Processing—Tim Morris–Macmillan International Higher Education. Palgrave Macmillan. Accessed: May 10, 2019. [Online]. Available: https://www.macmillanihe.com/page/detail/computer-vision-and-image-processing-tim-morris/?sf1=barcode&st1=9780333994511

[66] C. Steger, M. Ulrich, and C. Wiedemann, *Machine Vision Algorithms and Applications*. Hoboken, NJ, USA: Wiley, 2018.

[67] C.-F. J. Kuo, C.-L. Lee, and C.-Y. Shih, "Image database of printed fabric with repeating dot patterns part (I)—Image archiving," *Text. Res. J.*, vol. 87, no. 17, pp. 2089–2105, Oct. 2017.

[68] M. Yuan, I. R. Khan, F. Farbiz, S. Yao, A. Niswar, and M.-H. Foo, "A mixed reality virtual clothes try-on system," *IEEE Trans. Multimedia*, vol. 15, no. 8, pp. 1958–1968, Dec. 2013.

[69] G. A. Cushen and M. S. Nixon, "Markerless real-time garment retexturing from monocular 3D reconstruction," in *Proc. IEEE Int. Conf. Signal Image Process. Appl. (ICSIPA)*, Nov. 2011, pp. 88–93.

[70] Y. Zhao, J. Song, A. Montazeri, M. M. Gupta, Y. Lin, C. Wang, and W. J. Zhang, "Mining affective words to capture customer's affective response to apparel products," *Text. Res. J.*, vol. 88, no. 12, pp. 1426–1436, Jun. 2018.

[71] K. Liu, J. Wang, E. Kamalha, V. Li, and X. Zeng, "Construction of a prediction model for body dimensions used in garment pattern making based on anthropometric data learning," *J. Textile Inst.*, vol. 108, no. 12, pp. 2107–2114, Apr. 2017.

[72] A. F. Tehrani and D. Ahrens, "Modified sequential k-means clustering by utilizing response: A case study for fashion products," *Expert Syst.*, vol. 34, no. 6, Dec. 2017, Art. no. e12226.

[73] B.-R. Li, Y. Wang, and K.-S. Wang, "A novel method for the evaluation of fashion product design based on data mining," *Adv. Manuf.*, vol. 5, no. 4, pp. 370–376, Dec. 2017.

[74] M. Hamad, S. Thomassey, and P. Bruniaux, "A new sizing system based on 3D shape descriptor for morphology clustering," *Comput. Ind. Eng.*, vol. 113, pp. 683–692, Nov. 2017.

[75] K. Liu, X. Zeng, P. Bruniaux, J. Wang, E. Kamalha, and X. Tao, "Fit evaluation of virtual garment try-on by learning from digital pressure data," *Knowl.-Based Syst.*, vol. 133, pp. 174–182, Oct. 2017.

[76] A. Fallahpour, K. Y. Wong, E. U. Olugu, and S. N. Musa, "A predictive integrated genetic-based model for supplier evaluation and selection," *Int. J. Fuzzy Syst.*, vol. 19, no. 4, pp. 1041–1057, Aug. 2017.

[77] K. J. Ferreira, B. H. A. Lee, and D. Simchi-Levi, "Analytics for an online retailer: Demand forecasting and price optimization," *Manuf. Service Oper. Manage.*, vol. 18, no. 1, pp. 69–88, 2016.

[78] A. F. Tehrani and D. Ahrens, "Supervised regression clustering: A case study for fashion products," *Int. J. Bus. Anal.*, vol. 3, no. 4, pp. 21–40, 2016.

[79] P. Q. Brito, C. Soares, S. Almeida, A. Monte, and M. Byvoet, "Customer segmentation in a large database of an online customized fashion business," *Robot. Comput. Integr. Manuf.*, vol. 36, pp. 93–100, Dec. 2015.

[80] V. Mozafary and P. Payvandy, "Application of data mining technique in predicting worsted spun yarn quality," *J. Text. Inst.*, vol. 105, no. 1, pp. 100–108, 2014.

[81] C.-C. Chen, "RFID-based intelligent shopping environment: A comprehensive evaluation framework with neural computing approach," *Neural Comput. Appl.*, vol. 25, nos. 7–8, pp. 1685–1697, 2014.

[82] S. M. Darwish, "Soft computing applied to the build of textile defects inspection system," *IET Comput. Vis.*, vol. 7, no. 5, pp. 373–381, Oct. 2013.

[83] C.-Y. Tsai and C.-H. Hsu, "Developing standard elderly aged female size charts based on anthropometric data to improve manufacturing using artificial neural network-based data mining," *Theor. Issues Ergon. Sci.*, vol. 14, no. 3, pp. 258–272, 2013.

[84] J.-F. Liang, J.-M. Liang, and J.-P. Wang, "Empirical study on B/C apparel consumption behavior based on data mining technology," *J. Donghua Univ. (English Ed.)*, vol. 30, no. 6, pp. 530–536, 2013.

[85] H. L. Viktor, I. Peña, and E. Paquet, "Who are our clients: Consumer segmentation through explorative data mining," *Int. J. Data Mining, Model. Manage.*, vol. 4, no. 3, pp. 286–308, 2012.

[86] Y. Yu, T.-M. Choi, and C.-L. Hui, "An intelligent fast sales forecasting model for fashion products," *Expert Syst. Appl.*, vol. 38, no. 6, pp. 7373–7379, 2011.

[87] B. Karthikeyan and L. M. Sztandera, "Analysis of tactile perceptions of textile materials using artificial intelligence techniques: Part 1: Forward engineering," *Int. J. Clothing Sci. Technol.*, vol. 22, nos. 2–3, pp. 187–201, 2010.

[88] C.-H. Hsu, "Data mining to improve industrial standards and enhance production and marketing: An empirical study in apparel industry," *Expert Syst. Appl.*, vol. 36, no. 3, pp. 4185–4191, 2009.

[89] C. Altinoz, "Supplier selection for industry: A fuzzy rule-based scoring approach with a focus on usability," *Int. J. Integr. Supply Manage.*, vol. 4, nos. 3–4, pp. 303–321, 2008.

[90] A. E. Amin, A. S. El-Geheni, I. A. El-Hawary, and R. A. El-Beali, "Detecting the fault from spectrograms by using genetic algorithm techniques," *Autex Res. J.*, vol. 7, no. 2, pp. 80–88, 2007.

[91] P. N. Koustoumpardis, J. S. Fourkiotis, and N. A. Aspragathos, "Intelligent evaluation of fabrics' extensibility from robotized tensile test," *Int. J. Clothing Sci. Technol.*, vol. 19, no. 2, pp. 80–98, 2007.

[92] C.-H. Hsu and M.-J. J. Wang, "Using innovative technology to establish sizing systems," *Int. J. Innov. Learn.*, vol. 2, no. 3, pp. 233–245, 2005.

[93] I. Soufflet, M. Calonnier, and C. Dacremont, "A comparison between industrial experts' and novices' haptic perceptual organization: A tool to identify descriptors of the handle of fabrics," *Food Qual. Preference*, vol. 15, nos. 7–8, pp. 689–699, 2004.

[94] K.-Y. Jung, Y.-J. Na, and J.-H. Lee, "Creating user-adapted design recommender system through collaborative filtering and content based filtering," in *Proc. Portuguese Conf. Artif. Intell.* Berlin, Germany: Springer, 2003, pp. 204–208.

[95] S. Sette and L. Boullart, "An implementation of genetic algorithms for rule based machine learning," *Eng. Appl. Artif. Intell.* , vol. 13, no. 4, pp. 381–390, 2000.

[96] C. K. Park, D. H. Lee, and T. J. Kang, "A new evaluation of seam pucker and its applications," *Int. J. Clothing Sci. Technol.*, vol. 9, nos. 2–3, pp. 252–255, 1997.

[97] A. Aksoy and N. Öztürk, "Design of an intelligent decision support system for global outsourcing decisions in the apparel industry," *J. Text. Inst.*, vol. 107, no. 10, pp. 1322–1335, 2016.

[98] C. K. H. Lee, Y. K. Tse, G. T. S. Ho, and K. L. Choy, "Fuzzy association rule mining for fashion product development," *Ind. Manage. Data Syst.*, vol. 115, no. 2, pp. 383–399, 2015.

[99] Z.-H. Hu, C. Wei, and X.-K. Yu, "Apparel distribution with uncertain try-on time by evolutionary algorithm," *Int. J. Clothing Sci. Technol.*, vol. 27, no. 1, pp. 75–90, 2015.

[100] A. S. Kumar and V. M. Bhaskaran, "Multidirectional product decision support system for user activation assessment in textile industry using collaborative filtering methods," *Int. J. Appl. Eng. Res.*, vol. 10, no. 20, pp. 17205–17209, 2015.

[101] C. K. H. Lee, K. L. Choy, K. M. Y. Law, and G. T. S. Ho, "Application of intelligent data management in resource allocation for effective operation of manufacturing systems," *J. Manuf. Syst.*, vol. 33, no. 3, pp. 412–422, 2014.

[102] D. Nakandala, P. Samaranayake, and H. C. W. Lau, "A fuzzy-based decision support model for monitoring on-time delivery performance: A textile industry case study," *Eur. J. Oper. Res.*, vol. 225, no. 3, pp. 507–517, 2013.

[103] B. Rabenasolo and X. Zeng, "A risk-based multi-criteria decision support system for sustainable development in the textile supply chain," in *Handbook on Decision Making* (Intelligent Systems Reference Library), vol. 33, J. Lu, L. C. Jain, and G. Zhang, Eds. Berlin, Germany: Springer, 2012.

[104] A. Aksoy, N. Ozturk, and E. Sucky, "A decision support system for demand forecasting in the clothing industry," *Int. J. Clothing Sci. Technol.*, vol. 24, no. 4, pp. 221–236, 2012.

[105] D. Kumar, J. Singh, and O. P. Singh, "A decision support system for supplier selection for Indian textile industry using analytic hierarchy process based on fuzzy simulation," *Int. J. Bus. Perform. Supply Chain Model.*, vol. 3, no. 4, pp. 364–382, 2011.

[106] A. Majumdar, R. Mangla, and A. Gupta, "Developing a decision support system software for cotton fibre grading and selection," *Indian J. Fibre Text. Res.*, vol. 35, no. 3, pp. 195–200, 2010.

[107] S. Chakraborty and K. Prasad, "A quality function deployment-based expert system for cotton fibre selection," *J. Inst. Eng. E*, vol. 99, no. 1, pp. 43–53, Jun. 2018.

[108] V. Istrat and N. Lalić, "Association rules as a decision making model in the textile industry," *Fibres Text. Eastern Eur.*, vol. 25, no. 4, pp. 8–14, 2017.

[109] K. Santiago-Santiago, A. L. Laureano-Cruces, J. M. A. Antuñano-Barranco, O. Domínguez-Pérez, and E. Sarmiento-Bustos, "An expert system to improve the functioning of the clothing industry," *Int. J. Clothing Sci. Technol.*, vol. 27, no. 1, pp. 99–128, 2015.

[110] C. K. H. Lee, G. T. S. Ho, K. L. Choy, and G. K. H. Pang, "A RFID-based recursive process mining system for quality assurance in the garment industry," *Int. J. Prod. Res.*, vol. 52, no. 14, pp. 4216–4238, 2014.

[111] S. Jamal, H. Esmaeil, and S. E. Maryam, "Developing a hybrid intelligent model for constructing a size recommendation expert system in textile industries," *Int. J. Clothing Sci. Technol.*, vol. 25, no. 5, pp. 338–349, 2013.

[112] C. K. H. Lee, K. L. Choy, G. T. S. Ho, K. S. Chin, K. M. Y. Law, and Y. K. Tse, "A hybrid OLAP-association rule mining based quality management system for extracting defect patterns in the garment industry," *Expert Syst. Appl.*, vol. 40, no. 7, pp. 2435–2446, 2013.

[113] Y. Yu, C.-L. Hui, and T.-M. Choi, "An empirical study of intelligent expert systems on forecasting of fashion color trend," *Expert Syst. Appl.*, vol. 39, no. 4, pp. 4383–4389, 2012.

[114] W. K. Wong, S. Y. S. Leung, Z. X. Guo, X. H. Zeng, and P. Y. Mok, "Intelligent product cross-selling system with radio frequency identification technology for retailing," *Int. J. Prod. Econ.*, vol. 135, no. 1, pp. 308–319, 2012.

[115] W.-S. Lo, T.-P. Hong, and R. Jeng, "A framework of E-SCM multi-agent systems in the fashion industry," *Int. J. Prod. Econ.*, vol. 114, no. 2, pp. 594–614, 2008.

[116] C. Rong-Chang, L. Chih-Chang, and L. Shiue-Shiun, "An automatic decision support system based on genetic algorithm for global apparel manufacturing," *Int. J. Soft Comput.*, vol. 1, no. 1, pp. 17–21, 2006.

[117] T. W. Lau, P. C. L. Hui, F. S. F. Ng, and K. C. C. Chan, "A new fuzzy approach to improve fashion product development," *Comput. Ind.*, vol. 57, no. 1, pp. 82–92, 2006.

[118] I. P. Tatsiopoulos, S. T. Ponis, and E. A. Hadzilias, "An e-releaser of production orders in the extended enterprise," *Prod. Planning Control*, vol. 15, no. 2, pp. 119–132, 2004.

[119] Y. Liu and Z.-F. Geng, "Three-dimensional garment computer aided intelligent design," *J. Ind. Text.*, vol. 33, no. 1, pp. 43–54, 2003.

[120] W. D. Cooper and C. Saydam, "A general decision support systems approach to the port scheduling problem for pressure beck operations," *J. Text. Inst.*, vol. 94, nos. 1–2, pp. 1–11, 2003.

[121] C. Saydam and W. D. Cooper, "A decision support system for scheduling jobs on multi-port dyeing machines," *Int. J. Oper. Prod. Manage.*, vol. 22, nos. 9–10, pp. 1054–1065, 2002.

[122] C. Jarvis, S. Davis, B. Kernodle, W. Masuchun, and S. AngannaMuthu, "Decision support for balanced inventory flow replenishment system," *Int. J. Clothing Sci. Technol.*, vol. 12, no. 6, pp. 100–102, 2000.

[123] R. Convert, L. Schacher, and P. Viallier, "An expert system for the dyeing recipes determination," *J. Intell. Manuf.* , vol. 11, no. 2, pp. 145–155, 2000.

[124] C. Eckert, I. A. N. Kelly, and M. Stacey, "Interactive generative systems for conceptual design: An empirical perspective," *Artif. Intell. Eng. Des. Anal. Manuf.*, vol. 13, no. 4, pp. 303–320, 1999.

[125] C. A. B. e Costa, L. Ensslin, E. C. Corrêa, and J.-C. Vansnick, "Decision support systems in action: Integrated application in a multicriteria decision aid process," *Eur. J. Oper. Res.*, vol. 113, no. 2, pp. 315–335, 1999.

[126] L. J. Anderson, C. Warfield, M. Barry, and C. Emery, "Toward a national model of an electronic decision support system for domestic sourcing of textiles and apparel," *Clothing Text. Res. J.*, vol. 15, no. 2, pp. 65–75, 1997.

[127] C. K. Park, D. H. Lee, and T. Kang, "Knowledge-base construction of a garment manufacturing expert system," *Int. J. Clothing Sci. Technol.*, vol. 8, no. 5, pp. 11–28, 1996.

[128] E. K. Bye and M. R. DeLong, "A visual sensory evaluation of the results of two pattern grading methods," *Clothing Text. Res. J.*, vol. 12, no. 4, pp. 1–7, 1994.

[129] G. Martino, R. Iannnone, M. Fera, S. Miranda, and S. Riemma, "Fashion retailing: A framework for supply chain optimization," *Uncertain Supply Chain Manage.*, vol. 5, no. 3, pp. 243–272, 2017.

[130] C. K. H. Lee, K. L. Choy, G. T. S. Ho, and C. H. Y. Lam, "A slippery genetic algorithm-based process mining system for achieving better quality assurance in the garment industry," *Expert Syst. Appl.*, vol. 46, pp. 236–248, Mar. 2016.

[131] G. Martino, B. Yuce, R. Iannone, and M. S. Packianather, "Optimisation of the replenishment problem in the fashion retail industry using Tabu-Bees algorithm," *IFAC-PapersOnLine*, vol. 49, no. 12, pp. 1685–1690, 2016.

[132] F. Caro and J. Gallien, "Inventory management of a fast-fashion retail network," *Oper. Res.*, vol. 58, no. 2, pp. 257–273, 2010.

[133] S.-S. Li, R.-C. Chen, and C.-C. Lin, "A genetic algorithm-based decision support system for allocating international apparel demand," *WSEAS Trans. Inf. Sci. Appl.*, vol. 3, no. 7, pp. 1294–1299, 2006.

[134] N. Werghi, Y. Xiao, and J. P. Siebert, "A functional-based segmentation of human body scans in arbitrary postures," *IEEE Trans. Syst., Man, Cybern., B, Cybern.*, vol. 36, no. 1, pp. 153–165, Feb. 2006.

[135] S. Sette and L. Boullart, "Genetic programming: Principles and applications," *Eng. Appl. Artif. Intell.*, vol. 14, no. 6, pp. 727–736, 2001.

[136] N. I. Karacapilidis and C. P. Pappis, "Production planning and control in textile industry: A case study," *Comput. Ind.*, vol. 30, no. 2, pp. 127–144, 1996.

[137] Y. Shin, Y. Kim, and E. Y. Kim, "Automatic textile image annotation by predicting emotional concepts from visual features," *Image Vis. Comput.*, vol. 28, no. 3, pp. 526–537, 2010.

[138] C. W. M. Yuen, W. K. Wong, S. Q. Qian, L. K. Chan, and E. H. K. Fung, "A hybrid model using genetic algorithm and neural network for classifying garment defects," *Expert Syst. Appl.*, vol. 36, no. 2, pp. 2037–2047, 2009.

[139] W. K. Wong, C. W. M. Yuen, D. D. Fan, L. K. Chan, and E. H. K. Fung, "Stitching defect detection and classification using wavelet transform and BP neural network," *Expert Syst. Appl.*, vol. 36, no. 2, pp. 3845–3856, Mar. 2009.

[140] C. W. M. Yuen, W. K. Wong, S. Q. Qian, D. D. Fan, L. K. Chan, and E. H. K. Fung, "Fabric stitching inspection using segmented window technique and BP neural network," *Text. Res. J.*, vol. 79, no. 1, pp. 24–35, 2009.

[141] Q. Lu, Z.-J. Lyu, Q. Xiang, Y. Zhou, and J. Bao, "Research on data mining service and its application case in complex industrial process," in *Proc. IEEE Int. Conf. Autom. Sci. Eng.*, Aug. 2017, pp. 1124–1129.

[142] D. Banerjee, N. Ganguly, S. Sural, and K. S. Rao, "One for the road: Recommending male street attire," in *Proc. Pacific–Asia Conf. Knowl. Discovery Data Mining*, 2018, pp. 571–582.

[143] D. Venkataraman, N. Vinay, T. V. Vamsi, S. P. Boppudi, R. Y. Reddy, and P. Balasubramanian, ''Yarn price prediction using advanced analytics model,'' in *Proc. IEEE Int. Conf. Comput. Intell. Comput. Res. (ICCIC)*, Dec. 2016, pp. 1–8.

[144] C. Fiarni, H. Maharani, and R. Pratama, ''Sentiment analysis system for Indonesia online retail shop review using hierarchy Naive Bayes technique,'' in *Proc. 4th Int. Conf. Inf. Commun. Technol. (ICoICT)*, May 2016, pp. 1–6.

[145] W. Lin and Z. Miao, ''The construction of fabric grading model based on SOM algorithm,'' in *Proc. Int. Conf. Intell. Transp., Big Data Smart City (ICITBS)*, Dec. 2015, pp. 841–843.

[146] M. Wong, Y. Zhou, and H. Xu, ''Big data in fashion industry: Color cycle mining from runway data,'' in *Proc. 22nd Amer. Conf. Inf. Syst.*, 2016, pp. 1–10.

[147] A. P. Martins, P. Bruniaux, and S. Thomassey, ''Cluster-based sales forecasting of fast fashion using linguistic variables and ELM,'' in *Proc. 12th Int. FLINS Conf. Uncertainty Modeling Knowl. Eng. Decis. Making*, 2016, pp. 978–983.

[148] D. Siegmund, A. Kuijper, and A. Braun, ''Stereo-image normalization of voluminous objects improves textile defect recognition,'' in *Proc. Int. Symp. Vis. Comput.* Cham, Switzerland: Springer, 2016, pp. 181–192.

[149] J. B. Pérez, A. G. Arrieta, A. H. Encinas, and A. Q. Dios, ''Textile engineering and case based reasoning,'' in *Proc. 13th Int. Conf. Distrib. Comput. Artif. Intell.*, vol. 474, 2016, pp. 423–431.

[150] D. P. P. Mesquita, A. N. A. Neto, J. F. de Queiroz Neto, J. P. P. Gomes, and L. R. Rodrigues, ''Using robust extreme learning machines to predict cotton yarn strength and hairiness,'' in *Proc. 24th Eur. Symp. Artif. Neural Netw. (ESANN)*, 2016, pp. 65–70.

[151] C. D. Kreyenhagen, T. I. Aleshin, J. E. Bouchard, A. M. I. Wise, and R. K. Zalegowski, ''Using supervised learning to classify clothing brand styles,'' in *Proc. IEEE Syst. Inf. Eng. Design Symp. (SIEDS)*, Apr. 2014, pp. 239–243.

[152] A. Kitipong, W. Rueangsirasak, and R. Chaisricharoen, ''Classification system for traditional textile: Case study of the batik,'' in *Proc. 13th Int. Symp. Commun. Inf. Technol., Commun. Inf. Technol. New Life Style Beyond Cloud (ISCIT)*, Sep. 2013, pp. 767–771.

[153] P. F. Li, J. Wang, H. H. Zhang, and J. F. Jing, ''Automatic woven fabric classification based on support vector machine,'' in *Proc. Int. Conf. Autom. Control Artif. Intell. (ACAI)*, no. 598, Mar. 2012, pp. 581–584.

[154] N. A. Khalifa, S. M. Darwish, and M. A. El-Iskandarani, ''Automated textile defects recognition system using computer vision and interval type-2 fuzzy logic,'' in *Proc. 1st Int. Conf. Innov. Eng. Syst. (ICIES)*, Dec. 2012, pp. 148–153.

[155] E. Yesil, M. Kaya, and S. Siradag, ''Fuzzy forecast combiner design for fast fashion demand forecasting,'' in *Proc. Int. Symp. Innov. Intell. Syst. Appl.*, Jul. 2012, pp. 1–5.

[156] X. G. Wang, X. Z. Li, and Y. Li, ''Application of cluster algorithm in clothes shape classifying,'' *Appl. Mech. Mater.*, vols. 55–57, pp. 1058–1062, May 2011.

[157] X. Chen, Y. Luo, and F. Zhu, ''The application of data mining in FFE of the fashion product development,'' in *Proc. Int. Symp. Comput. Intell. Design (ISCID)*, vol. 1, Oct. 2010, pp. 215–217.

[158] L. Z. Fan and Q. Qiao, ''Research on a fashion knowledge management platform for women garment development,'' in *Proc. Int. Conf. Manage. Service Sci. (MASS)*, Aug. 2010, pp. 1–3.

[159] Y. Li, V. E. Kuzmichev, Y. Luo, and X. Wang, ''Garment industry oriented clothes shape classifying by cluster,'' in *Proc. 2nd Int. Conf. Ind. Mechatronics Automat. (ICIMA)*, vol. 2, May 2010, pp. 472–475.

[160] M. Selvanayaki, M. S. Vijaya, K. S. Jamuna, and S. Karpagavalli, ''Supervised learning approach for predicting the quality of cotton using WEKA,'' in *Proc. Int. Conf. Bus. Admin. Inf. Process.*, vol. 70, 2010, pp. 382–384.

[161] I. Peña, H. L. Viktor, and E. Paquet, ''Explorative data mining for the sizing of population groups,'' in *Proc. 1st Int. Conf. Knowl. Discovery Inf. Retr. (KDIR)*, 2009, pp. 152–159.

[162] L. Koehl, X. Zeng, M. Camargo, C. Fonteix, and F. Delmotte, ''Analysis and identification of fashion oriented industrial products using fuzzy logic techniques,'' in *Proc. 3rd Int. Conf. Intell. Syst. Knowl. Eng. (ISKE)*, Nov. 2008, pp. 465–470.

[163] J. De Armas, C. León, G. Miranda, and C. Segura, ''Remote service to solve the two-dimensional cutting stock problem: An application to the canary islands costume,'' in *Proc. 2nd Int. Conf. Complex, Intell. Softw. Intensive Syst. (CISIS)*, Mar. 2008, pp. 971–976.

[164] S. Ierace, R. Pinto, and S. Cavalieri, ''Application of neural networks to condition based maintenance: A case study in the textile industry,'' *IFAC Proc. Vols.*, vol. 40, no. 3, pp. 147–152, 2007.

[165] N. Y. Kim, Y. Shin, and E. Y. Kim, ''Emotion-based textile indexing using neural networks,'' in *Proc. Int. Symp. Consum. Electron. (ISCE)*, 2007, pp. 349–357.

[166] S. Da Silva Camargo and P. M. Engel, ''MiRABIT: A new algorithm for mining association rules,'' in *Proc. Int. Conf. Chilean Comput. Sci. Soc. (SCCC)*, Nov. 2002, pp. 162–166.

[167] Y. Kita and N. Kita, ''A model-driven method of estimating the state of clothes for manipulating it,'' in *Proc. IEEE Workshop Appl. Comput. Vis.*, Dec. 2002, pp. 63–69.

[168] T. Sano and H. Yamamoto, ''Intelligent CAD system for Japanese kimono,'' in *Proc. 26th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, vol. 1, Oct. 2000, pp. 942–947.

[169] J. Shao, Z. Zhao, J. Wang, and P. Song, ''Production management and decision system oriented to the textile enterprise based on multi-agent,'' in *Proc. Int. Conf. Comput. Design Appl. (ICCDA)*, vol. 4, Jun. 2010, pp. V445–V449.

[170] Y. Chen and L.-C. Wang, ''Fuzzy logic of matching sense on fashion image,'' in *Proc. 4th Int. Conf. Natural Comput. (ICNC)*, vol. 7, Oct. 2008, pp. 85–89.

[171] M. Min, ''A rule based expert system for analysis of mobile sales data on fashion market,'' in *Proc. Int. Conf. Inf. Sci. Appl. (ICISA)*, Jun. 2013, pp. 1–2.

[172] Z.-J. Lv, Q. Xiang, and J.-G. Yang, ''A novel data mining method on quality control within spinning process,'' *Appl. Mech. Mater.*, vol. 224, pp. 87–92, Nov. 2012.

[173] Z. Xue, X. Zeng, L. Koehl, and Y. Chen, ''Development of a fuzzy inclusion measure for investigating relations between visual and tactile perception of textile products,'' in *Proc. IEEE Int. Conf. Multisensor Fusion Integr. Intell. Syst.*, Sep. 2012, pp. 108–113.

[174] B. S. Villanueva and M. Sànchez-Marrè, ''Case-based reasoning applied to textile industry processes,'' in *Proc. Int. Conf. Case-Based Reasoning*. Berlin, Germany: Springer, 2012, pp. 428–442.

[175] L.-C. Wang, Y. Chen, and Y. Wang, ''Formalization of fashion sensory data based on fuzzy set theory,'' in *Proc. 4th Int. Conf. Natural Comput. (ICNC)*, vol. 7, Oct. 2008, pp. 80–84.

[176] J. L. Su, Z. Ouyang, and Y. Chen, ''Design of agile infrastructure for manufacturing system with FNN based Web-enabled technology solutions,'' in *Proc. 7th Int. Conf. Intell. Syst. Design Appl. (ISDA)*, Oct. 2007, pp. 79–83.

[177] R.-C. Chen, S.-S. Li, C.-C. Lin, and T.-S. Chen, ''Application of self-adaptive genetic algorithm on allocating international demand to global production facilities,'' in *Proc. World Congr. Intell. Control Automat. (WCICA)*, vol. 2, Jun. 2006, pp. 7152–7156.

[178] R.-C. Chen, S.-S. Li, C.-C. Lin, and C.-C. Feng, ''A GA-based global decision support system for garment production,'' in *Proc. Int. Conf. Neural Netw. Brain (ICNNB)*, vol. 2, Oct. 2005, pp. 805–809.

[179] M. H. F. Zarandi and M. Esmaeilian, ''A systematic fuzzy modeling for scheduling of textile manufacturing system,'' in *Proc. Annu. Conf. North Amer. Fuzzy Inf. Process. Soc. (NAFIPS)*, Jul. 2003, pp. 359–364.

[180] G. S. Loo, B. C. P. Tang, and L. Janczewski, ''An adaptable human-agent collaboration information system in manufacturing (HACISM),'' in *Proc. Int. Workshop Database Expert Syst. Appl. (DEXA)*, Sep. 2000, pp. 445–449.

[181] G. Gonçalves, J. B. De Sousa, and F. L. Pereira, ''The development of an integrated decision support system for a textile company: A systems engineering approach,'' in *Proc. Eur. Control Conf. (ECC)*, Jul. 1997, pp. 3543–3548.

[182] G. Brewka and C. Habel, ''KI-97: Advances in artificial intelligence,'' in *Proc. 21st Annu. German Conf. Artif. Intell.*, vol. 21. Freiburg, Germany: Springer, Sep. 1997.

[183] D. A. Xerokostas and K. G. Aravossis, ''A solution procedure for solving the nonrectangular cutting stock problem of the clothing industry using expert knowledge within an intelligent CAD environment,'' in *Proc. Int. Conf. Database Expert Syst. Appl.* Berlin, Germany: Springer, 1994, pp. 214–224.

[184] P. T. Kleeman, T. A. Calogero, C. L. Cromwell, J. D. Nan, P. F. Sanborn, and P. B. Wright, ''A computer integrated system for autonomous management of production (illustrated by applications in textile manufacturing),'' in *Proc. Rensselaer's 2nd Int. Conf. Comput. Integr. Manuf.*, May 1990, pp. 324–330.

[185] N. Klement, C. Silva, and O. Gibaru, "Solving a discrete lot sizing and scheduling problem with unrelated parallel machines and sequence dependent setup using a generic decision support tool," in *Proc. IFIP Int. Conf. Adv. Prod. Manage. Syst.*, vol. 513, 2017, pp. 459–466.
[186] A. Uber, Jr., P. J. de Freitas Filho, and R. A. Silveira, "E-HIPS: An extention of the framework HIPS for stagger of distributed process in production systems based on multiagent systems and memetic algorithms," in *Proc. Mex. Int. Conf. Artif. Intell.* Cham, Switzerland: Springer, 2015, pp. 413–430.
[187] P. Y. Mok, "Intelligent apparel production planning for optimizing manual operations using fuzzy set theory and evolutionary algorithms," in *Proc. 5th Int. Workshop Genetic Evol. Fuzzy Syst. Symp. Comput. Intell. (IEEE GEFS SSCI)*, Apr. 2011, pp. 103–110.
[188] L. S. Admuthe and S. D. Apte, "Computational model using ANFIS and GA: Application for textile spinning process," in *Proc. 2nd IEEE Int. Conf. Comput. Sci. Inf. Technol. (ICCSIT)*, Aug. 2009, pp. 110–114.
[189] L. Suyi and Z. Leduo, "Textile pattern generation technique based on quasi-regular pattern theory and their transform," in *Proc. Pacific-Asia Workshop Comput. Intell. Ind. Appl. (PACIIA)*, vol. 2, Dec. 2008, pp. 264–266.
[190] D. Wen, G. Liu, Y. Zhou, and S. Jin, "The study of enhancing authenticity of cloth surface intersection processing," in *Proc. Pacific-Asia Workshop Comput. Intell. Ind. Appl. (PACIIA)*, vol. 1, Dec. 2008, pp. 977–981.
[191] S. Vorasitchai and S. Madarasmi, "Improvements on layout of garment patterns for efficient fabric consumption," in *Proc. IEEE Int. Symp. Circuits Syst.*, vol. 4, May 2003, pp. IV552–IV555.
[192] J. Távora and H. Coelho, "A path planner for the cutting of nested irregular layouts," in *Proc. Portuguese Conf. Artif. Intell.*, in Lecture Notes in Computer Science, vol. 390, 1989, pp. 246–256.
[193] B. Kalra, K. Srivastava, and M. Prateek, "Computer vision based personalized clothing assistance system: A proposed model," in *Proc. 2nd Int. Conf. Next Gener. Comput. Technol. (NGCT)*, Oct. 2016, pp. 341–346.
[194] M. T. Habib, S. B. Shuvo, M. S. Uddin, and F. Ahmed, "Automated textile defect classification by Bayesian classifier based on statistical features," in *Proc. Int. Workshop Comput. Intell. (IWCI)*, Dec. 2016, pp. 101–105.
[195] Y.-I. Ha, S. Kwon, M. Cha, and J. Joo, "Fashion conversation data on instagram," in *Proc. 11th Int. Conf. Web Social Media (ICWSM)*, 2017, pp. 418–427.
[196] D. Siegmund, T. Samartzidis, B. Fu, A. Braun, and A. Kuijper, "Fiber defect detection of inhomogeneous voluminous textiles," in *Proc. Mex. Conf. Pattern Recognit.*, 2017, pp. 278–287.
[197] S. Jiang, M. Shao, C. Jia, and Y. Fu, "Consensus style centralizing auto-encoder for weak style classification," in *Proc. AAAI*, 2016, pp. 1223–1229.
[198] L. Fan and G. Jiang, "Optimized Gabor filter parameters for uniform texture flaw detection," in *Proc. IEEE Int. Conf. Intell. Syst. Knowl. Eng. (ISKE)*, Nov. 2010, pp. 173–176.
[199] V. Carvalho, F. Soares, and R. Vasconcelos, "Artificial intelligence and image processing based techniques: A tool for yarns parameterization and fabrics prediction," in *Proc. IEEE Conf. Emerg. Technol. Factory Automat. (ETFA)*, Sep. 2009, pp. 1–4.
[200] I. Amed, A. Balchandani, M. Beltrami, A. Berg, S. Hedrich, and F. Rölkens, "The state of fashion 2019: A year of awakening," McKinsey & Company, Nov. 2018. [Online]. Available: https://www.mckinsey.com/industries/retail/our-insights/the-state-of-fashion-2019-a-year-of-awakening
[201] T. G. Dietterich, "Ensemble learning," *Handbook Brain Theory Neural Netw.*, vol. 2, pp. 110–125, Mar. 2002.
[202] C. Zhang and Y. Ma, *Ensemble Machine Learning: Methods and Applications*. New York, NY, USA: Springer, 2012.
[203] K. Ramasubramanian and A. Singh, "Deep learning using keras and tensorflow," in *Machine Learning With R*. Berkeley, CA, USA: Apress, 2019, pp. 667–688.
[204] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 2818–2826.
[205] M. Boeckhout, G. A. Zielhuis, and A. L. Bredenoord, "The FAIR guiding principles for data stewardship: Fair enough?" *Eur. J. Hum. Genet.*, vol. 26, no. 7, pp. 931–936, May 2018.

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Article B

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Garment Categorization Using Data Mining Techniques

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Abstract: The apparel industry houses a huge amount and variety of data. At every step of the supply chain, data is collected and stored by each supply chain actor. This data, when used intelligently, can help with solving a good deal of problems for the industry. In this regard, this article is devoted to the application of data mining on the industry's product data, i.e., data related to a garment, such as fabric, trim, print, shape, and form. The purpose of this article is to use data mining and symmetry-based learning techniques on product data to create a classification model that consists of two subsystems: (1) for predicting the garment category and (2) for predicting the garment sub-category. Classification techniques, such as Decision Trees, Naïve Bayes, Random Forest, and Bayesian Forest were applied to the 'Deep Fashion' open-source database. The data contain three garment categories, 50 garment sub-categories, and 1000 garment attributes. The two subsystems were first trained individually and then integrated using soft classification. It was observed that the performance of the random forest classifier was comparatively better, with an accuracy of 86%, 73%, 82%, and 90%, respectively, for the garment category, and sub-categories of upper body garment, lower body garment, and whole-body garment.

Keywords: data mining; machine learning; classification; big data; decision trees; naïve bayes; bayesian forest; random forest

1. Introduction

Data mining and machine learning have been at the forefront of research, helping to solve analytical problems and overcoming business problems [1,2]. The power of data mining in analyzing big data has been proven in various studies [3,4]. The apparel industry is relatively new to the field of data mining and machine learning; however, it has a gamut of application areas in retail, production, and other business operations. Businesses, such as Myntra, Zalando, and StitchFix are trying to tap into the potential of data to gain deeper insight into their consumer bases [5–7]. They even provide smart recommendations based on customers' past purchases. Some retailers gather data using machine learning models and then use it to make important business decisions [8]. For instance, with the information extracted from data, they can learn what products sell best and which ones need refining. Mined data can be of immense use to marketing teams in designing appealing and targeted promotions to attract more customers.

With the advent of the internet and massive technological developments, there has also been a rise in e-commerce in the apparel industry. The number of retail channels has increased, with customers buying products through different retail channels, such as mobile commerce, social media commerce, and retail shops [9]. Due to increasing web interactions, there are more ways for customers to leave their digital footprints and for businesses to collect data. These data, available from a multitude of sources and channels, necessitate the adoption of the latest technologies, such as artificial intelligence, big data analytics, and machine learning.

As the contemporary customer relies on online retail channels to make purchases, the need also arises for powerful and intelligent systems that can recommend, personalize, or help the customer in making purchasing decisions. Such models (decision support systems) can help customers in finding the right garments, according to their requirements. The first step towards achieving this is to make the models recognize the different garment categories and corresponding garment attributes. It is important to recommend the right garment to the customer as it directly impacts the customer's shopping experience as well as the perception of the retailer itself [10]. Moreover, classifying products based on attributes can be beneficial for demand forecasting, as well as efficient assortment planning and comparison by retailers and producers [11]. In this context, this study proposes to utilize the big data available in the apparel industry to support the development of a classification framework by applying data mining and machine learning techniques.

Hence, the focus of this article is to build an integrated model that is capable of identifying garment attributes to predict garment type. Our approach applies data mining techniques to build an intelligent model, which learns from existing training dataset containing garment attributes, categories (upper wear, bottom wear, and whole-body wear garment), and sub-categories (shirt, jeans, dress, blouse, etc.). The classifiers are first individually trained to classify the garment categories (subsystem 1) and sub-categories (subsystem 2). After this, an integrated model is created that consists of both subsystems and provides a soft classification for any new instance that the model is provided with. Generally, this article is a preliminary attempt to use data mining and symmetry-based learning concepts, particularly classification, to support the decision-makers by evaluating product attribute data to identify the garment type.

The rest of the paper is structured as follows: Section 2 discusses the previous research carried in the field of data mining and machine learning in the apparel industry. Section 3 describes the data mining and machine learning algorithms used in this research. Section 4 briefly discusses the research framework adopted. Section 5 presents the results and findings and Section 6 provides the limitations, future scope, and conclusion.

2. Research Background

Even though the application of data mining and machine learning techniques are relatively new in the apparel industry, they have quickly gained popularity in related research. A considerable amount of work is done in improving various operations in the apparel production supply chain, with the help of data mining, which is discussed in the following section.

For instance, achieving a good garment fit has been a big issue in the apparel industry [12]. Nonetheless, attempts have been made to address the issue using various data mining techniques. There are a few sub-areas of research within this that are highly focused, including finding the most relevant body measurements to develop a new sizing system [13–15] and evaluating the fit of the garment using virtual try-on [16,17]. N. Zakaria et al. [18] employed principal component analysis, k-means clustering, and regression tree to address issues related to the identification of the most important body measurements. Similarly, Hsu and Wang [19] used Kaiser's eigenvalue criteria along with the Classification and Regression Trees (CART) decision tree algorithm to identify and classify significant patterns in the body data.

On the other hand, forecasting is another popular research area, where data mining has been used for sales forecasting [20–22] and demand forecasting [23,24]. An application of time series on e-commerce to forecast sales trends has been discussed in the study by S.V. Kumar et al. [25]. With their proposed method, it is possible to achieve both short-term and long-term forecasting. The study by Z. Al-halah et al. [26] used fashion images to predict the popularity of styles in the future. They trained a forecasting model using these style images to represent the trend over time. Yet another application of data mining extensively worked upon is recommender systems [27,28]. An excellent overview of the existing apparel recommendation systems is presented in [29]. It highlights the improvement required in creating a comprehensive apparel and user profile to improve the existing recommendation systems and shows the need for long-term recommendations in design and manufacturing. On these lines, Z.H.U. Ming et al. [30] considered both user preference and behavioral data to design an online recommendation system aiming to provide increased relevance of the recommendations. In the study [31], C. Skiada et al. generated association rules using real Point-of-Sales (POS) data to provide recommendations and to understand the customer's needs and behavior while shopping online or offline.

Furthermore, significant attention has been paid to utilizing image recognition and pattern recognition [32,33], and deep learning for classification of fashion images [34,35]. W. Surakarin et al. focused on classifying upper-body garments using Support Vector Machine (SVM) with a linear kernel to train the machine-learning model to classify clothing into sub-categories and realized an overall accuracy of 73.57%. On the other hand, C.-I. Cheng et al. [36] used neural network and fuzzy sets for garment characterization and measurements. More recently, generative adversarial networks were used by K.E.A. et al. [37] to translate target attributes into fashion images. This method has the advantage of working when the number of attributes to be manipulated in an image is large, which is usually the case with the data in the fashion and apparel industry [38]. This technique is still at a nascent stage, however, and holds immense potential to advance the task of automatic generation of fashion styles.

Classification techniques have also been used to categorize fabric and sewing defects in the industry using computer vision for different applications (e.g., see [39,40] for fabric defects and [41] for garment defects). It is interesting to note that the classification systems have also been employed in image retrieval systems. For example, A. Vuruskan et al. [42] created an intelligent system to select fashion for non-standard female bodies using a genetic algorithm and neural network. More recently, the convolutional neural network has become popular for the task of classification of clothing images. H. Tuinhof et al. [43] trained a convolutional neural network to classify images of fashion products and proposed a system that takes one image as input from the user and provides a range of similar recommendations. Luca Donati et al. [44] worked on automatic recognition and classification of various features of the garment, solely from rendering images of the products, and achieved an accuracy of 75%.

In some other works, Bossard et al. [45] focused on identifying the clothes worn by people in images by first locating the upper body in the image and then extracting the features for garment classification using Support Vector Machine and Random Forest with an accuracy of 35.03% and 38.29%, respectively. An interesting finding of this study was the different training accuracies between 38% and 71% for different garment categories. The study in [46] proposed a cross model search tool, which can do both image annotation and image search by training a neural network with fashion attributes.

When it comes to the classification of garments, most of the studies are associated with image recognition and computer vision. However, when a customer searches for a garment on an online retail channel, they often use certain keywords (garment attributes, categories, styles) while using a retailer's website, or use 'hashtags' while searching on social media retail channels, such as Instagram. Classifying garments using text instead of images can be useful in this scenario. An efficient classification framework for categorizing garment categories according to their attributes can be useful for customers—as it provides better user experience when they receive the correct product suggestions—as well as businesses, as it directly influences sales. In this context, in a study by Hammar, K. et al. [47], they train a classifier using data from Instagram of clothing attributes and used it to predict the clothing with an f1 score of 0.60. The study in [48] trained a support vector machine by using the text representing product description to classify fashion styles by brand and achieved an accuracy of 56.25%.

As has been realized by examining the extant literature in the field of data mining and machine learning in the apparel industry, most of the research related to the classification of an apparel product has been focused on using visual features, while the research using attributes as 'words' to train the classification model is scant. Consequently, this study uses 'words' to build a classification framework that can predict the category and sub-category of garments, given their product attributes.

3. Machine Learning Algorithms for Garment Classification

Constructing precise and effectual classifiers for big databases is one of the basic tasks of data mining and machine learning algorithms. Typically, classification is one of the initial steps to inspect whether a set of observations can be grouped based on some similarity. A classifier aims to find predictor, $M : F \rightarrow C$, where F represents the instance space, i.e., a feature vector of length m constituting the features set of the object to be classified, and C represents the object level denoting the classification into w unique classes [49]. The classification predictor M is often trained by training dataset X_{tr}, split from the original dataset of instances $X = (x_1, x_2, \ldots, x_n)$, where x_i represents feature-label set of i^{th} instance. Here, $x_i = (F_i,\ c_i)$ where $F_i = (f_1,\ f_2, \ldots, f_m)_i$ is the feature set for i^{th} object or instance and c_i is the label assigned to i^{th} object or instance. For the binary feature sets i.e., a set of binary variables if selected attributes are present is presented as $f_i = \{0, 1\} \forall i = 1, 2 \ldots m$, thus, $F_i = \{0, 1\}^m$.

Building these kinds of effective classification functions or systems is central to data mining. Provided a partial observation and a classification, a system can statistically identify the unobserved attribute. There are various kinds of techniques used for classification such as Decision Trees, Gradient Boost, Naïve Bayes, ensemble Learning methods, etc. However, this study employs four techniques: Decision Trees, Naïve Bayes, Random Forest, and Bayesian Forest, and are discussed in brief below.

3.1. Naïve Bayes (NB) Classification

Naïve Bayes classifier is a probabilistic machine-learning model, which is a collection of classification algorithms based on Bayes' Theorem. It is considered fast, efficient, and easy to implement. It assumes that the predictive features are mutually independent given the class [50]. In this study, the Bernoulli Naïve Bayes algorithm is used, where each feature is supposed to be a binary-valued variable. Assuming that we have an object F represented by a given feature vector of m-dimensions, i.e., $F_i = (f_1,\ f_2, \ldots, f_m)_i$, which is a Boolean expressing absence or presence of the i^{th} feature. Based on the features, the object can be classified into a class c_i in $C = (c_1, c_2, \ldots, c_w)$. Therefore, according to Bayes theorem [51],

$$P(c_i|F_i) = \prod_{i=1}^{m} [c_i P(f_i|c_i) + (1 - c_i)\big(1 - P(f_i|c_i)\big)] \tag{1}$$

where, $P(c_i|F_i)$ is called a posterior probability, i.e., probability of class c_i conditioned to a given feature vector F, $P(f_i|c_i)$ is known as the likelihood and defined as the probability of feature vector F_i conditioned to class c_i. The most common applications of the NB classifier include sentiment analysis, recommendation engines, and spam filtering, and is considered fast, efficient, and easy to implement [52].

3.2. Decision Trees (DT)

Decision trees are one of the most widely implemented supervised learning algorithms and are considered a structured approach for multiclass classification [53,54]. They are robust and can achieve high accuracy in various tasks while being accountable. The information gained by a decision tree during the training phase is formulated into a hierarchical structure. This structure is easy to interpret even by non-experts. The development of DT usually involves two steps—induction and pruning—in the formation of a tree-like structure. Induction involves tree building, i.e., the formation of nodes and branches of the decision tree. Each node (excluding the terminal nodes) splits the assigned attribute based on the magnitude or category and creates branching leading to nodes of the next attribute. A given node N_i is divided into N_i^l and N_i^r such that the training set F_i are classified into two subsets namely F_i^l and F_i^r based on the division of a particular feature a_j into f_j^l and f_j^r and $f_i^l \cup f_i^l = f_i$; $f_i^l \cap f_i^l = \phi$. The splitting of the feature at the node is carried out such that it creates the node, which is purer (i.e., homogenous in terms of their features) in the divided datasets. Therefore, a feature resulting in better segregation of the training data is placed near to the root node (first node of the tree hierarchy) and, subsequently, the other attributes are divided into an iterative process and placed in the tree hierarchy. In this context, Gini impurity or Gini index is used to determine the homogeneity or purity of the split data, based on the attribute, based on the following formulation [55],

$$g = 1 - \sum_{i=1}^{w} (p_i)^2 \tag{2}$$

where w is the total number of classes, and p_i is the fraction of objects labeled in i^{th} class.

If the elements of f_i^l or f_i^r are of the same class label, no further splitting is done and that particular node is labeled as a terminal node. On the other hand, a node having a mixed labels dataset is further divided into two nodes based on another feature.

Pruning is the process where unnecessary structures are removed from the tree. This reduces the complexity and chances of overfitting making the tree easier to interpret. The basic algorithm iterates through the tree in the top to bottom approach, where the top node with no incoming branch is the root node, the nodes with outgoing branches are internal nodes and all others are leaves. The attributes of a model are depicted by the root and internal nodes, while the target class is depicted by the leaves. To decide the target class of a new instance, the decision tree algorithm begins at the root node, advancing towards the bottom through the internal nodes until it reaches a leaf node. At each node, an assessment is made to choose one of the branches. The new instance is labeled with the class of the concluding leaf node [56].

3.3. Random Forest (RF)

A random forest is an ensemble of multiple decision trees. It is a popular and highly efficient ensemble method for supervised learning algorithms and can be used for both regression and classification. Since the decision tree approach mentioned in Section 3.2 involves a single decision network, the main issue remains that the formed single decision tree may not be suitable for all data. In RF, bootstrap aggregating (bagging) technique is applied to a large set of decision tree learners [57]. Bagging is the process of creating sub-training datasets using the existing data with replacement [58]. Thus, there could be duplicate values in the sample datasets. As the name suggests, the random forest algorithm stochastically selects training sets to create decision trees. During the phase of testing, the RF receives predictions from each tree and then chooses the most efficient solution with the help of voting [59]. In a classification problem, every tree created provides a unit vote and assigns each input to the most probable target class. This collection of trees is also called the forest. It is comparatively a faster method that can identify non-linear patterns in data and is a good solution to a common problem with decision trees of overfitting. It works well for both numerical and categorical data.

3.4. Bayesian Forest (BF)

A Bayesian Forest is another ensemble learning method where the decision tree formation relies on the Bayesian statistics [60]. In RF, the training of the multiple random trees takes place and the appropriate tree configuration is selected, which results in the best classification. In a Bayesian-based random forest method, the Bayesian statistics are used for the selection of random decision trees from a collection of trees. As explained in Section 3.1, the Bayesian approach starts with a prior distribution. Subsequently, it estimates a likelihood function for each set of data in a decision tree. Bayesian forest draws the weights of the trees from an exponential distribution and the prediction is an approximate posterior mean. The mathematical formulation of the method and the computational steps followed can found in [60].

4. Research Methodology

Figure 1 shows an overview of the research framework. The research consists of three steps. The first step explains the dataset and tools used and provides details about the feature and target variables. Second is the data pre-processing step that includes data cleaning, data integration, feature selection, and data reduction. Lastly, the model-building step presents the development of the two subsystems, their integration, and the evaluation methods used.

Following the above-mentioned steps, the aim was to develop a classification model that can predict the garment types based on their attributes. The classification model consists of two-level hierarchy, the first level for classifying the garment category, and the other for classifying the garment sub-category. Hence, the classification system first gives an initial decision on whether a garment is for upper, lower or whole body and then based on this further provides a final class decision i.e., shirt, blouse, trousers, jeans, dress, kimono, and other garment sub-categories.

4.1. Tools and Dataset

The dataset used in this study is an open-source dataset named DeepFashion [61] The original dataset contains 289,222 images of apparel products tagged with 50 garment sub-categories (e.g., shirt, jeans, dresses, etc.) and 1000 garment attributes (A-line, long-sleeve, zipper, etc.). The tagged information was extracted from the dataset to build the classification model while the apparel product images were not used. The garment sub-categories are further grouped into three garment categories: upper wear, bottom wear, and whole-body wear (the list of garment sub-categories within each garment category is available in the Supplementary Materials as Table S1).

The open source dataset consists of different files, out of which four files were required to develop the classification model. The following files were used to extract information relevant to this study:

i. List of garment sub-categories tagged in the images along with the corresponding garment categories.
ii. List of 289,222 image names with the corresponding garment category (upper, lower, whole).
iii. List of garment attributes containing the attribute name (A-line, long-sleeve, zipper, etc.) and the corresponding attribute type.
iv. List of 289,222 image names with 1000 columns for each garment attributes providing the presence or absence of the attribute in that image by (−1, 0, 1).

4.2. Data Preprocessing

This section briefly discusses data pre-processing carried out in two steps (data extraction and cleaning and integration) and features selection and data reduction. The following section describes these steps in detail.

4.2.1. Data Extraction, Cleaning, and Integration

As discussed in the previous section, it was important to extract information from different files and then integrate to create a dataset that can be provided as an input to the classification algorithm. The first and second files were used to get a list of image names with corresponding garment categories and sub-categories tagged in that image. As in the fourth file, the garment attributes were represented by numbers (1 to 1000), and the third file contained the attribute names corresponding to each number; the third file was used to replace these numbers by actual attribute names. The resulting dataset and integration of the first and second files were further integrated to get the final dataset.

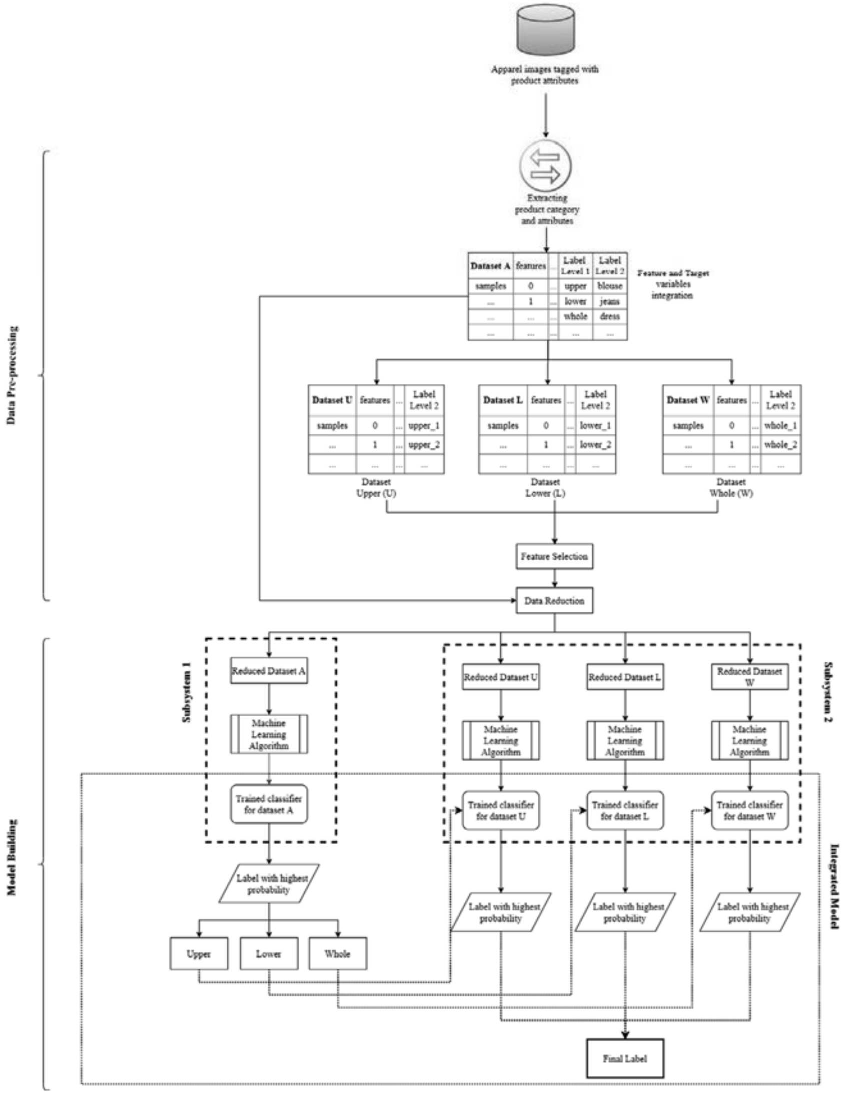

Figure 1. Research framework.

Finally, this dataset was filtered at two levels. At the first level, dataset A was used that consisted three garment categories as the target variable, i.e., upper wear (referred as Upper or U), bottom wear (referred as Lower or L), and whole-body wear (referred as Whole or W). While at the second level, there were garment sub-categories for each category mentioned at the first level represented by dataset U, L, and W respectively, which included shirts, dresses, jeans, etc.

The resulting dataset was split and transformed to give a dataset for each garment category, as shown in Figure 1. This step was carried to develop the two subsystems of the classification model, discussed in detail in the sections to follow. After splitting, there were four datasets, the initial dataset A containing all the instances of the three garment categories, a dataset U containing instances of upper wear (U), a dataset L containing instances of bottom wear, and a dataset W containing instances of whole-body wear. The garment categories and sub-categories in each dataset were considered as target labels and the garment attributes as the feature variables.

4.2.2. Feature Selection and Data Reduction

For efficient training of the classifier, it was necessary to select the features that are most relevant for the target class. Since, dataset A has all three garment categories as the target classes, having all the garment attributes is understandable. However, after splitting the dataset for each garment category, not all garment attributes might be relevant. Therefore, this step illustrates feature selection for the datasets U, L, and W. This study uses tree-based feature importance measures. Due to the applicability of random forests to a wide range of problems, the capability to create accurate models, and provide variable importance measures, it was chosen as the preferred algorithm to implement the feature selection.

In case of this type of feature selection, the importance of m^{th} feature in F_m for predicting w^{th} class in C_w is calculated by adding weighted Gini decreases for the nodes t where F_m is used, averaged over all the trees N_t in the forest. Therefore, the importance of each feature is calculated by [62]:

$$\text{Imp } (F_m) = \frac{1}{N_T} \sum_{T} \sum_{t \in T: v(s_t) = F_m} p(t) \vartriangle g(s_t, t) \tag{3}$$

where,

$p(t)$ is the proportion $\frac{N_t}{N}$ of samples reaching t.
$\vartriangle g$ is the impurity function, i.e., Gini importance or mean decrease Gini.
$v(s_t)$ is the feature used in the split s_t.

This method was chosen, as it is straightforward, fast, and the most accurate method for selecting suitable features for machine learning. Once the feature importance was calculated, the features with a threshold value above '1.25 * median' were selected. The table of most relevant features can be found in the Supplementary Materials as Table S3. After the selection of the most important features for each dataset, the data reduction step was carried out by removing the rows in all four datasets that did not have any attribute tagged in the corresponding image. This resulted in reduced datasets A, U, L, and W; the final number of attributes and observations for these four reduced datasets are summarized in Table 1.

Table 1. Number of observations and attributes after data reduction.

Dataset	Initial		Final	
	No. of Data Points	**No. of Attributes**	**No. of Data Points**	**No. of Attributes**
A	289222	1000	276253	1000
U	137770	1000	131620	430
L	56037	1000	55915	467
W	82446	1000	82202	453

4.3. Model Building

The main objective of the proposed methodology is to build a classification that predicts the garment type based on its attributes. As depicted in Figure 1, to accomplish this, the model building process in itself was split into two phases—the development of subsystems and integration of the subsystems. In the first phase, the classifiers were trained individually for each dataset. The classifier trained with dataset A led to the formation of subsystem 1. While the classifiers trained with dataset U, L, and W led to the formation of subsystem 2. As discussed in Section 3, the chosen machine learning techniques for training the classifiers were Decision Trees, Naïve Bayes, Bayesian Forest, and Random Forest. The framework of the integrated system with an explanatory instance is depicted in Figure 2.

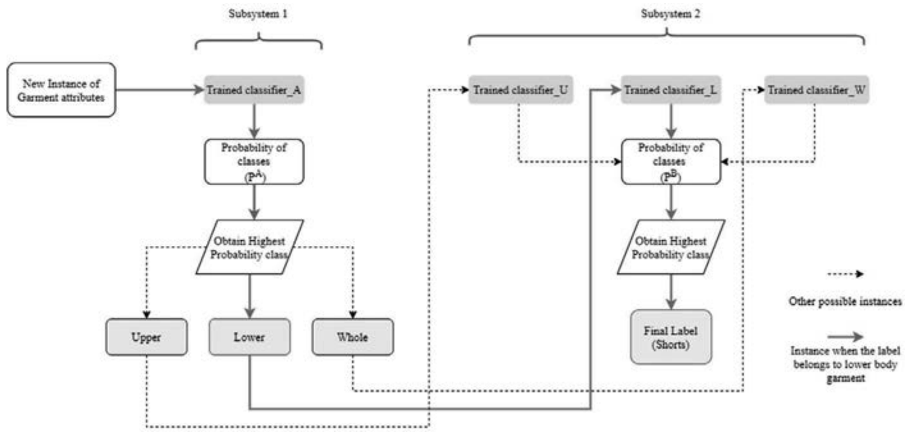

Figure 2. Framework of the Integrated System.

4.3.1. Development of Subsystems

Model Development

In general, data classification is a two-step process. The first step indicates the learning or training phase, where a model is developed by providing a predetermined set of classes and the corresponding set of training instances. Each instance is assumed to represent a predefined class. The second step, the testing phase, uses a different set of data instances to estimate the classification accuracy of the model. If the model achieves acceptable accuracy, it can be used to classify future unlabeled data instances. Finally, the model acts as a classifier in the decision-making process. The primary focus of this study is the classification of garment attribute data. The process of testing and training is shown in Figure 3.

In order to create the classification models (i.e., $M : F \rightarrow C$), the four datasets were first split into two parts, 80% used for building the model and the remaining 20% as the validation set for computing the performance of the integrated model. The dataset used for model building was further split into a set of features, $F = f_1, f_2, \ldots, f_m$, and target variables, $C = c_1, c_2, \ldots, c_w$. All of the garment attributes constitute the feature space, while the garment categories and sub-categories constitute the target space. Next, the target and feature datasets were split into train and test using stratified k (=10) fold cross-validation. The advantage of using stratified k-fold cross-validation is that it rearranges the data to ensure that each fold is a good representation of the entire dataset and, hence, is generally considered a good strategy for classification problems [63]. Stratified cross-validation is a common preference when dealing with multi-class classification problems, especially in the case of class imbalance [64]. A final evaluation was done using the test set. The following are the steps followed to accomplish stratified k-fold cross-validation:

i. The dataset was randomly split into k (=10) equal size partitions.
ii. From the k partitions, one was reserved as the test dataset for the final evaluation of the model, while the other k-1 partitions were used to model training.
iii. The process was repeated for each model and machine learning technique k times with each of the k-partitions used exactly once as the test data.

iv. The k results acquired from each of the test partitions were combined by averaging them, to produce a single estimation.

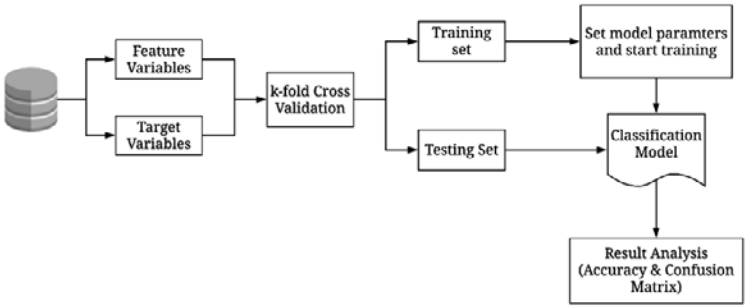

Figure 3. General testing and training framework for building classifiers.

Following this procedure, all four classifiers were trained separately for each dataset. The classifiers trained using dataset A belonged to subsystem 1, while all the other classifiers belonged to subsystem 2. These classifiers were further integrated into the next section to predict the label of new data instances.

Evaluation

Evaluation is one of the important steps in model building. With this, the accuracy of the classifier can be judged. There are many evaluation metrics available to determine the performance of a classification model. However, for a multiclass classifier, accuracy is the most widely used metric and is calculated as the number of correctly predicted labels divided by the total number of labels. [65]. Besides, a confusion matrix is widely adopted to measure the performance of a supervised machine-learning algorithm. The number of correct and incorrect predictions is aggregated by count values and broken down by category [66]. Hence, this study adopts accuracy and confusion matrix to assess the classification model. Moreover, the precision, recall, and f1-score of all the classifiers are also evaluated. The results from each evaluation metric are discussed in detail in Section 5.

4.3.2. Integration of Subsystems

Up to this point, the two subsystems trained independently, i.e., an instance can be classified into either a garment category or a garment sub-category, and each trained classifier, worked separately to give a prediction. Moreover, there was no way to handle ambiguous cases, where the classifier could not perform a hard classification and resulted in lower accuracy. To tackle these limitations, the concept of soft classification was adopted, which evaluates the conditional probabilities of each class and then realizes the classification based on the evaluated probabilities [67]. The two subsystems were combined by taking advantage of this characteristic. This section discusses the process of achieving the same in detail.

Model Development

Most classification algorithms compute the posterior probability of a class, given the learning data. In case of hard classification, the model directly yields the predicted class, while a soft classification yields a list of probabilities of all the classes in the form $(n,\ C)$, where n is the number of data instances and C_w is the number of classes [68]. Given the complexity of an apparel product, there are more chances of an ambiguous case occurring in the prediction phase of a classification model. Hence, the concept of soft classification was adopted, which indicates the confidence of a model in its prediction.

Thus, the test dataset from each dataset was used to compute the probability of the target classes. For every data instance, the classifier assigned an estimated posterior probability to each class. If the probability mass concentrates in one class, then it is very likely that the instance belongs to that class. However, if the probability mass is highly distributed, then that is considered as an ambiguous case, and making the final prediction using a threshold value becomes important. By using a threshold, a classifier considers the class with a probability above the given threshold and classifies the instance in question accordingly.

For the mathematical computation of this model, let us consider that the apparel product dataset X is represented by $X = (x_1, x_2, \ldots, x_n)$, where n being the total number of instances in the dataset. Each instance is of the form (F, C), where $F-$ is a set of product attributes represented by $F = (f_1, f_2, \ldots, f_m)$ and C is a set of target classes represented by $C = (c_1, c_2, \ldots, c_w)$. The set of instances X is divided into two sets, train set X_{tr} and test set X_{te}. The instances in X_{tr}, i.e., $(F, C)_{tr}$ are used to train the model M_A, i.e., model to classify garment categories (upper, lower, and whole). Similarly, models M_U, M_L, and M_W are trained to classify garment sub-categories belonging to upper, lower, and whole-body garments, respectively. The datasets used for training these models are explained in Section 4.2.2.

Following this, the test set X_{te} was used to integrate the functionality of the trained models. In this case, the set of features F_{te} from $(F, C)_{te}$ was used. When the first instance from F_{te} is given to the model M_A, it makes a decision d_i^A among the class probabilities $P^A = (p_1,\ p_2, \ldots, p_r)$, and the final decision is made using the following formulation,

$$d_i^A = j \,\exists\, p_j = \max\left(P^A\right) \tag{4}$$

Depending on the decision d_i^A, the instance F_{te} passes through one of the classifiers from M_U, M_L, and M_W, where M signifies classifier, subscript indicates the respective dataset U, L, or W as described in Section 4.2.1. If d_i is lower (L), then M_L will be utilized for making further classification of the instance and make a decision $\left(d_i^B\right)_L$ from the class probabilities in $\left(P_k^B\right)_L = (p_1,\ p_2, \ldots, p_l)$, where l is the number of target classes in lower body garment categories, as explained below,

$$\left(d_i^B\right)_j = \begin{cases} k \,\exists p_k^B = \max\left(\left(P_i^B\right)_j\right) & if \max\limits_1\left(P_i^B\right)_j - \max\limits_2\left(P_i^B\right)_j > th \\ \{k,\ l\}\exists p_k^B = \max\limits_1\left(P_i^B\right)_j, p_l^B = \max\limits_2\left(P_i^B\right)_j & \text{otherwise} \end{cases} \tag{5}$$

where, $\max\limits_1\left(\left(d_i^B\right)_j\right)$ represents the maximum in $\left(P_i^B\right)_j$, and $\max\limits_2\left(\left(P_i^B\right)_j\right)$ represents the second-highest in $\left(P_i^B\right)_j$.

The accuracy of the model is calculated by checking whether the final label is the same as the class C in the test dataset, i.e., if $C \in \left(d_i^B\right)_j$. Hence, the resultant class provided by the model will be given by $\left(d_i^B\right)_j$. (a comprehensive table of the mathematical symbols used is available in the supplementary file as Table S2).

Evaluation

After integrating the two subsystems to create a single model, the validation dataset (not used during the model building process) was used to evaluate the model again to see if the accuracy of the classifiers changed positively, as discussed in detail in the next section.

5. Experimentation and Results

This section summarizes the results of the experiments. First, the results from the classification of the individual subsystems are discussed with a comparison between the performances of the four algorithms—Naïve Bayes, Decision Trees, Bayesian Forest, and Random Forest for each dataset. Further, the confusion matrix for each algorithm and subsystem is presented. Following this, the results from the integration of the two subsystems using soft classification are described. Finally, for better comprehension of the working of the entire system, a brief description is provided.

5.1. Analysis of Subsystems

In this study, four algorithms were used to classify the garment data—Naïve Bayes, Decision Trees, Bayesian Forest, and Random Forest. All the classifiers were provided with the same dataset and the model parameters of each classifier are presented in Table 2. As described in Section 4.3.2, the dataset was divided into training and testing data, using ten-fold cross-validation. Figure 4 shows the accuracy of the four classification models for each dataset (A, U, L, and W) as achieved during the k cross-validation implementation. The box plot represents the overall pattern of accuracies achieved by each classifier for each dataset. Further, the evaluation of this model is carried out with a validation dataset to calculate accuracy, precision, recall, and f-score as shown in Table 3. It should be noted that this validation dataset was not used during the model building process. As is evident in Figure 4 and Table 3, for all the datasets, RF achieved the highest performance in terms of accuracy, precision, and recall. The boxplot for RF is comparatively shorter for dataset A, indicating less variation in accuracy during the different training cycles. While for datasets U and W, this variation seems larger. This could correspond to the fact that there are a larger number of target classes for these two datasets. For dataset L, even though the box plot is short, the data is skewed towards the quartile 3 and 4. Besides, there is the presence of an outlier, which is also the case for DT and RF. An outlier can be seen in DT for all datasets, except dataset W. Apart from this, the boxplot for NB is comparatively consistent for all datasets, although the accuracy attained by this classifier is lowest amongst all the classifiers as resulted from the k cross-validation presented in the box plot in Figure 4.

Table 2. Model Parameters for each classification algorithm.

S. No.	Data Mining Algorithm	Model Parameters
1	Naïve Bayes	The prior probability distribution is represented by Bernoulli's Naïve Bayes.
2	Decision Trees	Minimum number of samples required to be at a leaf node = 3, Seed value = 1000.
3	Random Forest	Minimum number of samples required to be at a leaf node = 3, Number of trees in the forest = 200, Seed value = 1000.
4	Bayesian Forest	Minimum number of samples required to be at a leaf node = 3, Number of trees in the forest = 200, Bootstrap = True, Seed value = 1000.

As can be further analyzed from Figure 4, dataset U achieved the lowest accuracy for all the classifiers, while datasets A and W, the highest. One of the reasons for the low accuracy for dataset U could be more variation in the product types, i.e., the product attributes used in each upper body garment sub-category highly varied. This corresponds to the fact that in general, there is a higher number of styles available in the upper wear garment category.

To further validate the proposed method, a confusion matrix for all the classifiers and datasets was constructed using the validation dataset (data instances unseen by the model). As an example, Figure 5 shows the confusion matrix for the RF classifier (the confusion matrix for all of the other classifiers can be found in Supplementary Materials, Figures S1–S3). Each row represents the instances of the true label, while each column represents the instances of the predicted label. The diagonal represents the number of correct classifications and the off-diagonal instances represent the miss-classifications by the model.

As can be seen in Figure 5a, the number of correctly classified upper, lower, and whole-body garment categories are 35,402, 11,710, and 18,524, respectively, out of 39,486, 16,775, and 24,661. As in Figure 5b, the most correctly classified garment sub-categories (in lower) are shorts, skirts, and jeans. Similarly, in Figure 5d, tee, blouse, and tank, and Figure 5c, dress, romper, and jumpsuit, are the top three most correctly classified garment sub-categories.

Table 3. Evaluation metrics for all classifiers and datasets.

	Accuracy	Precision	Recall	F-Score
Naïve Bayes				
Dataset A	0.7513	0.7530	0.7513	0.7502
Dataset U	0.5539	0.5444	0.5539	0.5417
Dataset L	0.6734	0.6684	0.6734	0.6682
Dataset W	0.8242	0.7888	0.8242	0.7975
Decision Trees				
Dataset A	0.7957	0.7947	0.7957	0.7940
Dataset U	0.6130	0.6085	0.6130	0.6064
Dataset L	0.7429	0.7384	0.7429	0.7341
Dataset W	0.8577	0.8389	0.8577	0.8388
Random Forest				
Dataset A	0.8658	0.8656	0.8658	0.8652
Dataset U	0.7331	0.7323	0.7331	0.7305
Dataset L	0.8232	0.8223	0.8232	0.8206
Dataset W	0.9024	0.8966	0.9024	0.8975
Bayesian Forest				
Dataset A	0.7946	0.7947	0.7946	0.7920
Dataset U	0.6113	0.6090	0.6113	0.5963
Dataset L	0.7386	0.7396	0.7386	0.7173
Dataset W	0.8488	0.8395	0.8488	0.8089

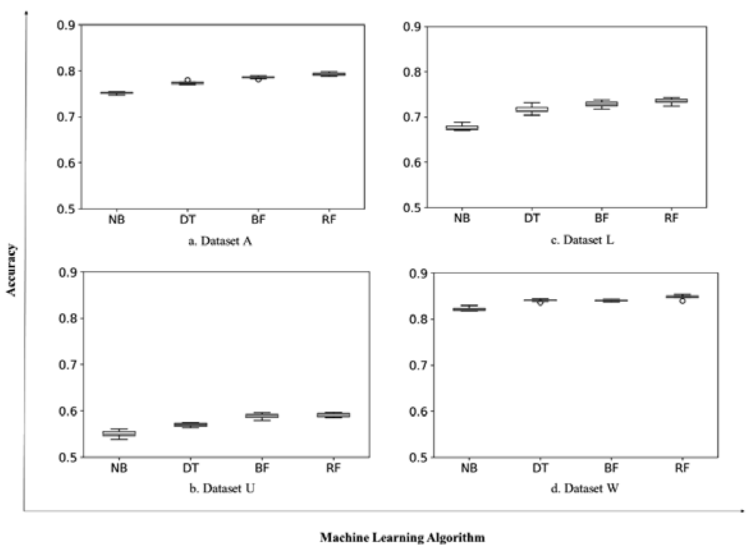

Figure 4. Ten-fold cross validation results for (**a**) Dataset A, (**b**) Dataset U, (**c**) Dataset L, and (**d**) Dataset W.

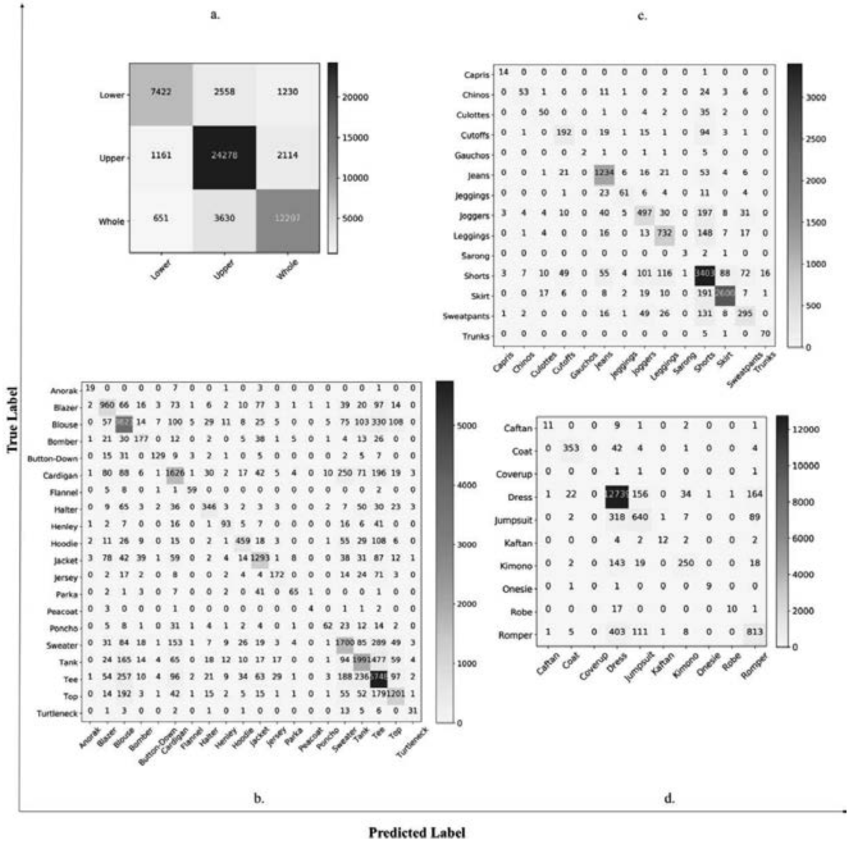

Figure 5. Confusion Matrix for Random Forest Classifier for dataset (**a**) A, (**b**) U, (**c**) L, and (**d**) W.

5.2. Analysis of the Integrated System

Until this point, the two subsystems worked independently, with an average accuracy of 71%. To integrate the two subsystems and handle ambiguous cases and improve the accuracy of classification, the concept of soft classification was introduced, as discussed in Section 4.3.2. To do this, the pre-trained classifiers provided the probability of the classes instead of yielding the predicted class. Subsystem 1 predicted the probability of the garment categories (upper, lower, or whole-body garment), and subsystem 2 predicted the probability of garment sub-categories (dress, blouse, tee, capris, trousers, etc.). The integrated model was presented in Section 4.3 with an instance shown in Figure 2.

To present an overview of the working of the whole system, let us consider the following instance. When subsystem 1 receives a string of garment attributes, it will first try to label the data instance into one of the three target classes, upper, lower, or whole-body garments. The class with the highest probability will be considered as the resultant label from subsystem 1. If the label of the new set of data is lower body garment, the string of garment attributes will now pass through the second subsystem. Since it is already determined that it is a lower-body garment, the classifier trained with dataset L will get activated and further try to label the data instance into a specific lower garment sub-category. In this case, the classifier will compute the probabilities of all the lower garment sub-category classes and compare these values to a pre-set threshold value. Based on this value, subsystem 2 will decide the label of the new data instance based on the highest probability. In another case, where at subsystem 2, if two labels have equal or very close probabilities, if the classifier provides the class with the highest probability, even if the difference between the two values is as low as 0.1, the classification result can be considered biased. This would mean that even though the new data instance is close to more than one type of lower garment sub-category, the classifier does not handle this ambiguity well. Due to this reason, having subsystem 2 provide probabilities of these two classes, instead of a single predicted class, can help make an intelligent decision, in turn improving the model accuracy for future data instances. In this way, the system becomes equipped with handling ambiguous cases, which can occur frequently in a large dataset, given the complexity of an apparel product.

The change in classification accuracy due to the aforementioned algorithm can be seen in Figure 6. To compute the accuracy of the integrated model, the validation set (not used throughout the model building process) was used. As is visible, the accuracy for all the classifiers at different thresholds (0.1, 0.2, 0.3, and 0.4) for datasets U, L, and W improved considerably. In Figure 6d), the accuracy for dataset U increased from 75% to around 85%. A similar increment can be observed for this dataset for other classifiers as well. Dataset W reached an accuracy greater than 95% for random forest classifiers, which is considered as good performance for a classification model. For all the datasets, the accuracy is still the greatest with the random forest classifier, in correspondence to the results presented in Figures 4 and 5.

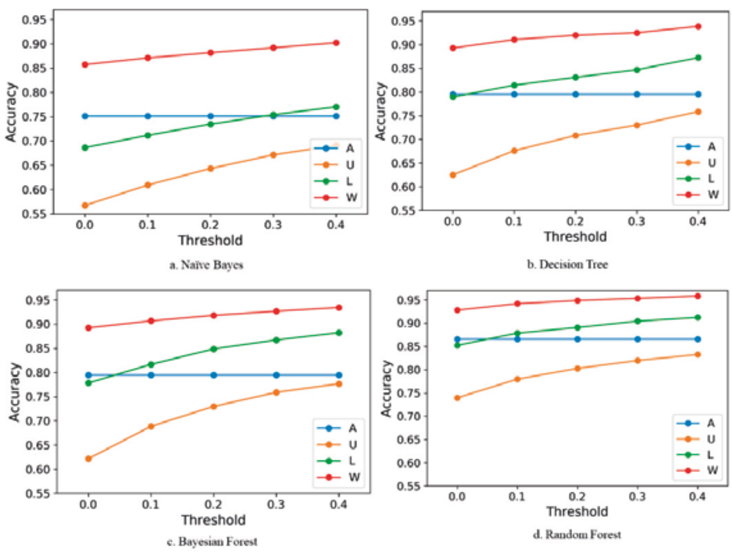

Figure 6. Accuracies at different thresholds for (**a**) Naïve Bayes, (**b**) Decision Trees, (**c**) Bayesian Forest, and (**d**) Random Forest.

6. Conclusions

The term big data has become extremely prevalent in the business world, leading to an increase in the use of techniques, such as data mining, machine learning, and artificial intelligence. Businesses are excessively applying these techniques to help collect data on sales trends to understand, better, everything from marketing and inventory needs to acquiring new leads. Data mining is one of the most used techniques due to its ability to analyze a large amount of data for solving business problems. These problems can be targeted by focusing on the business database already present, of customer choices, past transactions, and product profiles.

This study recognizes the importance of product data and uses open-source product attribute data (namely Deep Fashion) from the apparel industry to create a classification model that can identify the garment category (upper, lower, or wholebody garment) and garment sub-category (dress, blouse, capris, trousers etc.). To do this, four classification algorithms were employed: Decision Trees, Naïve Bayes, Bayesian Forest, and Random Forest. The classification model consists of two individual subsystems: (1) to identify the garment category and (2) to identify the garment subcategory. After this, the two subsystems were integrated using soft computation to handle ambiguous cases and improve the overall accuracy of the classification model. It was observed that the performance of the Random Forest classifier was comparatively better with an accuracy of 86%, 73%, 82%, and 90%, respectively, for the garment category, and sub-categories of upper body garment, lower body garment, and whole-body garment. The reason behind a comparatively better performance of random forest classifiers lies in that it creates a large number of uncorrelated trees that are averaged to reduce bias and variance, and handles unbalanced data very well.

Every garment retailer and/or production house collects similar data related to the garment, i.e., the garment categories and attributes in the archive. In addition, these are also the details present on the product pages of the e-commerce websites. Hence, the data can be obtained from these sources and used to create a segmentation based on the attributes used in various garments. This segmentation can be used to classify the data based on the methodology described in this article. Such a classification can have various applications, such as in improving the existing recommendation algorithms by providing words instead of images, and enhancing the parsing algorithms, etc. In addition, as discussed in [69], living in a digital age, there is the availability of massive datasets in various formats, making it essential to design approaches to handle the access and integration of such data. The presented model can be trained with additional data formats and, hence, incorporate accessing and integrating data from multiple resources (especially data from the internet) as it provides a uniform terminology of garment categories, sub-categories, and their attributes.

This study presents a preliminary investigation and, hence, there are several potential avenues for future work, such as in-depth evaluation of why the upper body garment dataset exhibits the lowest classification accuracy for all the algorithms and how it can be improved. The threshold of the feature selection process can be varied to observe how it affects the model performance. The accuracy of the model can be further improved with the help of a richer dataset as the dataset employed in this study deals with a few limitations, such as data imbalance and the presence of too many negative attributes. Moreover, an application of the proposed model can be realized in a decision support system or a recommendation system that can support the customer in decision making during purchase. Additionally, the proposed framework can be tested with advanced techniques, such as deep learning, to enhance model performance. Further, with data growing at an unprecedented rate, its handling and management incur additional costs (especially when manually labeling data collected through the internet, it is not only expensive but labor-intensive). Hence, the proposed model can be utilized to support the transfer from manual labeling to automatic labeling of the internet data. In the future, we would also like to work on comparing the performance of algorithms based on the input being textual or visual.

Supplementary Materials: The following are available online at http://www.mdpi.com/2073-8994/12/6/984/s1. Figure S1. Confusion Matrix for Bayesian Forest Classifier for data set a) A, b) U, c) L and d) W. Figure S2: Confusion Matrix for Naïve Bayes Classifier for data set a) A, b) U, c) L and d) W. Figure S3: Confusion Matrix for Decision Tree Classifier for data set a) A, b) U, c) L and d) W, Table S1. List of Clothing sub-categories, Table S2. Table of Mathematical Symbols Used. Table S3. Table of most relevant features for dataset upper, lower and whole body garments.

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References

1. Guleria, P.; Sood, M. Big data analytics: Predicting academic course preference using hadoop inspired mapreduce. In Proceedings of the 2017 4th International Conference on Image Information Processing, ICIIP 2017, Shimla, India, 21–23 December 2017; pp. 328–331.
2. Hsu, C.-H. Data mining to improve industrial standards and enhance production and marketing: An empirical study in apparel industry. *Expert Syst. Appl.* **2009**, *36*, 4185–4191. [CrossRef]
3. Lu, Q.; Lyu, Z.-J.; Xiang, Q.; Zhou, Y.; Bao, J. Research on data mining service and its application case in complex industrial process. In Proceedings of the IEEE International Conference on Automation Science and Engineering, Xi'an, China, 20–23 August 2017; pp. 1124–1129.
4. Buluswar, M.; Campisi, V.; Gupta, A.; Karu, Z.; Nilson, V.; Sigala, R. *How Companies are Using Big Data and Analytics*; McKinsey & Company: San Francisco, CA, USA, 2016.
5. Xiao, H.; Rasul, K.; Vollgraf, R. Fashion-MNIST: A Novel Image Dataset for Benchmarking Machine Learning Algorithms. *arXiv* **2017**, arXiv:1708.07747.
6. Adhikari, S.S.; Singh, S.; Rajagopal, A.; Rajan, A. Progressive Fashion Attribute Extraction. *arXiv* **2019**, arXiv:1907.00157.
7. Zielnicki, K. Simulacra and Selection: Clothing Set Recommendation at Stitch Fix. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, Paris, France, 18 July 2019; pp. 1379–1380.
8. Griva, A.; Bardaki, C.; Pramatari, K.; Papakiriakopoulos, D. Retail business analytics: Customer visit segmentation using market basket data. *Expert Syst. Appl.* **2018**, *100*, 1–16. [CrossRef]
9. Juaneda-Ayensa, E.; Mosquera, A.; Murillo, Y.S. Omnichannel Customer Behavior: Key Drivers of Technology Acceptance and Use and Their Effects on Purchase Intention. *Front. Psychol.* **2016**, *7*, 1117. [CrossRef]
10. Manfredi, M.; Grana, C.; Calderara, S.; Cucchiara, R. A complete system for garment segmentation and color classification. *Mach. Vis. Appl.* **2014**, *25*, 955–969. [CrossRef]
11. Ghani, R.; Probst, K.; Liu, Y.; Krema, M.; Fano, A. Text mining for product attribute extraction. *ACM SIGKDD Explor. Newsl.* **2006**, *8*, 41–48. [CrossRef]
12. Gill, S. A review of research and innovation in garment sizing, prototyping and fitting A review of research and innovation in garment sizing, prototyping and fitting. *Text. Prog.* **2015**, *47*, 1–85. [CrossRef]
13. Kausher, H.; Srivastava, S. Developing Structured Sizing Systems for Manufacturing Ready-Made Garments of Indian Females Using Decision Tree-Based Data Mining. *Int. J. Mater. Text. Eng.* **2019**, *13*, 571–575.
14. Zakaria, N.; Ruznan, W.S. Developing apparel sizing system using anthropometric data: Body size and shape analysis, key dimensions, and data segmentation. In *Anthropometry, Apparel Sizing and Design*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 91–121.
15. Pei, J.; Park, H.; Ashdown, S.P. Female breast shape categorization based on analysis of CAESAR 3D body scan data. *Text. Res. J.* **2019**, *89*, 590–611. [CrossRef]
16. Liu, K.; Zeng, X.; Bruniaux, P.; Wang, J.; Kamalha, E.; Tao, X. Fit evaluation of virtual garment try-on by learning from digital pressure data. *Knowl.-Based Syst.* **2017**, *133*, 174–182. [CrossRef]
17. Lagė, A.; Ancutienė, K. Virtual try-on technologies in the clothing industry: Basic block pattern modification. *Int. J. Cloth. Sci. Technol.* **2019**, *31*, 729–740. [CrossRef]
18. Zakaria, N.; Taib, J.S.M.N.; Tan, Y.Y.; Wah, Y.B. Using data mining technique to explore anthropometric data towards the development of sizing system. In Proceedings of the Proceedings—International Symposium on Information Technology, Kuala Lumpur, Malaysia, 26–28 August 2008; Volume 2.
19. Hsu, C.H.; Wang, M.J.J. Using decision tree-based data mining to establish a sizing system for the manufacture of garments. *Int. J. Adv. Manuf. Technol.* **2005**, *26*, 669–674. [CrossRef]
20. Thomassey, S. Sales forecasts in clothing industry: The key success factor of the supply chain management. *Int. J. Prod. Econ.* **2010**, *128*, 470–483. [CrossRef]
21. Zhang, Y.; Zhang, C.; Liu, Y. An AHP-Based Scheme for Sales Forecasting in the Fashion Industry. In *Analytical Modeling Research in Fashion Business*; Springer: Singapore, 2016; pp. 251–267.
22. Craparotta, G.; Thomassey, S. A Siamese Neural Network Application for Sales Forecasting of New Fashion Products Using Heterogeneous Data. *Int. J. Comput. Intell. Syst.* **2019**, *12*, 1537–1546. [CrossRef]
23. Beheshti-Kashi, S.; Thoben, K.-D. The Usage of Social Media Text Data for the Demand Forecasting in the Fashion Industry. In *Dynamics in Logistics*; Springer: Cham, Switzerland, 2016; pp. 723–727.

24. Yang, S.J.; Jang, S. Fashion trend forecasting using ARIMA and RNN: Application of tensorflow to retailers' websites. *Asia Life Sci.* **2019**, *18*, 407–418.
25. Kumar, S.V.; Poonkuzhali, S. Improvising the Sales of Garments by Forecasting Market Trends using Data Mining Techniques. *Int. J. Pure Appl. Math.* **2018**, *119*, 797–805.
26. Al-halah, Z.; Stiefelhagen, R.; Grauman, K. Fashion Forward: Forecasting Visual Style in Fashion Supplementary Material. In Proceeding of the IEEE International Conference on Computer Vision, Venice, Italy, 22–29 October 2017; pp. 388–397.
27. Stan, I.; Mocanu, C. An Intelligent Personalized Fashion Recommendation System. In Proceedings of the 2019 22nd International Conference on Control Systems and Computer Science (CSCS), Bucharest, Romania, 28–30 May 2019; pp. 210–215.
28. Sugumaran, P.; Sukumaran, V. Recommendations to improve dead stock management in garment industry using data analytics. *Math. Biosci. Eng.* **2019**, *16*, 8121–8133. [CrossRef]
29. Guan, C.; Qin, S.; Ling, W.; Ding, G. Apparel Recommendation System Evolution: An empirical review. *Int. J. Cloth. Sci. Technol.* **2016**, *28*, 854–879. [CrossRef]
30. Sun, W.; Lin, H.; Li, C.; Wang, T.; Zhou, K. Research and Application of Clothing Recommendation System Combining Explicit Data and Implicit Data. In Proceedings of the International Conference on Artificial Intelligence and Computing Science (ICAICS 2019), Wuhan, China, 24–25 March 2019.
31. Skiada, M.; Lekakos, G.; Gkika, S.; Bardaki, C. Garment Recommendations for Online and Offline Consumers. In Proceedings of the MCIS 2016 Proceedings, Paphos, Cyprus, 2016.
32. Chen, Y.; Qin, M.; Qi, Y.; Sun, L. Improving Fashion Landmark Detection by Dual Attention Feature Enhancement. In Proceedings of the IEEE International Conference on Computer Vision Workshops, Seoul, Korea, 27–28 October 2019.
33. Karessli, N.; Guigourès, R.; Shirvany, R. SizeNet: Weakly Supervised Learning of Visual Size and Fit in Fashion Images. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, Long Beach, CA, USA, 16–20 June 2019.
34. Surakarin, W.; Chongstitvatana, P. Classification of clothing with weighted SURF and local binary patterns. In Proceedings of the ICSEC 2015—19th International Computer Science and Engineering Conference: Hybrid Cloud Computing: A New Approach for Big Data Era, Chiang Mai, Thailand, 23–26 November 2015.
35. Bhimani, H.; Kaimaparambil, K.; Papan, V.; Chaurasia, H.; Kukreja, A. Web-Based Model for Apparel Classification. 2nd International Conference on Advances in Science & Technology (ICAST) 2019 on 8th, 9th April 2019 by K J Somaiya Institute of Engineering & Information Technology, Mumbai, India. 2019. Available online: https://ssrn.com/abstract=3367732 (accessed on 2 June 2020).
36. Cheng, C.-I.; Liu, D.S.-M. An intelligent clothes search system based on fashion styles. In Proceedings of the International Conference on Machine Learning and Cybernetics, Kunming, China, 12–15 July 2008; Volume 3, pp. 1592–1597.
37. Ak, K.E.; Lim, J.H.; Tham, J.Y.; Kassim, A.A. Attribute Manipulation Generative Adversarial Networks for Fashion Images. In Proceedings of the IEEE International Conference on Computer Vision, Seoul, Korea, 27 October–2 November 2019; pp. 10541–10550.
38. Yildirim, P.; Birant, D.; Alpyildiz, T. Data mining and machine learning in textile industry. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2018**, *8*, e1228. [CrossRef]
39. Tong, L.; Wong, W.K.; Kwong, C.K. Fabric Defect Detection for Apparel Industry: A Nonlocal Sparse Representation Approach. *IEEE Access* **2017**, *5*, 5947–5964. [CrossRef]
40. Wei, B.; Hao, K.; Tang, X.S.; Ren, L. Fabric defect detection based on faster RCNN. In *Advances in Intelligent Systems and Computing*; Springer: Cham, Switzerland, 2019; Volume 849, pp. 45–51.
41. Gries, T.; Lutz, V.; Niebel, V.; Saggiomo, M.; Simonis, K. Automation in quality monitoring of fabrics and garment seams. In *Automation in Garment Manufacturing*; Elsevier Inc.: Amsterdam, The Netherlands, 2017; pp. 353–376.
42. Vuruskan, A.; Ince, T.; Bulgun, E.; Guzelis, C. Intelligent fashion styling using genetic search and neural classification. *Int. J. Cloth. Sci. Technol.* **2015**, *27*, 283–301. [CrossRef]
43. Tuinhof, H.; Pirker, C.; Haltmeier, M. Image-based fashion product recommendation with deep learning. In *International Conference on Machine Learning, Optimization, and Data Science*; Springer: Cham, 2019; pp. 472–481.

44. Donati, L.; Iotti, E.; Mordonini, G.; Prati, A. Fashion product classification through deep learning and computer vision. *Appl. Sci.* **2019**, *9*, 1385. [CrossRef]
45. Bossard, L.; Dantone, M.; Leistner, C.; Wengert, C.; Quack, T.; van Gool, L. Apparel classification with style. In *Asian conference on computer vision*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 321–335.
46. Laenen, K.; Zoghbi, S.; Moens, M.-F. Cross-modal Search for Fashion Attributes. In Proceedings of the KDD 2017 Workshop on Machine Learning Meets Fashion, Halifax, NS, Canada, 14 August 2017.
47. Hammar, K.; Jaradat, S.; Dokoohaki, N.; Matskin, M. Deep Text Mining of Instagram Data Without Strong Supervision 4 th Mihhail Matskin. In Proceedings of the 2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI), Santiago, Chile, 3–6 December 2018; pp. 158–165.
48. Kreyenhagen, C.D.; Aleshin, T.I.; Bouchard, J.E.; Wise, A.M.I.; Zalegowski, R.K. Using supervised learning to classify clothing brand styles. In Proceedings of the 2014 IEEE Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA, 25 April 2014; pp. 239–243.
49. Rutkowski, L.; Jaworski, M.; Pietruczuk, L.; Duda, P. The CART decision tree for mining data streams. *Inf. Sci.* **2014**, *266*, 1–15. [CrossRef]
50. Fuster-Parra, P.; García-Mas, A.; Cantallops, J.; Ponseti, F.J.; Luo, Y. Ranking Features on Psychological Dynamics of Cooperative Team Work through Bayesian Networks. *Symmetry* **2016**, *8*, 34. [CrossRef]
51. Mccallum, A.; Nigam, K. A Comparison of Event Models for Naive Bayes Text Classification. In *AAAI-98 Workshop on Learning for Text Categorization*; Madison, Wisconsin, 1998; pp. 41–48. Available online: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.65.9324&rep=rep1&type=pdf (accessed on 2 June 2020).
52. Cheng, J.; Greiner, R. Comparing Bayesian network classifiers. In Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence, Stockholm, Sweden, 30–31 July 1999; pp. 101–108.
53. Liu, L.; Su, J.; Zhao, B.; Wang, Q.; Chen, J.; Luo, Y. Towards an Efficient Privacy-Preserving Decision Tree Evaluation Service in the Internet of Things. *Symmetry* **2020**, *12*, 103. [CrossRef]
54. Song, Y.Y.; Lu, Y. Decision tree methods: Applications for classification and prediction. *Shanghai Arch. Psychiatry* **2015**, *27*, 130–135.
55. Farid, D.; Zhang, L.; Rahman, C.; Hossain, M.A.; Strachan, R. systems with, and U. 2014, "Hybrid decision tree and naïve Bayes classifiers for multi-class classification tasks. *Expert Syst. Appl.* **2014**, *41*, 1937–1946. [CrossRef]
56. Shalev-Shwartz, S.; Ben-David, S. *Understanding Machine Learning: From Theory to Algorithms*; Cambridge University Press: Cambridge, UK, 2014.
57. Siddiqui, M.F.; Mujtaba, G.; Reza, A.W.; Shuib, L. Multi-Class Disease Classification in Brain MRIs Using a Computer-Aided Diagnostic System. *Symmetry* **2017**, *9*, 37. [CrossRef]
58. Aggarwal, C. *Data Classification: Algorithms and Applications*; CRC Press: Boca Raton, FL, USA, 2014.
59. Mao, W.; Wang, F.-Y. Cultural Modeling for Behavior Analysis and Prediction. In *Advances in Intelligence and Security Informatics*; Elsevier: Amsterdam, The Netherlands, 2012; pp. 91–102.
60. Taddy, M.; Chen, C.-S.; Yu, J. Bayesian and Empirical Bayesian Forests. *arXiv* **2015**, arXiv:1502.02312.
61. Liu, Z.; Luo, P.; Qiu, S.; Wang, X.; Tang, X. DeepFashion: Powering Robust Clothes Recognition and Retrieval with Rich Annotations. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 1096–1104.
62. Louppe, G.; Wehenkel, L.; Sutera, A.; Geurts, P. Understanding variable importances in forests of randomized trees. In *Advances in Neural Iinformation Processing Systems*; Neural Information Processing Systems Foundation, Inc.: La Jolla, CA, USA, 2013; pp. 431–439.
63. Kohavi, R. A study of cross-validation and bootstrap for accuracy estimation and model selection. *IJCAI* **1995**, *14*, 1137–1145.
64. Sechidis, K.; Tsoumakas, G.; Vlahavas, I. On the stratification of multi-label data. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*; Springer: Berlin/Heidelberg, Germany, 2011; pp. 145–158.
65. Hossin, M.; Sulaiman, M. A review on evaluation metrics for data classification evaluations. *Int. J. Data Min. Knowl. Manag. Process* **2015**, *5*, 1.
66. Gupta, D.L.; Malviya, A.K.; Singh, S. Performance analysis of classification tree learning algorithms. *Int. J. Comput. Appl.* **2012**, 55.
67. Liu, Y.; Zhang, H.H.; Wu, Y. Hard or soft classification? large-margin unified machines. *J. Am. Stat. Assoc.* **2011**, *106*, 166–177. [CrossRef] [PubMed]

68. Wahba, G. Soft and hard classification by reproducing kernel Hilbert space methods. *Proc. Natl. Acad. Sci. USA* **2002**, *99*, 16524–16530. [CrossRef]
69. Tu, D.Q.; Kayes, A.S.M.; Rahayu, W.; Nguyen, K. ISDI: A New Window-Based Framework for Integrating IoT Streaming Data from Multiple Sources. In *Advanced Information Networking and Applications*; AINA 2019. Advances in Intelligent Systems and Computing; Barolli, L., Takizawa, M., Xhafa, F., Enokido, T., Eds.; Springer: Cham, Switzerland, 2020; Volume 926, pp. 498–511.

Article C

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Modeling the knowledge of an expert using artificial intelligence

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Abstract: In this study, an intelligent knowledge-based inference is proposed to support digital product development by automating fabric selection. This was achieved by modeling the relationship between technical properties of the fabric, and abstract fashion elements. Since the garment design and development are rather subjective and depend on the perception of the designer, the study adopted a sensory evaluation based methodology to acquire expert knowledge and applied a popular artificial intelligence technique widely used to analyze uncertain data i.e. fuzzy logic. To do this, we first collected real fabric swatches, their technical properties, and four pair of fabric handle descriptors. Next, we selected nine apparel style descriptors and their representative images to create mood boards. A questionnaire was administered to conduct semi-structured interviews during the sensory evaluation with experts in fashion and apparel from industry and academia. The collected data was then processed using fuzzy logic to create a set of 51 design rules helpful in conceptualizing products digitally.

Keywords. Artificial intelligence, fuzzy logic, sensory evaluation, product development, automation, apparel industry.

1. Introduction

In today's globalized and digitized world, computer technology has grown rapidly to assist humans in almost every field. Every industry is adopting the latest technologies like artificial intelligence, internet of things, big data analytics, virtual reality, augmented reality to increase business profitability [1]. The apparel industry has not been behind in adopting these new technologies and strategies, to enhance customer experience, satisfaction, and retention, and to improve the operations in the supply chain thereby making the business model more lucrative [2], [3]. Some of the applications including CAD software that are available to help in designing and creating patterns of the garments[4], Computer-aided manufacturing aids faster manufacturing [5], and 3D scanners help to get accurate sizes of the customers[6]. Most of the developed applications tend to simplify various manual operations and also bring accuracy in fashion design and manufacturing.

In the past, customizing and producing garments for individual customers was the norm. Though this helped in making every garment unique for the customer, it came at a cost. The number of tailors, machines, wastage of resources, and other factors restrained the production adding to the cost and hence, restrained further development of customization. In the early 1990s, as the outcome of the growing standardization in various industries, mass production of garments became the basic model for the apparel industry [7]. This model exhibited the benefits of economies of scale by delivering a higher quantity of products at a lower manufacturing cost. Even though this model is still practiced by most of the apparel industry, there has been growing concern with the customers' dissatisfaction with the current offerings, and increasing demands for a garment that is much closer to their requirements [8]. To provide the customer with a product that offers a higher value offering requires the industry to shift from masses to individuals i.e. standardization to customization [9].

The apparel industry has always been resource-driven, whether it is the raw materials that go into developing a product or the human resource that is required to bring those materials into realization as a product. However, to customize and cater to individual needs, without the added costs, the industry needs to be driven by knowledge. Knowledge, which is derived from the enormous amount of data generated by various supply chain activities, and the expertise of the human resources involved. It is crucial for both the stakeholders to work in tandem to make the industry agile enough for rising consumer demands. And hence, the utilization of the latest digital technologies to make use of this big data and extract knowledge from industry experts is an important and popular topic of research within the context of the apparel industry [10], [11].

A few studies have worked in this direction in order to digitalize the supply chain activities, promote agility, quick response, and promote the adoption of mass customization strategies in the apparel industry [12]–[15]. In the area of product development, there have been attempts to digitalize the pattern making process by creating a 3D garment pattern that encodes a pattern maker's knowledge to develop an interactive pattern making tool and support virtual try-on technologies [6], [16], [17].

In addition, a few studies have been carried out in order to transmit the designer's knowledge into a system that helps to produce intelligent recommendations, based on the stated requirements [18]–[20]. These algorithms are often focused on one of the aspects of a garment i.e. fit, style, material, or color. With the integration of all the aspects of a garment and related data, a system can be developed that can help to digitalize the supply chain processes, making it agile and efficient. A system that is based on modularization and standardization of garment style, fit, and material. The basic idea should be to offer customization of style at the designer's end and follow the mass-production model at the production end. The key to successful mass customization is to fulfill the customer's individual and diverse needs. Whether the needs of the customer are satisfied, will be evaluated by customer feedback. Hence, the requirement of a feedback mechanism is also a necessity. The system should include a recommendation engine that helps the customer in realizing their needs and receiving alternative options in case of dissatisfaction with the previous recommendation. The system would be further enhanced by the incorporation of modern digital technologies which provides customers a better visualization of their needs.

However, in order to build such a system a huge amount of data related to the product and other related operations is required. Since the apparel industry is dynamic in nature and requires human intervention in most of its operations, it is important to capture the expert's knowledge and thus, create a knowledge base consisting of design rules. Therefore, the purpose of this article is to tap into one of the expert categories of the apparel industry i.e. product designer's mind, and capture valuable knowledge that can help in creating such a knowledge base. With the help of this, a data-driven design process is realized, which will help product designers in the fashion and apparel industry to develop products faster according to the various design criteria.

2. Fundamental of sensory evaluation and soft computing

2.1. Sensory Evaluation

Sensory testing has been carried out for a long time to evaluate the perception of food, automobile, and other consumable products [21]–[23]. It is the technique used to assess, examine, and interpret the perception of products measured through sensory descriptors. The evaluator can be a trained professional i.e. objective testing or a consumer i.e. subjective testing [24]. However, it is most widely been measured using the consumers as evaluators to investigate their intention to buy a new product [25], [26]. This application of sensory evaluation is beneficial in decision-making in various operations ranging from product conception to monitoring post-launch perception. It can provide valuable insights into consumer behavior related to product acceptance and use. It can support the businesses to decide whether to scale up or down the production of a certain product by using these insights. Subjective testing is also widely adopted in research to investigate the adoption of the latest technologies and to understand consumer behavior at a much deeper level [27].
However, a few instances of application of objective testing were also found in research, where researchers collected data through a panel of experts evaluating products in order to create decision support or recommendation systems [16], [28], [29]. In the study by Krüsemann et. al., a sensory assessment was conducted among a panel of 20 experts to evaluate tobacco products [29]. The study in [28] explains the importance of creating knowledge during sensory evaluations among experts. The adoption of sensory testing as a tool in the consumable goods industry indicates that it is also relevant to be applied in the apparel industry. Therefore, this study uses sensory evaluation as an instrument to collect data from a panel of experts with working experience in product development in the apparel industry.

2.2. Soft computing- Fuzzy logic

Soft computing is a group of modeling techniques like fuzzy logic, bayesian statistics, and artificial neural network that helps in replicating the behavior of biological systems. As opposed to hard computing, soft computing is lenient towards uncertainty, inaccuracy, estimation, and partial truth [30]. These techniques are widely adopted to solve automation problems. Since the goal of this study is to model human knowledge, the adoption of soft computation techniques is not only beneficial but also a logical choice. Therefore, in this study, one such soft computing technology is used to model the collected sensory data.

Fuzzy logic was first introduced by Zadeh [31] as an approach to depict human knowledge, which is vague and imprecise by nature. Unlike the tradition set theory, in fuzzy logic, a fuzzy set consists of elements with partial membership ranging from 0 to 1 to define variability of classes that have unclear boundaries. For instance, if X is the universe of discourse with x representing its elements, then a fuzzy set P in X is defined as:

$$P = \{x, \mu_P(x) \mid x \in X\}$$

Here, $\mu_P(x)$ is the membership function of x in fuzzy set P.

A fuzzy inference system or a FIS maps the input space to an output space using the fuzzy rule base. A FIS builds fuzzy IF-THEN rules and tries to formalize a reasoning process based on human perception. The fuzzy IF-THEN rules, in their most basic form, follows the following pattern:

'If x is P then y is Q',

Here, P_i and Q_i are linguistic values defined by fuzzy sets in the universe of discourse x and y respectively, while x and y respectively are the input and output variables respectively.

At the most fundamental level, a FIS consists of four modules, fuzzification module, knowledge base, inference engine, and defuzzification module as shown in figure 1. The fuzzification module transforms the crisp inputs into fuzzy sets by applying a fuzzification function. In this step, for every set, a membership function is created. Membership function can be triangular, Gaussian, and trapezoidal. This study used a triangular membership function that is a collection of three points forming a triangle. Triangular fuzzy numbers, thus, defines each membership function, calculated using the following equations:

$$\mu(x) = \begin{cases} \dfrac{x - L}{m - L}, & for\ L < x < m \\ \dfrac{R - x}{R - m}, & for\ m < x < R \\ 0, & otherwise \end{cases}$$

Here, μ is the membership function of x, m is the best value, L and R are the smallest and largest values that m can take.

The knowledge base is the storage of the IF-THEN rules created by the system. The inference engine is the brain of the model i.e. the decision-making unit of the system as it simulates human reasoning by making fuzzy inference on the inputs and the rules. The defuzzification module transforms the fuzzy set back to the crisp values.

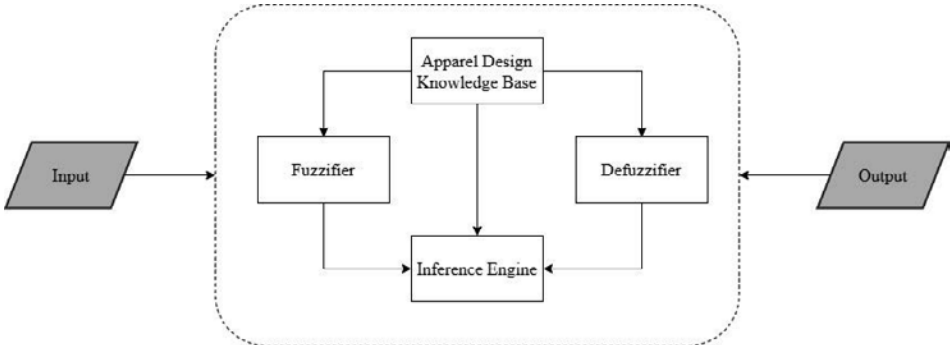


Figure 1. A general Fuzzy Inference System

The fuzzy inference system is mainly of two types, the Sugeno-type and the Mamdani-type [32]. In the former, the output membership functions are either linear or constant, while the latter has fuzzy membership functions of the output. Hence, Sugeno-type FIS can only be used for multiple input single output systems, whereas Mamdani-type FIS can be used for both multiple input single output and multiple input multiple output systems. This study uses Mamdani-type FIS to model the relationship between fabric and style parameters.

3. Material and Methods

This introduces a model for fabric selection to support product conceptualization and development in the apparel industry. The research framework adopted to build the model is shown in figure 1. The proposed method commences with the selection of real fabric swatches, fabric sensory descriptors, and apparel style descriptors and corresponding images. Using these, a sensory evaluation was conducted with the product designers, fashion designers, textile designers working in the industry or academia with an experience of more than four years. The sensory-based evaluation is considered to be an effective approach that can easily transform qualitative human perception into quantitative measurements, which can further support conceptualizing products digitally.

In this study, we designed eight following experimental procedures, as shown in figure 1, for the acquisition of data and the overall perception of the experts related to the fabric and style themes. These experiments are described in detail in the sections to follow.

3.1. Subjects

For experiments, one and two, five experts from textile design were invited to select the fabric swatches and to shortlist sensory descriptors of fabric handle. The five experts were based in France, and the two experiments were conducted in person. Similarly, for experiment three, five experts from fashion design were invited to shortlist the apparel style descriptors. In the same experiment, an online survey was conducted to select five representative images for each apparel style descriptor. The survey followed snowball methodology i.e. it shared with fashion designers in France, China, India, and Germany, who then shared the survey with their contacts.

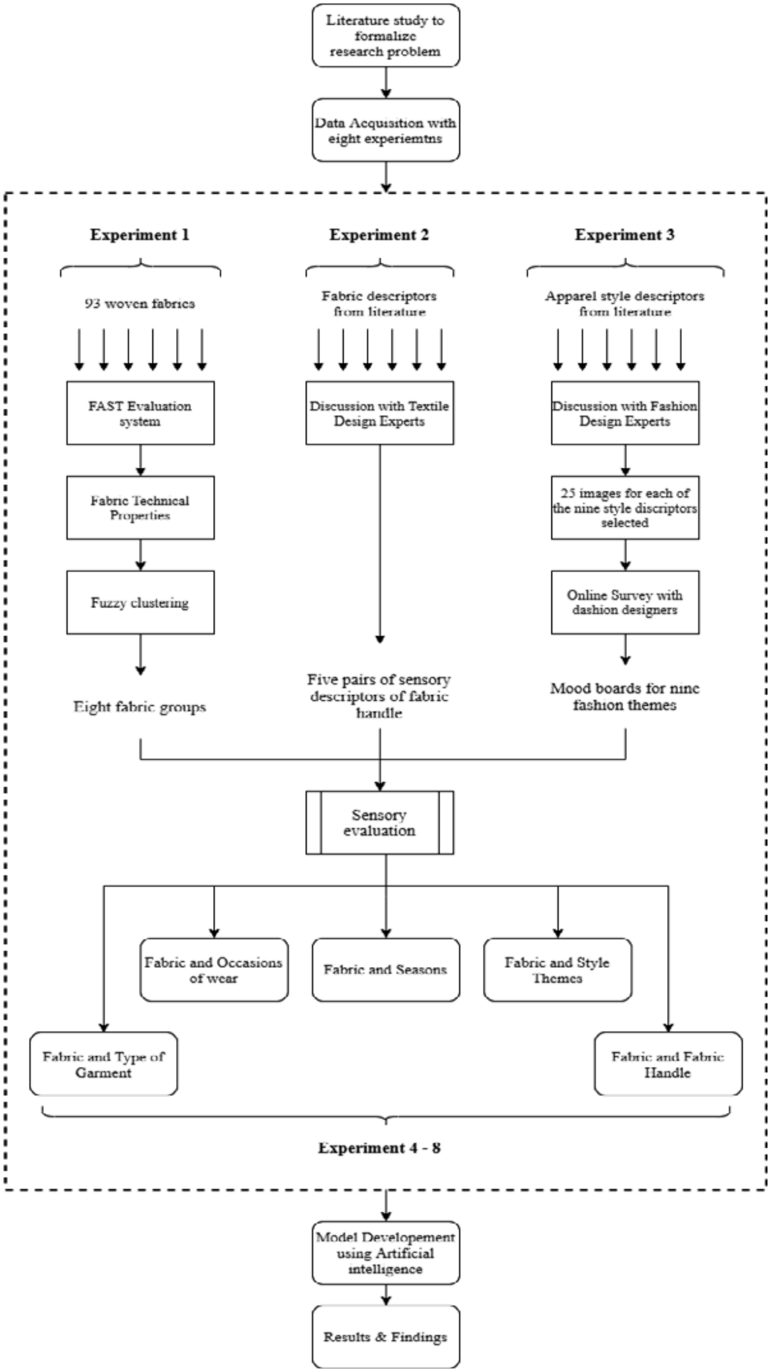


Figure 2 .Research Framework

The evaluators that formed the panel for sensory evaluation were carefully selected based on their expertise and years of experience. The panel comprised 20 participants with 1) expertise in fashion design, product development, or textile design, 2) at least four years of experience in one of the mentioned areas, and 3) worked closely with apparel products in the industry or academia. The participants were from China, India, and Sweden, and sensory evaluation experiments were conducted within a period of one year. The results from this panel are considered the tool that will help in the most suitable fabric

3.2. Experiment 1: Acquisition of real fabric swatches and their technical properties

Fabric is one of the most important attributes in a garment. The same style produced with a different fabric can completely change the look and drape of the garment. As much as it is important, it is also difficult to choose the right fabric according to the customer requirement, especially in an agile production environment. Hence, the first experiment was to select real fabric swatches and collect corresponding technical properties.

3.2.1. Collection of fabric swatches

Due to the availability of a huge amount of fabrics, it is important to restrict the scope. Hence, this study focuses on the book by Clive Hallete and Amanda Johnston, “Fabric for Fashion: The Swatch Book” [33]. The book has 125 most recognized and widely used varieties of fabrics. To further limit the scope, only woven fabrics have been considered, which constitute approximately 80% of the fabrics (100) in the book. The first step of this study was to collect the fabric swatches, which were collected from a book of swatches.

3.2.2. Collection of Fabric technical and mechanical properties

The next step was to collect fabric technical properties like density, weight, and mechanical properties like tensile strength, bending resilience. These properties of the chosen fabric were extracted from Lectra’s software Modaris. Modaris makes use of the same fabrics for the virtual prototyping of apparel. Once the data was extracted, the incomplete and missing data were removed, which reduced the number of fabrics to 93. During the sensory evaluation process, the panel will be given these real fabric swatches for assessment. However, to find a large number of participants was challenging, and hence, in order to collect enough responses per fabric, k-means clustering was performed on the fabric technical properties.

3.2.3. Clustering fabrics based on technical properties

As discussed in the previous section the need for performing clustering, in this step k-means clustering was performed on technical properties of 93 fabrics. Before the clustering was conducted, a principal component analysis (PCA) was performed to identify the most important properties. Based on the results of PCS, k-means clustering was implemented.

3.3. Experiment 2: Acquisition of fabric sensory descriptors

Fabric sensory descriptors: Fabrics are often judged by their hand feel, due to which it is important to consider sensory descriptors of fabric handle, and establish a relation between the technical properties and hand feel. To do this, the related literature was reviewed and 115 sensory descriptive words were collected. This list of words was scanned for synonyms and duplicates and then provided to five experts specializing in textile design to shortlist the most relevant descriptors. In consequence, five pairs of sensory descriptors were selected.

3.4. Experiment 3: Acquisition of apparel style descriptors and images

Another important aspect of a garment is its 'Style'. Style can be perceived in different ways. For some people, it represents their personality, and for others, it is the way of being a statement. Based on the perception, different customers want different styles every day. Hence, it is also important to study how style relates to basic customer requirements and to different fabrics.

3.4.1. Collection and selection of apparel style descriptors

There is a gamut of styles evolving every season and it is sometimes difficult to keep up. However, it is possible to consider a few basic and broad themes to establish a connection between the styles and fabrics. Therefore, simultaneous to the previous step relevant literature was studied to find apparel style descriptors. A total of 53 descriptors were collected, which after removing synonyms and duplicates and shortlisting by five experts specializing in fashion design were reduced to nine apparel styles.

3.4.2. Collection and selection of apparel style images

Style mood boards: Style themes are incomplete without a visualization. For any designer to develop and customers to select, it is important to provide style descriptors in a visual format. Therefore, for each theme 25 representative images were collected. These images were then presented theme-wise in an online survey, where the fashion and apparel designers from France, India, Germany, and China selected the five most relevant images. After receiving 67 responses, the survey was concluded. The selected images were then used to create style mood boards for each style descriptor.

3.5. Sensory Evaluation

Sensory-based methods translate qualitative expert knowledge into quantitative results as discussed in section 2.1. Hence, the purpose of the sensory experiments in this study is to acquire expert knowledge on the relations between fabric and style of a garment by quantitatively evaluating a set of real fabric swatches and mood boards of style descriptors. It included experiments 4-8 as shown in table 1. In order to conduct the experiments, 20 experts with specialization in apparel product development from industry and academia were carefully selected. All the experts had extensive experience working closely with the product.

Table 1. Experiments for Sensory Evaluation

Experiment #	Purpose
4	Sensory evaluation of fabric and style themes
5	Sensory evaluation of fabric and seasons
6	Sensory evaluation of fabric and occasion of wear
7	Sensory evaluation of fabric and type of garment
8	Sensory evaluation of and fabric handle

The fabric swatches collected in experiment 1, the fabric handle descriptors collected in experiment 2, and the apparel style descriptors collected in experiment 3 with their corresponding mood board were used during the sensory evaluation. Each participant was given eight fabrics, each representing a fabric cluster formed in experiment 1, and the mood boards of the nine apparel styles to evaluate, and a questionnaire to record their responses. The participants were given 1.5 hours to complete the assessment, during which they were asked to feel the fabric and answer the questions. The quantification of their knowledge was done with the help of an evaluation scale presented in Table 2. The scale is defined to describe the suitability of a fabric for a style, season, garment type, and occasion of wear. Moreover, they were also asked to rate the handle of the fabric on a similar scale.

Table 2. Evaluation scores and Linguistic terms used for sensory evaluation

Evaluation Scores	Evaluation Terms	Linguistic Terms
1	Extremely Unsuitable	Poor
2	Unsuitable	Very Bad
3	Slightly Unsuitable	Bad
4	Intermediate	Fair
5	Slightly Suitable	Good
6	Suitable	Very Good
7	Extremely Suitable	Excellent

3.6. Data Analysis using artificial intelligence

Consequently, the data collected through the sensory experiments were analyzed using a popular artificial intelligence technique in soft computing i.e. fuzzy logic. More, specifically, a fuzzy inference system of type-Mamdani was designed using the logic presented in figure 1 in section 2.2, which ultimately helped in formulating 51 design rules. The results from the various experiments are presented in detail in the next section.

4. Results and Discussions

The results of the experiments are the following: In Experiment 1) 93 fabrics are clustered using their technical properties, Experiment 2) and 3) availed expertise of fabric and fashion designers to create a semantic space of fabric and style, and select representative images of apparel style, with Experiment 4) to 8) sensory evaluation with 20 experts was conducted to examine their perception regarding the relationship between fabric, styles, season, occasion of wear and fabric handle.

4.1. Experiment 1

In experiment 1, after selecting the 93 fabrics from the book [33], the number of fabrics were reduced using k-means clustering. This was done in order to reduce the number of samples that will be used for the sensory experiments. Before applying the clustering method, principal component analysis (PCA) was implemented to identify the optimal number of features that capture the maximum amount of variance in the data and thereby, reduce the dimensionality. There were 13 features in the original data, which were reduced to eight with the application of dimensionality reduction.

These eight features were further used to cluster the 93 fabrics, by initially fitting the top PCA components to the k-means algorithm to determine the optimal number of clusters. The result indicated that forming eight clusters with k-means clustering, i.e. k= 8 is the most optimum scenario for the data in use. Finally, the k-means algorithm was executed resulting in eight fabric clusters as shown in figure 3.

These eight clusters of fabrics were further provided to 5 experts from textile design (invited for experiment 2) to select one representative fabric from each cluster, keeping in mind the application of the fabrics in the apparel industry. The eight chosen fabrics are Wool Barathea, Cotton Mousseline, Linen Heavy, Polyester Chiffon, Wool Basketweave, Silk with elastane, Linen Holland, and Polyester Sateen, and their real-swatches as used during the sensory assessment are shown in figure 4. The technical properties of these fabrics (as assessed by the FAST evaluation method) can be found in table A2 in appendix A.

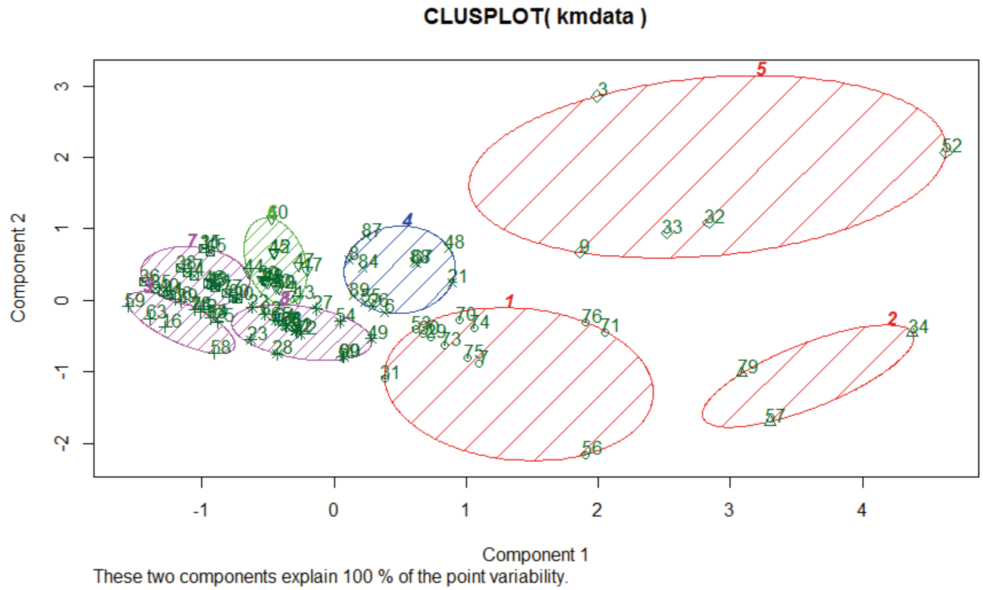


Figure 3. Eight fabric clusters using k-means clustering

Figure 4. Fabric swatches (Top, left to right: Wool Barathea, Cotton Mousseline, Linen Heavy, Polyester Chiffon. Bottom left to right Wool Basket weave, Silk with elastane, Linen Holland, and Polyester Sateen)

4.2. Experiment 2

This experiment aimed to find sensory descriptors that best describe the fabric handle. In order to do this, the extant literature related to the textile or fabric handle that discusses the different descriptors of fabric handles were studied. Out of the 115 descriptors collected, duplicates and synonyms were removed during the first step of data reduction. In the second step, five experts from textile design were invited to select the pairs of fabric handle descriptors that can describe the selected fabrics in the most efficient way.
Finally, four pairs of sensory descriptors were shortlisted:

a. Soft - Hard
b. Rough - smooth
c. Compact weave - Loose weave
d. Light weight- Heavy weight

4.3. Experiment 3

This experiment was conducted in three phases. In the first phase, apparel style descriptors were collected from the literature. Out of 53 descriptors, further nine descriptors were shortlisted with the help of experts from fashion design. The nine apparel style descriptors selected are Trendy, Preppy, Feminine (girly), Elegant, Hipster, Edgy, Casual, Boho, and Athletic (sporty). In the second phase, 25 representative images for each descriptor were collected ensuring that they obey copyright guidelines. These 25 images were further shortlisted by the fashion designers through an online survey conducted amongst fashion designers. They selected the top five images that they believed best represented that particular style descriptor. The survey concluded with the receipt of 67 responses in one month. In the third phase, according to the responses of the survey, mood boards were created using the top five representative images for each theme. Figure 5 shows nine style themes and the corresponding mood board. These mood boards along with the fabric swatches from experiment one and fabric handle descriptors from experiment two made the evaluation material for sensory testing, discussed in detail in the next section.

4.4. Experiment 4-8

In these experiments, 20 experts invited from the apparel industry and academia participated in the sensory evaluation. The scale used during the evaluation is presented in table 2, and questionnaire used to record the answers during the evaluation can be found in appendix B. The averaged evaluation from each designer for eight fabrics is presented in table A1 in appendix A. As discussed in section 3.6, the responses received were analyzed using a popular artificial intelligence method, fuzzy logic, which is widely used to examine uncertain data. As shown in figure 2, two fuzzy inference systems were developed discussed in the next section.

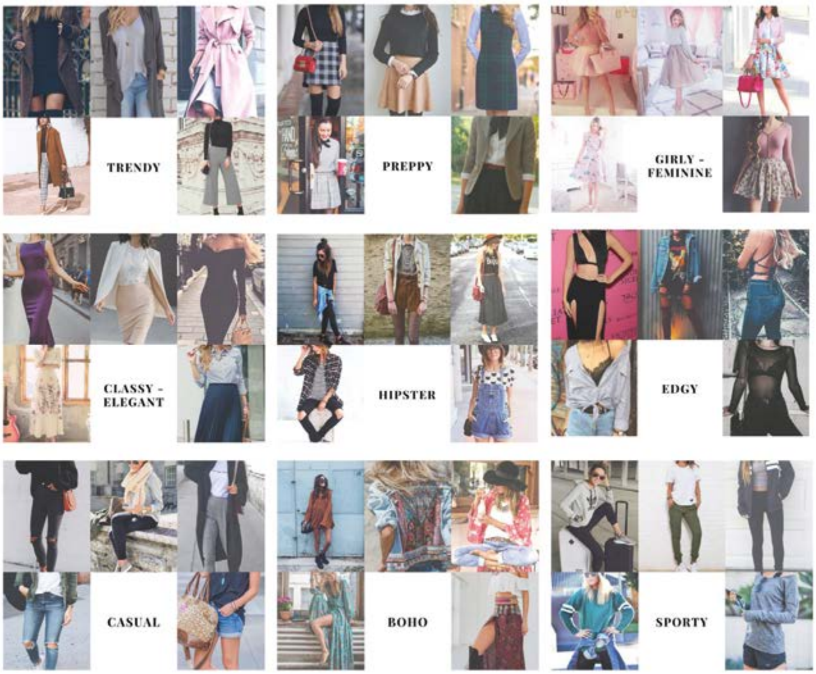


Figure 5. Mood boards for nine style descriptors

4.4.1. Development of Fuzzy inference systems

Fuzzy inference systems, as discussed in section 2.2, were realized to model human knowledge and create a decision support system that can help in digitally developing products. The fuzzy inference system based on the Mamdani algorithm is implemented on the fuzzy logic toolbox of MATLAB® software package. In order to synthesize fuzzy relations, the max-min composition method was selected. Input and output variables used in the two FIS models, along with their membership functions presented in table 3. As seen in figure 6, the triangular membership functions were employed to fuzzify the inputs in both the inference systems.

Table 3. Inputs of the Fuzzy Inference System

FIS #	Inputs	Sensory descriptors	Membership function range
	Type of Garment	Top wear, Bottom wear	0-1
	Occasion of wear	Casual, Work, Sport, Party	0-4
1	Season	Spring, Summer, Autumn, Winter	0-4

	Style Themes	Trendy, Preppy, Hipster, Feminine, Edgy, Elegant, Casual, Boho, Athletic	0-9
	Fabric handle: Soft-Hard	Extremely soft, soft, slightly soft, intermediate, slightly hard, hard, extremely hard	0-7
2	Fabric handle: Rough-Smooth	Extremely rough,…, Extremely smooth	0-7
	Fabric handle: Compact weave-Loose weave	Extremely compact weave,…, Extremely loose weave	0-7
	Fabric handle: Light weight-Heavy weight	Extremely lightweight,…, Extremely heavy weight	0-7
Output	Fabric	Wool Barathea, Cotton Mousseline, Linen Heavy, Polyester Chiffon, Wool Basket weave, Silk with elastane, Linen Holland, and Polyester Sateen	0-8

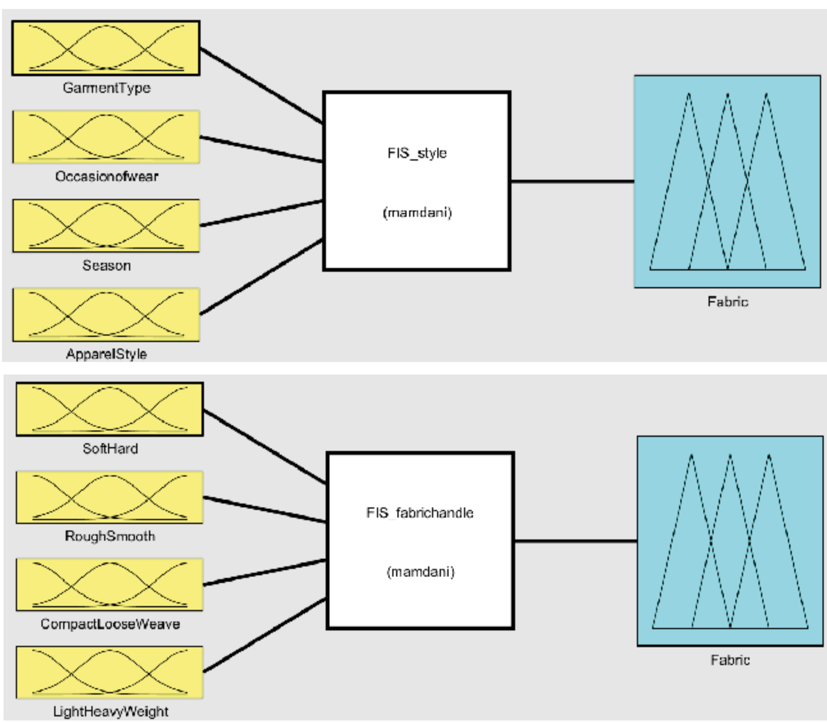


Figure 6.Structure of Fuzzy Inference Systems. Top, based on style. Bottom, based on fabric handle

In the next step, fuzzy if-then rules were constructed, which represent the fuzzy relations between input and output variables. Based on the experts' knowledge collected through sensory experiments, the rule base of the fuzzy model is constructed. A sample of the fuzzy if-then rules of the model established in MATLAB® software package for both the models are presented in figures 7 and 8.

Figure 7. Fuzzy rules for style

Figure 8. Fuzzy rules for style

Finally, the defuzzification process is implemented on fuzzy values to be converted into crisp ones. In this paper, the centroid method is employed for the defuzzification process. This step marked the completion of the development process of the FIS model. However, to show the working of the model and to make sure that it can be integrated with the existing information systems, a graphical user interface (GUI) was build using the app designer in MATLAB. The basic interface of the GUI for both the models is depicted in figure 9.

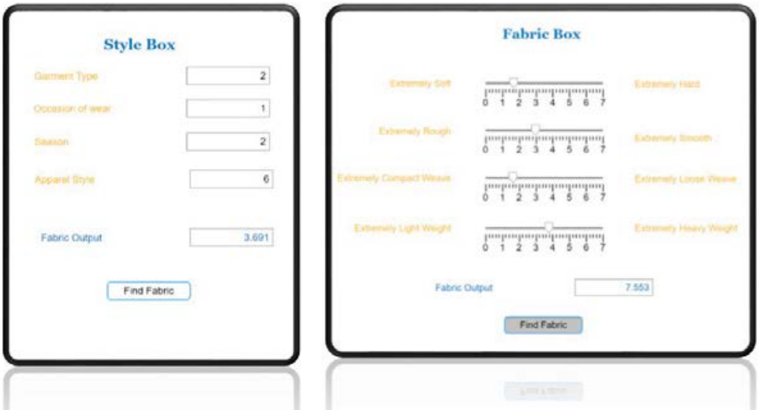


Figure 9. Graphical user interface for fabric selection, FIS 1 (left) and FIS 2 (right)

In order to get the desired output i.e. the most suitable fabric group, the user has to input values in the app. As shown in figure 9, by using the slider, a value between 0-7 can be chosen to depict the fabric handle. While as presented in figure 10, a user can provide a value between 0-1 for the garment type, between 0-4 for the occasion of wear and season, and between 0-9 for apparel styles. After pressing the Find fabric button, the output field will present a number between 0-8 depicting one of the fabric groups.

5. Conclusion

In a highly dynamic and changing environment, apparel businesses have to build effective systems in order to fulfill the growing customer demands and to improve the efficiency of the current production model to have a cost-effective business. With increasing customer awareness and evolving needs, and due to the advent of the internet, the apparel industry readily adopted the flexible manufacturing business strategy. However, the adoption of this strategy involves numerous challenges for the industry, such as 1) to accurately predict and forecast future demand, 2) to have a flexible production system that works efficiently with producing as less as one garment per style, 3) to have a platform that can facilitate interactions among the supply chain actors as well as between customer and producer. These challenges can be overcome with the help of technologies like artificial intelligence and big data analytics, which can support the digitalization of industrial operations.

In this article, one such application of artificial intelligence is discussed i.e. automating the fabric selection process during the conceptualization of a garment at the product development stage. Here, a tool is developed by using fuzzy logic on information extracted from expert knowledge. With the help of this information, 51 design rules were created and integrated into the system. The relation between input and output information in the fuzzy proposed system is described as linguistic variables, which are more flexible and realistic in reflecting real situations. The proposed decision support system has a potential application in digital prototyping and development of products. The purpose of the system is to provide aid to the human resources working in the supply chain in making quick decisions for complex problems.

In the future, we would integrate multiple fuzzy inference systems in order to automate the entire product development process. Additional experiments with experts can be considered to get a close representation of the entire process. In addition, a classification model presented in one of our earlier publications can be combined to enrich the knowledge base of this model [34]. Moreover, images of the fabrics and styles can be integrated to introduce a visual representation of the output and inputs. This can be beneficial for the apparel industry as it will be computationally more efficient and can be integrated with the existing information systems. However, it is a complex procedure that requires further in-depth research and hence, is one of the most important subjects to be considered in future researches.

6. Acknowledgment

7. References

[1] P. Gomes, N. Magaia, and N. Neves, “Industrial and Artificial Internet of Things with Augmented Reality,” in *In Convergence of Artificial Intelligence and the Internet of Things*, Springer, Cham, 2020, pp. 323–346.

[2] C. Giri, S. Jain, X. Zeng, and P. Bruniaux, “A Detailed Review of Artificial Intelligence Applied in the Fashion and Apparel Industry,” *IEEE Access*, vol. 7, pp. 95364–95384, 2019.

[3] P. Yildirim, D. Birant, and T. Alpyildiz, “Data mining and machine learning in textile industry,” *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 8, no. 1, p. e1228, Jan. 2018.

[4] W. Cheng and Z. Cheng, “Applications of CAD in the modern fashion industry,” *Applied Mechanics and Materials*, vol. 152–154. pp. 1505–1508, 2012.

[5] P. Wang, “Discussion on the Important Role of Computer-Aided Intelligent Manufacturing in the Transition of Garment Industry to Softening Production,” 2018, pp. 403–412.

[6] A. Lagė and K. Ancutienė, “Virtual try-on technologies in the clothing industry: basic block pattern modification,” *Int. J. Cloth. Sci. Technol.*, vol. 31, no. 6, pp. 729–740, Nov. 2019.

[7] M. T. Fralix, “From Mass Production to Mass Customization,” *J. Text. Apparel, Technol. Manag.*, vol. 1, no. 2, pp. 1–7, 2001.

[8] G. Da Silveira, D. Borenstein, F. S. Fogliatto, G. Da Silveira, D. Borenstein, and H. S. Fogliatto, “Mass customization : Literature review and research directions,” *Int. J. Prod. Econ.*, vol. 72, no. 49, pp. 1–13,

2001.

[9] T. L. Lewis and S. Loker, “Trying on the Future : Exploring Apparel Retail Employees ’ Perspectives on Advanced In-Store Technologies,” *Fash. Pract.*, vol. 9, no. 1, pp. 98–122, 2017.

[10] W. M. . Wong, W.K., Zeng, X.H. and Au, “A decision support tool for apparel coordination through integrating the knowledge-based attribute evaluation expert system and the T–S fuzzy neural network,” *Expert Syst. Appl.*, vol. 36, no. 2, pp. 2377–2390, 2009.

[11] A. Griva, C. Bardaki, K. Pramatari, and D. Papakiriakopoulos, “Retail business analytics: Customer visit segmentation using market basket data,” *Expert Syst. Appl.*, vol. 100, pp. 1–16, Jun. 2018.

[12] H.-T. Yeung, T.-M. Choi, and C.-H. Chiu, “Innovative Mass Customization in the Fashion Industry,” in *Innovative Quick Response Programs in Logistics and Supply Chain Management*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 423–454.

[13] S. Martínez, A. Errasti, and M. Rudberg, “Adapting Zara’s ‘Pronto Moda’ to a value brand retailer,” *Prod. Plan. Control*, vol. 26, no. 9, pp. 723–737, 2015.

[14] Z.-C. Liu, Y. Li, and Y.-Y. Wang, “Discover the digital technology application in fashion business models,” in *Textile Bioengineering and Informatics Symposium Proceedings 2018 - 11th Textile Bioengineering and Informatics Symposium, TBIS 2018*, 2018, pp. 768–778.

[15] K. L. K. Moon, J. Y. Lee, and S. yeung C. Lai, “Key drivers of an agile, collaborative fast fashion supply chain: Dongdaemun fashion market,” *J. Fash. Mark. Manag.*, vol. 21, no. 3, pp. 278–297, 2017.

[16] X. Tao, X. Chen, X. Zeng, and L. Koehl, “A customized garment collaborative design process by using virtual reality and sensory evaluation on garment fit,” *Comput. Ind. Eng.*, vol. 115, pp. 683–695, Jan. 2018.

[17] S. P. Ashdown and L. Dunne, “A study of automated custom fit: Readiness of the Technology for the apparel industry,” *Cloth. Text. Res. J.*, vol. 24, no. 2, pp. 121–136, 2006.

[18] H. Peifeng, C. Yuzhe, S. Jingping, and H. Zhaomu, “Smart wardrobe system based on Android platform,” in *Proceedings of 2016 IEEE International Conference on Cloud Computing and Big Data Analysis, ICCCBDA 2016*, 2016, pp. 279–285.

[19] A. Vuruskan, T. Ince, E. Bulgun, and C. Guzelis, “Intelligent fashion styling using genetic search and neural classification,” *Int. J. Cloth. Sci. Technol.*, vol. 27, no. 2, pp. 283–301, Apr. 2015.

[20] L. C. Wang, X. Y. Zeng, L. Koehl, and Y. Chen, “Intelligent Fashion Recommender System: Fuzzy Logic in Personalized Garment Design,” *IEEE Trans. Human-Machine Syst.*, vol. 45, no. 1, pp. 95–109, Feb. 2015.

[21] C. . M. B. and L. C. Phat, “Evaluation of umami taste in mushroom extracts by chemical analysis, sensory evaluation, and an electronic tongue system,” *Food Chem.*, pp. 1068–1077, 2016.

[22] W. J. . Kim, G. W. . Shin, J. H. . Lee, Y. S. Lee, and M. H. and Yun, “Identifying the visual interference by design and tactile properties of leathers using automobile interior,” in *In 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 2016, pp. 272–275.

[23] M. Raihan and C. S. and Saini, “Evaluation of various properties of composite flour from oats, sorghum,

amaranth and wheat flour and production of cookies thereof," 2017.

[24] G. and V. P. Ares, "Trained vs. consumer panels for analytical testing: Fueling a long lasting debate in the field," *Food Qual. Prefer.*, vol. 61, pp. 79–86, 2017.

[25] H. S. G. . V. Y. T. and S. M. Tan, "How will better products improve the sensory-liking and willingness to buy insect-based foods?," *Food Res. Int.*, vol. 92, pp. 95–105, 2017.

[26] K. O. . O. J. J. . M. R. M. . K. J. N. and A. M. H. Pambo, "The role of product information on consumer sensory evaluation, expectations, experiences and emotions of cricket-flour-containing buns," *Food Res. Int.*, vol. 106, pp. 532–541, 2018.

[27] M. . I. S. . M. M. and M. C. Jreissat, "Consumer driven new product development in future re-distributed models of sustainable production and consumption," *Procedia CIRP*, vol. 63, pp. 698–703, 2017.

[28] U. Savela-Huovinen, H. Muukkonen, and A. Toom, "Sensory expert assessor's learning practices at workplace: Competencies and contexts in sensory evaluation," *J. Sens. Stud.*, vol. 33, no. 2, Apr. 2018.

[29] E. J. . L. M. P. . de G. C. . de W. R. A. . P. P. H. . van T. L. . C. J. W. . van de N. S. . B. S. and T. R. Krüsemann, "Sensory analysis of characterising flavours: evaluating tobacco product odours using an expert panel," *Tob. Control*, vol. 28, no. 2, pp. 152–160, 2019.

[30] D. Ibrahim, "An Overview of Soft Computing," in *Procedia Computer Science*, 2016, vol. 102, pp. 34–38.

[31] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, 1965.

[32] L. Zadeh, "Fuzzy logic," *Computer (Long. Beach. Calif).*, vol. 21, no. 4, pp. 83–93, 1988.

[33] C. Hallett and A. Johnston, *Fabric for fashion : the swatch book*. Laurence King, 2010.

[34] S. Jain and V. Kumar, "Garment Categorization Using Data Mining Techniques," *Symmetry (Basel).*, vol. 12, no. 6, p. 984, Jun. 2020.

Appendix A

A 1. Averaged evaluation results from 20 experts

Descriptors	Aggregated evaluation result							
	f1	f2	f3	f4	f5	f6	f7	f8
Tw	5.15	2.6	5.5	5.25	4.7	5.35	5.2	4.7
Bw	5.5	4.9	3.15	4.5	4.95	3	2.45	3.7
Sh	4.2	5.15	2.5	5.1	3.7	2	2.1	3.25
Rs	4.05	3.8	5.1	4.25	4.25	5.6	5.3	5.25
Cl	3.7	4.8	5.4	5.65	3.9	2.5	4.85	3.45
Lh	3.95	5.35	2.7	4.4	4.05	2.3	1.65	2.6
Tn	5.55	3.85	4.95	2.9	4.05	4.85	5.6	4.55
Cs	3.6	5.3	5.1	4.3	3.5	4.1	4.8	4.3
Wr	5.9	4	2.8	2.85	4.6	3.9	4.75	4.75
So	2.55	2.4	3.9	2.45	3.55	2.85	2.15	2.45
Pa	5.25	3.95	2.9	1.9	3.85	5.9	4.8	5.95
Si	2.25	5.45	4.9	3.15	3.15	5.1	5.2	4.2
Su	2.05	5.3	5.2	3.85	3.8	4.85	5.2	4.3
Au	5.8	3.55	3.5	4.25	4.25	3.9	3.05	3.2
Wi	6.2	4.4	2.2	4.15	5.6	3.55	2.8	2.6
Tr	5.65	3.9	4.65	3.75	4.15	5.5	4.7	5.15
Pr	5.85	3.7	3.95	2.95	4	3.2	3.3	3.55
Hi	2.45	4.6	3.85	4.6	4.55	3.75	3.9	3.4
Gf	4.15	4.05	5	3.55	4.15	5.1	4.55	5.55
Ed	3.35	3.95	3.65	4	3.7	3.6	4.6	4.45
Ce	5.35	4.95	4.15	3.45	4.3	5.4	5.45	5.55
Ca	2.65	3.65	3.9	4	3.6	4.25	4.95	4.6
Bo	3.2	4.25	4.1	2.75	4.2	3.8	3.45	3.75
Sp	2.4	2.6	3.2	2.35	3.8	2.6	2.2	3
Sl	4.55	4.45	3.8	3	4.15	3.3	4.8	4.45
Cw	4.95	3.85	4.2	3.8	4.25	3.3	4	4
Ww	4.95	4.5	4.45	3.45	3.85	4.05	4.2	4.4
Hw	4.6	3.5	3.7	4.9	4.15	3.7	4.1	3.9
Tl	4.45	4.45	4.1	4.15	4.3	3.6	3.65	4.3
Bl	3.6	3.3	3.85	5.6	3.95	3.45	3.5	3.5
He	3.4	3.8	3.65	4.05	3.9	3.55	3.55	3.5
Ar	3.8	3.3	3	4.55	4.15	3	5.4	3.85

Table A2. Fabric Technical Properties

Cluster	**Fabrics**	Density	Material thickness	BR - Warp	BR - Weft	E5 - Warp	E5 - Weft	E20 - Warp	E20 - Weft	E100 - Warp	E100 - Weft	SR - Warp	SR - Weft
Cluster 1	Cotton Canvas	340	0.05	321.257	467.654	1.03434	0.489413	2.36327	1.26206	3.29088	1.68268	29.6211	29.6211
	Wool Barathea	276	0.05	14.0602	12.8557	0.688949	0.314383	1.89265	1.00406	3.51066	2.54406	9.3829	9.3829
	Wool Worsted Herringbone	266	0.05	31.417	22.0652	0.140476	0.723704	0.474129	2.14576	1.24804	5.01703	4.22582	4.22582
	Worsted Suiting Weight	296	0.03	10.3586	9.35688	0.364622	0.606749	1.11733	2.16213	2.7189	6.28288	7.47581	7.47581
	Linen	256	0.05	71.6703	21.2356	0.308733	0.305974	0.63335	0.678279	0.834933	1.46688	9.86118	9.86118
	Linen, natural	523	0.04	112.781	285.977	0.348965	0.466079	0.944315	1.05593	2.47499	1.97805	42.6398	42.6398
	Cotton Duck	274	0.06	132.554	76.7096	0.018746	0.25452	0.081589	0.730675	0.621346	1.6407	64.1697	64.1697
	Cotton Denim	385	0.08	97.3622	38.3066	0.009274	0.078016	0.114332	0.284151	1.03224	1.68484	1470	1470
	Cotton Moleskin	295	0.05	37.217	82.5888	0.291194	0.327404	0.560633	0.943755	0.717392	3.07502	816.166	816.166
	Cotton Jacquard	293	0.06	34.6059	32.3498	0.201751	0.280628	0.559572	0.948526	1.22229	2.81191	9.31876	9.31876
	Cotton Velvet	325	0.05	45.145	27.983	0.071637	0.204001	0.277711	0.507025	1.17945	1.37763	46.5644	46.5644
	Cotton Corduroy	360	0.08	58.3255	29.8626	0.222755	0.241679	0.480533	0.762091	1.57974	3.50424	96.4039	96.4039
Cluster 2	Wool Melton	591	0.13	165.458	95.7509	0.313484	0.254064	0.903075	0.76929	2.43925	2.34485	30.1773	30.1773
	Linen, heavy	605	0.08	215.348	215.348	0.284031	0.514137	0.684375	1.12741	1.46106	2.32587	4.97305	4.97305
	Jute	527	0.09	682.424	349.401	0.046509	0.017927	0.122301	0.069892	0.299448	0.307497	618.823	618.823

Cluster 3	Cotton Poplin	106	0.02	51.2801	12.5196	0.024804	0.161084	0.100275	0.401299	0.450234	1.22961	24.8128	24.8128
	Polyester Chiffon	86	0.01	1.74571	2.4526	0.072297	0.0747	0.268789	0.288543	0.837288	0.927394	4.56958	4.56958
	Wool Gauze	85	0.02	3.28208	2.9746	0.503689	0.953398	1.41171	2.97997	2.76514	6.58888	15.8367	15.8367
	Wool Delaine	115	0.02	7.24806	4.8842	0.258676	0.398288	0.681694	1.44324	1.32606	4.59818	34.4134	34.4134
	Silk georgette	66	0.02	0.684352	0.792223	1.50216	2.54804	3.53405	6.32969	5.20207	10.523	0.488816	0.488816
	Silk Charmeuse, sand washed	92	0.02	5.11255	1.45083	0.283953	0.769473	0.744552	2.20072	1.48194	5.31916	9.16263	9.16263
	Cotton Mousseline	151	0.01	12.5257	5.28429	0.277919	0.586145	0.582697	1.57675	0.769948	3.90923	5.19112	5.19112
	Cotton Organdie	37	0.01	105.36	10.3586	0.176379	0.5458	0.38368	1.11326	0.416311	1.53144	3.80868	3.80868
	Cotton Batiste	66	0.01	7.7952	3.6677	0.252141	0.7134	0.540675	1.56142	0.933699	3.04742	90.7165	90.7165
	Ramie	85	0.02	37.7264	301.811	0.061197	0.338482	0.176284	1.2457	0.398867	4.53764	3.08203	3.08203
	PU-coated polyester twill	106	0.02	57.9609	24.1277	0.296733	0.235999	0.619435	0.468125	0.69924	0.558152	35.7833	35.7833
	Metallic Hair	59	0.02	3.56784	12.7229	0.512187	0.048556	1.42242	0.144433	2.88036	0.408497	8.58001	8.58001
Cluster 4	Cotton Duck	214	0.05	54.024	46.0671	0.295481	0.296438	0.590568	0.681976	0.765037	2.03244	22.5434	22.5434
	Cotton Domette	126	0.06	11.2556	14.8817	1.11563	0.946706	2.49132	2.82393	3.00665	7.03168	9.34774	9.34774
	Viscose Satin	223	0.07	90.8819	6.3449	0.344937	0.032107	0.705254	0.147378	0.808797	0.729382	7.01381	7.01381
	Botony Wool Serge	199	0.05	8.45179	4.03013	0.408276	1.08618	1.21089	3.00361	3.00735	6.44887	7.45504	7.45504

	Silk Viscose Velvet	178	0.08	3.60484	1.84568	0.529846	0.325952	1.44379	0.799455	2.76559	1.55633	0.503702	0.503702
	Linen, Holland	189	0.05	52.9128	91.4334	0.356518	0.463964	0.736251	1.0506	0.869355	1.48637	8.95765	8.95765
	Cotton Satin	175	0.07	31.8929	20.6691	0.290106	0.288874	0.652424	0.727745	0.969539	1.67371	87.3449	87.3449
	Dogtooth poly-viscose twill	145	0.06	5.07431	5.07431	0.454924	0.3404	1.08709	0.963374	2.06815	2.20099	4.8247	4.8247
	Suedette	108	0.07	2.1872	120.016	0.333129	0.253981	0.933301	0.547233	1.89277	0.597209	75.3578	75.3578
	Piece-dyed poly viscose	173	0.07	8.05812	4.92227	0.338134	0.55447	1.41039	2.01512	4.47872	5.99035	3.57057	3.57057
	Yarn_dyed poly-viscose	173	0.05	5.46872	3.50358	0.574203	0.50251	1.41863	1.58552	2.70234	4.02444	6.79776	6.79776
Cluster 5	Silk seersucker with elastane	90	0.15	2.29604	1.0803	11.9537	16.3068	36.9439	40.3932	65.7475	59.2022	0.9469	0.9469
	Brushed Cotton	270	0.1	58.2234	12.0132	0.270245	0.314599	0.880097	1.67848	3.09284	6.6531	60.2358	60.2358
	Wool Tweed	320	0.13	26.5446	26.5446	4.63352	5.78217	12.2226	14.9606	17.969	21.0851	0.288296	0.288296
	Wool, Basket weave	305	0.12	70.8654	49.771	0.78464	1.18167	2.47173	3.47949	5.42532	7.5539	3.7893	3.7893
	Silk Noil Canvas	391	0.19	21.7283	13.6832	0.940017	0.852011	2.79196	2.74614	6.18965	5.85591	7.20489	7.20489
Cluster 6	Cotton Poplin with Elastane	129	0.04	20.9	4.51439	0.025475	0.381348	0.164939	2.40687	0.778107	12.9651	45.814	45.814
	Silk Organza	24	0.03	22.6769	10.6697	0.708943	0.779055	1.5413	1.69205	1.79646	1.95816	5.4502	5.4502
	Silk crepe de chine	68	0.05	0.70509	1.37713	0.568075	0.788689	1.76257	2.45202	4.24772	6.76881	6.97439	6.97439

	Cotton Sateen	140	0.04	12.0542	15.4572	0.020667	0.023359	0.07703	0.089399	0.26924	0.388579	499.762	499.762
	Polyester crepe de chine	111	0.05	1.15096	1.53192	3.50549	4.87563	8.48455	12.1162	10.0886	16.7652	0.072869	0.072869
	Polyester Sateen	100	0.04	8.933	8.61015	0.168011	0.118625	0.465641	0.3102	1.09535	0.793297	20.8813	20.8813
	Polyester and cotton poplin	95	0.04	4.03477	3.94095	0.046736	0.13328	0.273597	0.411808	1.33177	1.46597	107.546	107.546
	Silk Crepon	74	0.04	2.85734	1.49864	0.675988	2.77329	1.89928	7.21726	3.76304	14.4899	8.29756	8.29756
	Silk Crepe de chine	67	0.05	2.11794	1.5263	0.512681	0.932856	1.60419	2.44553	3.79148	5.99216	7.17222	7.17222
	Silk Shantung	100	0.05	4.44934	20.9814	0.323827	0.04372	1.09845	0.147754	2.57681	0.522071	272.24	272.24
	Silk Dupion	92	0.04	3.55237	40.9004	0.408622	0.116832	1.01627	0.314387	2.77633	0.593789	6.14746	6.14746
	Cotton Broderie Anglaise	115	0.04	6.39069	4.02446	0.044872	0.527597	0.22486	1.92172	1.07275	6.42431	14.8124	14.8124
	Cotton Cheesecloth	115	0.04	15.9744	0.555058	0.174924	8.87827	0.653476	22.9081	2.00146	43.9906	0.051912	0.051912
	Polyester cotton	98	0.04	9.41065	4.16219	0.362524	0.331176	0.781901	0.805894	1.03064	2.07953	18.3933	18.3933
	Rayon (Spun)	111	0.04	15.9108	7.8944	0.094183	0.276056	0.224474	0.874485	0.415479	2.55353	21.9612	21.9612
Cluster 7	Cotton gauze	43	0.03	2.38956	0.516145	0.039851	0.693463	0.168568	2.74933	0.549792	8.49853	8.32081	8.32081
	Cotton lawn	70	0.03	6.2531	2.44967	0.026855	0.245542	0.115383	0.911127	0.563643	3.23685	84.9122	84.9122
	Silk Chiffon	15	0.04	0.524929	0.341709	4.30233	2.43254	10.1731	6.09733	11.794	8.07558	0.844526	0.844526
	Nylon Organza	23	0.04	3.29683	7.4541	1.92621	2.43602	4.66855	5.76039	5.41847	6.50873	0.006011	0.006011
	Silk Satin	100	0.03	14.6508	10.7196	0.170101	0.059363	0.365418	0.218962	0.491105	0.779716	123.637	123.637
	Silk Chiffon	15	0.04	0.637069	0.155535	0.432771	0.601207	1.16149	1.72348	2.35458	3.69033	6.09614	6.09614

	Silk mousseline	17	0.02	0.234619	1.63246	0.152433	3.17759	0.425934	8.10446	1.01514	14.2741	0.486398	0.486398
	Silk muslin	34	0.03	1.18984	1.88942	0.265558	0.417988	0.72695	0.932571	1.42316	1.42904	7.23275	7.23275
	Silk Organza	24	0.06	3.02782	10.6697	1.35436	1.44681	3.27282	3.50996	3.6851	4.1216	0.622788	0.622788
	Silk Habotai	42	0.02	2.1396	7.22113	1.04824	0.612911	2.38827	1.38147	2.96946	1.59093	2.64435	2.64435
	Silk Habotai, sand-washed	48	0.02	1.67977	1.36572	0.265235	0.470741	0.688939	1.14082	1.32062	2.45808	9.66022	9.66022
	Silk Charmeuse	65	0.03	10.531	1.31637	0.37062	0.462671	0.845611	1.18721	1.27743	2.6848	8.91734	8.91734
	Silk Twill	61	0.03	9.88292	2.13471	0.34571	0.423252	0.709832	0.964195	0.860422	1.847	0.315872	0.315872
	Bamboo and Silk	85	0.03	7.0546	2.16962	0.240465	0.268988	0.602765	0.548067	0.943591	0.89777	8.98154	8.98154
	Polyester Chiffon	95	0.03	3.32455	1.70217	0.527117	0.405662	1.05118	0.950338	1.3414	1.94799	8.72271	8.72271
	Polyester Taffeta	71	0.03	20.7501	11.4272	0.205149	0.210805	0.414077	0.442518	0.450668	0.681564	36.8593	36.8593
	Silver lamé	32	0.02	7.68104	2.27586	0.035792	0.446098	0.123737	1.06399	0.429809	1.98634	32.6123	32.6123
Cluster 8	**Silk satin with elasane**	166	0.03	9.22482	1.72125	1.06768	1.91188	2.49118	6.0612	4.12076	17.9393	0.570485	0.570485
	Acetate Satin	120	0.03	14.6508	10.7196	0.170101	0.059363	0.365418	0.218962	0.491105	0.779716	123.637	123.637
	Polyester (crepe-back) satin	159	0.02	5.56425	4.52394	0.309005	0.401738	0.912555	1.34892	2.13502	4.16157	0.589246	0.589246
	Wool Voltaire	165	0.04	9.16925	6.3711	0.338126	0.820605	1.04448	2.54482	2.73611	6.92814	8.01523	8.01523
	Wool Crepe	194	0.02	11.7315	7.49087	0.624598	0.589418	1.4136	1.6917	2.79905	4.76037	3.59122	3.59122

	Silk Noil Plain Weave	238	0.04	13.2259	8.32887	0.444571	0.808633	1.09381	2.35163	1.99333	5.64966	8.05309	8.05309
	Natural Silk	177	0.03	2.79127	63.0027	0.684048	0.284832	1.67748	0.600079	3.26095	0.920507	18.1848	18.1848
	Linen with silk	196	0.04	87.1356	10.892	0.083454	0.28262	0.306255	0.809796	0.913997	1.80335	1.59117	1.59117
	Cotton Voile	164	0.03	5.73922	4.6662	0.431224	0.901693	1.01668	1.98836	2.00354	3.88762	4.35652	4.35652
	Cotton Poplin	155	0.03	7.55286	5.70003	0.088565	0.121701	0.624798	0.420189	3.4531	2.01266	124.505	124.505
	Cotton Chintz	151	0.03	32.562	11.6096	0.220879	0.276439	0.468278	0.673627	0.691441	1.74114	31.1381	31.1381
	Cotton Sateen	165	0.03	74.9371	21.5025	0.011782	0.031835	0.06183	0.134767	0.330942	0.655331	607.346	607.346
	Cotton Twill	164	0.03	43.6562	23.5079	0.168351	0.281926	0.387259	0.722772	0.771188	1.75186	75.8011	75.8011
	Cotton Drill	241	0.03	93.9479	36.7495	0.239392	0.279621	0.522341	0.698854	0.877779	1.85478	54.0178	54.0178
	Cotton Bark Weave	185	0.03	44.9929	17.1381	0.043359	0.062316	0.168575	0.515163	0.718682	2.79961	74.0842	74.0842
	Microfibre	137	0.03	4.79435	5.81857	0.251169	0.222556	0.718251	0.519674	1.5121	0.778773	34.8423	34.8423
	Viscose Cotton Grosgrain	242	0.03	41.5815	67.7086	0.164873	0.008935	0.448441	0.033428	1.28739	0.144099	70.0573	70.0573
	Polyester cotton	179	0.03	9.94724	7.60236	0.375289	0.368234	0.975488	0.913425	2.11899	1.79858	8.41264	8.41264

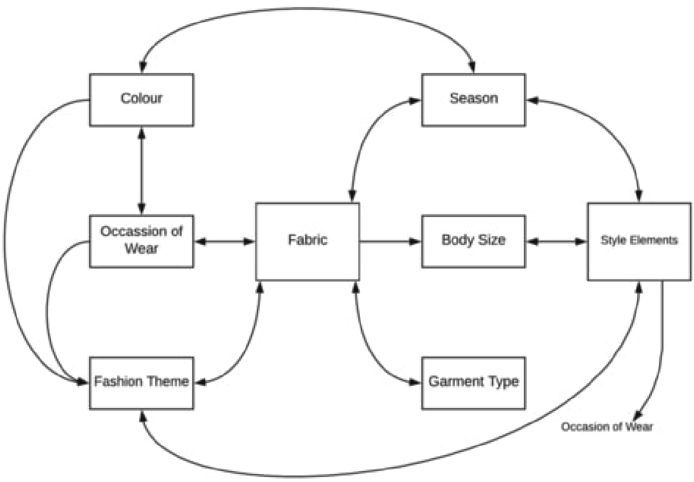
Appendix B

Sensory Experiments

Purpose of the Sensory Experiment

The purpose of the study is to establish a relationship of fabric with fashion themes, occasion of wear, seasons, fit and color. This sensory experiment is being conducted with fashion experts to empirically acquire fashion design knowledge by evaluating real fabric swatches and fashion theme mood boards. Each expert will be provided with at least 5 fabrics and 9 mood-boards to evaluate the belongingness of each fabric with the fashion mood-board, occasion of wear, seasons, fit and color on a Likert scale. The findings of the study will be used to design a designer-oriented recommendation system that can provide personalized recommendation to the customers. The interviews should take up to 1-1.5 hours per designer.

Please look at the image carefully.



Now answer the next question.

Do you agree with the connections shown in the previous image?

Evaluation based on Fashion Themes

Please provide some keywords for the fashion themes. *

1.
2.
3.
4.
5.
6.
7.
8.
9.

Rate each fashion themes from 1 to 7 based on suitability to the occasion of wear.

1: Extremely Unsuitable, 2: Unsuitable, 3: Slightly unsuitable, 4: Intermediate, 5: Slightly suitable; 6: Suitable; 7: Extremely Suitable

	Casual wear	Work wear	Sports wear	Party wear	Other special occasions
Trendy					
Preppy					
Hipster					
Girly/Feminine					
Edgy					
Classy/Elegant					
Casual					
Boho					
Sporty					

Evaluation based on Fabric Swatch

How often do you find inspiration from a fabric to design a garment?

		Rare	Slightly rare	Intermediate	Slightly often	Often		
Extremely Rare	○	○	○	○	○	○	○	Extremely often

Provide some keywords for the fabric. *

For which type of garment is the fabric most suitable?

	Extremely Unsuitable	Unsuitable	Slightly unsuitable	Intermediate	Slightly suitable	Suitable	Extremely Suitable	
Top wear	○	○	○	○	○	○	○	Bottom Wear

Rate the fabric handle.

	Extremely		Slightly	Intermediate	Slightly		Extremely	
Soft	○	○	○	○	○	○	○	Hard/Harsh
Rough	○	○	○	○	○	○	○	Smooth
Compact Weave	○	○	○	○	○	○	○	Loose Weave
Light Weight	○	○	○	○	○	○	○	Heavy Weight
Tailored	○	○	○	○	○	○	○	Not-Tailored

Please provide a rating from 1-5 on the basis of suitability of the fabric swatch with the following occasions.

1: Extremely Unsuitable, 2: Unsuitable, 3: Slightly unsuitable, 4: Intermediate, 5: Slightly suitable; 6: Suitable; 7: Extremely Suitable

	Rating
Casual Wear	
Work Wear	
Sports wear	
Party Wear	
Other special occasion	

Please provide a rating from 1-5 on the basis of suitability of the fabric swatch for the following seasons.

1: Extremely Unsuitable, 2: Unsuitable, 3: Slightly unsuitable, 4: Intermediate, 5: Slightly suitable; 6: Suitable; 7: Extremely Suitable

	Rating
Spring	
Summer	
Autumn	
Winter	

Please provide a rating from 1-7 on the basis of suitability of the fabric swatch with the following fashion themes.

1: Extremely Unsuitable, 2: Unsuitable, 3: Slightly unsuitable, 4: Intermediate, 5: Slightly suitable; 6: Suitable; 7: Extremely Suitable

	Rating
Trendy	
Preppy	
Hipster	
Girly/Feminine	
Edgy	
Classy/Elegant	
Casual	
Boho	
Sporty	

The fabric is most suitable for a body with:

	Extremely		Slightly	Intermediate	Slightly		Extremely	
Narrow Shoulder	○	○	○	○	○	○	○	Broad Shoulder
Narrow Chest	○	○	○	○	○	○	○	Wide Chest
Narrow Waist	○	○	○	○	○	○	○	Wide Waist
Narrow Hip	○	○	○	○	○	○	○	Wide Hip
Short Torso	○	○	○	○	○	○	○	Long Torso
Short Bodice	○	○	○	○	○	○	○	Long Bodice
Short Height	○	○	○	○	○	○	○	Long Height
Short Arm	○	○	○	○	○	○	○	Long Arm

Article D

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Toward a conceptualization of personalized services in apparel e-commerce fulfillment

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Abstract

Background

Today, customers´ perceived value does not only depend on the products, but also on the services provided by a firm. In e-commerce, it is important to shift the focus beyond the product and discuss the value of personalized services in the context of e-commerce fulfillment. Therefore, the purpose of the paper is twofold: 1) to develop a conceptual framework proposing satisfaction through personalized services as a middle-range theory, and 2) to suggest foundational premises supporting the theoretical framework, which in turn shape middle-range theory within the context of apparel e-commerce fulfillment.

Methodology

In this theory-driven paper, the authors apply the Scientific Circle of Enquiry (SCE), as it demonstrates the role of theorizing with the help of middle-range theory and empirical evidence and as such provides a methodological scaffolding that connects theory formulation and verification. The authors synthesize literature related to customer perceived value and satisfaction, followed by abduction focusing on understanding the empirical domain as it occurred in practice from company cases. The presented case studies are based on semi-structured interviews with three Swedish online retailers within the apparel industry. The theory-driven analysis results in suggestions of foundational premises.

Findings

Based on the theoretical foundations and empirical generalizations, three propositions are suggested. The premises regarding satisfaction through personalized service applied in the domain of apparel e-commerce fulfillment are: a) to ensure customer satisfaction require a value co-creation perspective using data during the pre-purchase phase, b) to ensure customer satisfaction and retention require added-value perspective during the post-purchase phase of the shopping journey, and c) to ensure satisfaction and convenience require an added-value perspective at the last mile.

Practical Implications: The apparel firms lose a substantial amount of revenue due to poor online customer satisfaction, leading to e-commerce not reaching its full potential. To enhance customer value, online retailers need to find a resort in advanced technologies and analytics in order to address customer satisfaction, and it is suggested that retailers shift their focus beyond the products and find ways to improve personalized service offerings to gain market advantage, improve fulfillment, drive sales, and increase customer perceived value.

Originality

To consider personalized services as a source for improving e-commerce fulfillment and customer perceived value, the main contribution of this study is conceptual as it presents a theoretical model developed from general theory, middle-range theory and verified with empirical claims.

Keywords. Personalized services, customer perceived value, customer satisfaction, apparel industry, e-commerce fulfillment.

1. Introduction

The advent of technology and increased globalization of apparel brands have transformed apparel online business models (Hagberg et al., 2016; Mollá-Descals et al., 2011). As an effect of globalization, cross-border restrictions have become less stringent, digital services have developed and conventional retailers face competition from both local and global brands (Dumitrescu and Vinerean, 2010; Holt et al., 2004). While as an effect of technology proliferation, contemporary customers are constantly connected through internet-enabled devices and have access to all the brands, increasing their choices. Due to this, customers are becoming more aware and demanding, and hence, have more expectations with the products and services offered (Botsman, R. and Rogers, 2010; Wang and Zhang, 2012). This is forcing the industry to niche themselves, for instance, by producing individually tailored products and delivering higher value to the customer. Instead of just buying a branded product, the customer gets to buy a product that is tailor-made for him.

Clearly, in a contemporary apparel market, it has become essential to increase perceived value and customer satisfaction by providing the best value offering and building strong customer relationships. As a consequence, apparel retailers are finding a resort in new technologies like the internet of things, artificial intelligence and big data analytics to gain a better understanding of consumers' behaviours, needs and wants (Amed et al., 2017). Today's technology, business models, and social context allow for widespread use and development of big data. Big data, for one, offers unique opportunities to make the visions of a perfect apparel product for customers a reality. There have been instances in research trying to utilize the power of big data with advanced analytics and artificial intelligence to improve perceived value and satisfaction by focusing on the product offering. More of it is associated with improving the manufacturing operations or providing limited garment customization options (Banica and Hagiu, 2016; Fogliatto et al., 2012; Shang et al., 2013). However, the application of digital technologies to tackle business-to-consumer challenges is scant (Giri et al., 2019), and there is a lack of research focusing on digital technologies and consumer-related services. The apparel industry is facing a pressing challenge with customer's dissatisfaction with the current way it operates and requires new ideas expanding the view on customer demand and how to raise customer value and satisfaction with augmented service offerings. Also, apparel managers are facing new challenges and opportunities in COVID-19 pandemic times. The year of 2020 so far has proven particularly difficult for apparel businesses as revenue dramatically decrease as a result of this event.

It is suggested that creating an exceptional customer experience all through the customer journey is one of the main goals to drive business profitability. During the quarantine, people have had more time to stay at home and shop online, and as a result, online retailing have a potential to drive future apparel businesses to a much greater extent than before. It is thus important to understand people's satisfaction with apparel e-commerce. The customer's purchase experience does not only depend on the product itself, but retailers might also exploit big data into consumer insights, and transform such knowledge into augmented services integrated in the marketing strategies (Bonetti et al., 2020). In a purchasing process followed in a traditional fixed store setting, customers are responsible for unit-level fulfillment services like picking products off the store shelf, moving these to the checkout lane, and providing delivery to homes and other consumption points. Hence, in such settings, the customer has the first-hand experience with the product before the actual purchase, and the delivery point (i.e. when the customer takes their product home) is usually a routine task. However, in terms of e-commerce, the physical distribution activities are much more important to the customer as the delivery point will be the first time when the customer actually interact with the product. Therefore, it makes sense to focus on a personalized experience during order fulfillment, improving satisfaction and perceived customer value better with non-product related experiences, and thus, making the relationship with the customer stronger (Cao, L. and Li, 2015; Davis-Sramek et al., 2008). Before and on delivery, apparel retailers need to provide customers with more than just the product. It is important to inculcate trust and feeling of loyalty to the firm by also providing memorable experiences with the help of personalized services. Some services, however, might be an additional cost to the company, albeit if it increases customer engagement and loyalty, then it contributes to the firm's overall growth. Although the interest in personalized products has grown considerably in recent years, little attention has been paid to analyze customer perceived value and satisfaction of personalized services in the context of online apparel. Hence, for a firm to have a competitive advantage, it needs to think beyond the product and add value through different stages of the customer journey. This can be achieved through superior experiences by implementing personalized services during both pre-purchase and post-purchase phases.

The value-adding attributes and unique experiences across various buying channels and shopping phases are of major importance to the customer when they choose between different retailers (Verhoef et al., 2015). The probability of re-purchase will be greater if the retailer succeeds in providing something unique and of value to the customer. We believe that personalized services can contribute to unique value additions to a customer's shopping journey, and identify the need for conceptualizing personalized services to tailor apparel e-commerce fulfillment. Hence, this paper suggests re-thinking customer perceived value by extending its focus to personalized service offerings and more specifically, satisfaction through personalized services related to pre-purchase and post-purchase phases. In order to advance the science and practice of personalized services, the purpose of this paper is to provide foundations and bridging the domains of apparel e-commerce fulfillment using satisfaction through personalized services as a middle-range theory to bridge Customer Perceived Value (CPV) theory and empirical research by applying the Scientific Circle of Enquiry (Brodie et al., 2011) The Scientific Circle of Enquiry (SCE) demonstrates the role of theorizing with the help of middle-range theory and empirical evidence and as such provides a methodological scaffolding that connects theory formulation and verification. The rationale is that general theory is too broad and abstract to easily be linked to empirical research, alas the middle-range theories act as a bridge to connect them (Brodie et al., 2011; Kolyperas et al., 2019). Three Swedish business cases are used to suggest propositions to support the framework and serve as exemplars of the suggested middle-range theory.

The rest of the article is structured as follows. Section 2 describes the overall methodology followed for empirical data collection, analysis, and model conceptualization. Section 3 presents the findings from the literature review on customer perceived value and satisfaction through personalized services in the online customer journey, and the empirical generalizations of apparel e-commerce fulfillment as deduced from the three cases. Finally, sections 4 address the discussion and conclusion of the study.

2. Method

In order to broaden conceptual thinking on personalized services, the authors sought a path of guidance from customer perceived value literature and empirical studies from the field. In this study, as shown in figure 1, satisfaction through personalized services are used to bridge the gap between customer perceived value and the empirical domain of personalized services in apparel e-commerce fulfillment.. An abductive way of theorizing was chosen where the focus was on understanding the empirical domain as it occurred in practice in the presented cases, reading, interpreting, and comparing transcript interviews with the help of theory. In the first phase of the study, relevant literature was used to bring an understanding of the concepts involved i.e. customer perceived value and satisfaction through personalized services at pre- and post-purchase.

The authors analyzed the articles and searched for concepts and ideas that could support the challenges of providing apparel e-commerce fulfillment, and identified a pattern to interpret the interviews. The transcript interviews served as empirical evidence and claims. Finally, the conceptual understanding was used to fill in the 'question marks' in the model by identifying empirical claims and to present foundational premises in this paper.

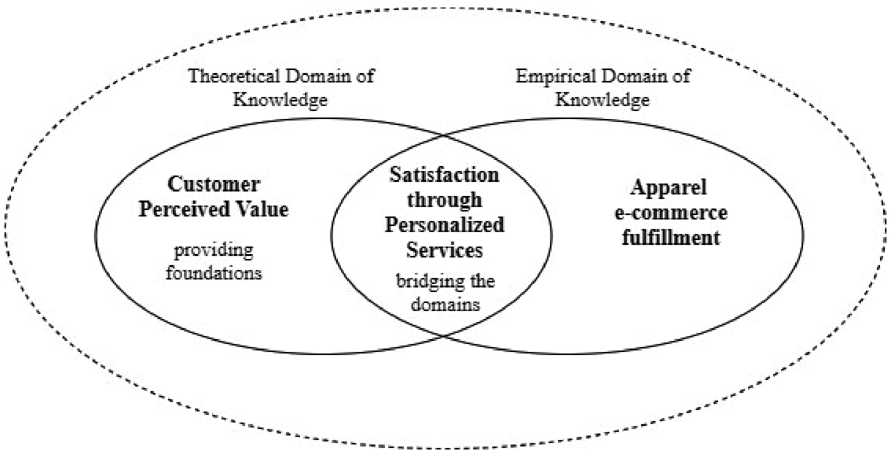

Figure 1: A framework of the conceptual model for viewing and using satisfaction through personalized services, based on customer perceived value.

2.1. *Data collection and analysis*

The empirical data was part of a research project between 2016-2018 and commissioned at collecting practice-oriented cases that serve as illustrations and/or explorations of the retail phenomenon, customer experience and customer satisfaction. During the research project semi-structured interviews were conducted with key-employees in 10 different types of retail companies, including industries such as apparel, cosmetics, home textiles and home electronics. The companies operated different channel formats that included bricks-and-mortar stores, online, both online and offline selling. This study present purposefully selected empirical findings from three of these companies as they are matching pairs and offer on-line strategies and apparel. The cases were audio-recorded and labelled according to the company name, informants' designation and function, description of the session, and duration (as depicted in Table I). The interviews were done with key employees from three companies and performed in Swedish and then translated into English. In order to avoid bias, the informants were selected based on their experience and knowledge, and from different hierarchical levels and functions. The data consist of seven in-depth interviews with employees at the three firms, both at senior and junior management level, as well as handling operational functions such as logistics and supply chain management. The informants in the study are described below in Table I. The lowercase 'a' and 'b' refer to different sessions of the interviews.

In order to ensure confidentiality in this paper the three retailers are referred to as A, B, and C. The online apparel retailers are particularly suitable for illuminating and extending relationships and logic among constructed propositions discussed in the next section. They provide a strong base for theoretical development; clarify the context of discovery, and the proposed middle-range theory. Thereby, enhancing the understanding of satisfaction through personalized services. An overview of the case exemplars regarding operations is presented in Table II. The data collected through the interviews and extensive review of the literature were analyzed in depth by breaking the interviews down, code it in MS Excel with the help of a general theoretical foundation, bridge the domain with the help of middle-range theory, resulting in an empirical generalization of personalized services within apparel e-commerce fulfillment that can be supported and verified with the suggested conceptual framework. Thusly, the theory-driven analysis captures empirical claims with the help of foundational premises that can extend the notion of personalized services in apparel e-commerce, presented in figure 1.

Table I: Informants in the study

Company	Informant's designation and function	Description of sessions	Duration
A	1. CEO, Senior Manager	In-depth interview 1a	60 min
A	2. Head of Logistics, Junior Manager	In-depth interview 2a	45 min
B	3. CEO, Founder, Senior Manager	In-depth interview 3a, & 3b	60 min and 45 min
B	4. Business Developer, Founder, Senior Manager	In-depth interview 4a, & 4b	45 min and 45 min
C	5. CEO, Senior Manager	In-depth interview 5a & 5b	60 min and 60 min
C	6. Supply Chain Manager, Junior Manager	In-depth interview 6a & 6b	60 min and 60 min
C	7. COO, Senior Manager	In-depth interview 7a	60 min

Table II: An overview of the case exemplars

Company	Operational descriptions	Target group/groups	Personalized/tailored variables in shopping process
A	Focusing on customer relationship marketing (CRM), using advanced customer data to tailor each offering to relevance. The most important moment in the customer journey is when the customer receives the suggested outfit (based on historical transactions and style/preferences).	Middle-aged customers, premium	**Diagnosis of aesthetic preferences** Personal taste regarding packaging
B	Focusing on customer relationship marketing (CRM) where the delivery is seen as an important point of interaction. When the customer receives the package (a beautiful box), it should be a joyful event.	Middle-aged customers, premium	**Personal recommendations based on historical transactions** Designed craft beautiful boxes
C	Focusing on CRM, using data analysis to offer a convenient and smooth delivery option.	Young customers (10-25 years), premium	**A variety of delivery options** located according to customer convenience

3. Foundational constructs and empirical claims

In theory's most recent form, customer perceived value is considered to be a general theory as it is broad in scope and more abstract in nature. Customer perceived value has been a popular concern both to researchers and business practitioners across disciplines (Zauner et al., 2015). Based on the extant literature related to customer perceived value, it was noticed that customer perceived value is mostly associated with the product (Suryadi et al., 2018), but has also been used within the service literature to understand service quality (see e.g. Arslanagic-Kalajdzic and Zabkar, 2017; Behnam et al., 2020; Xuan Nguyen et al., 2020).. The understanding of perceived customer value helps to explain different areas such as behaviour and repeat purchasing as it describes the perceived net gains associated with the products/services acquired (Grewal, D., Iyer, G.R., Krishnan, R. and Sharma, 2003). When the perceived value is higher than the perceived cost, customer satisfaction is positively influenced (Cronin Jr, J.J., Brady, M.K. and Hult, 2000), which in turn contributes to customer loyalty (Colgate and Stewart, 1998; Tam, 2004; Zeithaml et al., 1996).

3.1. Ideas of value

The value that customers perceive is different for different customers and is closely related to price, quality, sacrifice and satisfaction (Fazal-e-Hasan et al., 2018). In addition, for customers value is an important attribute to make reasonable purchase decisions. Value for consumers involve both utilitarian and hedonic consequences as acknowledge by extensively cited studies by (Holbrook, 1999; Sheth et al., 1991). While utilitarian value is the easiest to provide, the competitive advantage for any business lies in how they offer hedonic value to their customers and know the difference between hedonic- and utilitarian value. Hence, customer value is “the fundamental basis for all marketing activity” (Holbrook, 1994, p. 22) and should be of concern to managers seeking to strengthen fulfillment.

Ever since the birth of modern marketing management, customer satisfaction has been a pursuit among the marketing community (Kohli and Jaworski, 1990; Kotler, 1968; Levitt, 1960; Piercy, 1995) (and a critical focus for effective customer care (e.g. Yang and Peterson, 2004) and loyalty (e.g. Kumar et al., 2013). However, the definitions on customer satisfaction are not clear but the most popular perspectives are either a transaction-specific approach or a cumulative and overall approach. Regardless of which approach is chosen, satisfaction is usually described as an end-result and a desirable goal among most managers; companies want their customers to be satisfied. But in order to understand satisfaction, one needs to explore why and with what satisfaction has aroused. Therefore, when elaborating on fulfillment, customer perceived value is the foundational construct, accompanied with utilitarian and hedonic value.

3.2. Ideas of customer involvement and engagement

Customer perceived value arises at nearly all phases in the customer journey, including but not limited to the pre-purchase phase, post-purchase phase, and the last mile, while customer satisfaction is considered to be a post-purchase or post-use assessment (Chi and Kilduff, 2011). Traditionally, the pre-purchase phase took place in a brick and mortar store setting; where the customer could interact with the product as well as take help from the sales assistants to make the purchase decision. However, today, with a lot of sales taking place online (websites or social media platforms), the possibility to influence the purchase decisions largely falls under how well does a brand guide and handle the purchase experience. The possibility of improving perceived value at this stage is an important strategy that a brand has to develop to gain consumer confidence and trust. In such a context, it is important to examine value as perceived from personalized services (Roy et al., 2017), and how such services lead to satisfaction. By considering personalizing services to be a resource for generating new forms of value, these services can be seen as a valuable source of gaining competitive advantage and attain customer loyalty. Today, apparel firms are struggling with immense competition due to globalization (Hagberg et al., 2016). By providing personalized services during the customer online journey, firms in the apparel industry can achieve higher customer perceived value by engaging and involve their customers through the journey. This is in line with Harrison and Hoek (2008), that says the key to increasing the customer value is by focusing on service quality, which gives an additional competitive advantage, as it is difficult to imitate by the competitors. Customer involvement and engagement will allow apparel retailers to improve fulfillment in an era when customer journeys are dispersed across different retail channels and the route to purchase may take a few minutes or many weeks. Therefore, when elaborating on fulfillment, customer perceived value is the foundational construct, accompanied with involvement and engagement.

3.3. *Ideas of retention, loyalty, and customer convenience*

Personalization in retail is the process of using customer data to provide tailored experiences to customers during different stages of the shopping journey. Every path to purchase is different, and with personalization, each path can be served based on specific needs and behavior, which will increase the possibilities of retention and loyalty. However, most retailers are nowhere close to delivering the personalized experiences that their customers indicate when leaving digital footprints. In addition, many retailers are unclear about which capabilities to build and create a truly personalized experience (Mark Abraham et al., 2019) and how to create customer loyalty. Providing personalized services should be in line with the goal to utilize the latest technology to tailor critical touchpoints in a manner that support retention. To better understand and examine the customer perceived value within personalized services at different shopping stages, it is important to identify the different stages. A customer's shopping journey begins with searching for the required product, to placing an order, and ends with the delivery of goods (Medini, 2015). This is a basic process, and if rightly understood an opportunity for providing a convenient shopping journey, which in turn might lead to both retention and loyalty. However, the criticality of this increases manifold when the shopping process is taking online as the customer can easily wander off to other retailers in search of a better value offering. For e-commerce businesses, the last mile is the only stage during which customers interact with the product for the first time, and is, therefore, a valuable determinant of customer experience (Croxton, 2003). A successful shopping process involves several activities, executed by different functional entities, and is heavily interdependent among the tasks, resources, and agents involved (Lin and Shaw, 1998).

Customers, nowadays, seek value in personalized experiences and expect their occurrence much earlier in the shopping process (Bilgihan et al., 2016; Walsh and Godfrey, 2000). Hence, personalizing services involves knowing how to connect the customer with the product and by extension the firm as early as the customers search for the product. Providing such a level of personalization is challenging and requires extensive domain experience in product, service, and order management with expert knowledge of digital business to evaluate existing technical outlook, recognize gaps and surface opportunities. One possibility of achieving the expected level of personalization is by finding a resort in the latest technologies and big data collected by businesses on the internet. This data can be used to deduce optimal shopping scenarios, create urgency to purchase and deliver the service personalization and convenience that the customers demand inherently driving perceived value. Therefore, when elaborating on fulfillment, customer perceived value is the foundational construct, accompanied with retention, loyalty and convenience. The following are three instances of apparel retailers, who have tried to harness the essence of value by targeting one of the aforementioned dimensions.

3.4. Case A – Empirical claims

Case A is an online retailer selling branded fashion to men with the promise to help them in designing a personalized wardrobe matching their style. Two entrepreneurs started this company, who believed there was a market for young men that wanted to buy high branded fashion but did not have the time/energy/skill/self-confidence to choose their outfit. The company wants to take care of its customers by helping them in expressing themselves with the help of fashion and providing personal service based on true commitment and concern. As one of the managers said: *"We live by the idea of helping our customers and every day we try to think that caretaking and commitment make us unique."* (Table 1, Interview 1a)

The system supporting this vision is based on a concept of mass customizing the shopping process by focusing on the individual customers' profile. This is an advanced form of personalized service, which can help the customers in making decisions when shopping for apparel online. Customers are invited to enjoy a *"diagnosis"* (Table 1, Interview 2a) of their aesthetic preferences and the information is stored as *"personal taste"* (Ibid). This information is then processed to find suitable garments that can meet the customers' individual preferences. In this way, the firm secures the possibility to offer customers individualized fashion styles and at the same time, reduce efforts for the customer in terms of the anxiety caused by the decision-making process. In addition, by including the customer more closely by capturing and responding to their preferences co-creates greater value. Moreover, when the customers realize that the retailer or brand is committed to listening, involving, and providing their exact requirements, they are more engaged in the entire shopping process. Here, co-creation is the basis for providing unique experiences and value to each individual. In doing so, the rationale of the brand is that a firm must create value for their customers in a manner that engages them in designing their own experiences, and hence, deliver personalized experience during that moment.

3.5. Case B – Empirical claims

Case B is a Swedish online actor selling fashion to female customers with a virtual store as the only retail channel, building their fulfilments on information flows and customer data. Two young entrepreneurs started the company in 2014. They built the company with the idea of personalization, as they use designed and handcrafted boxes to ship orders and invest a lot in the packaging process. One of the owners said he dislikes plastic bags: *"I really find plastic bags ugly and I have always believed in using branded packaging"* (Table 1, Interview 3a). Hence, while packaging a product, it is placed in a handcrafted box, silk paper is used for wrapping and a silk ribbon around the garment with a bow. The other owner added, "*We really strive to visually convey each order as a personalized offering and we try to imagine the customer opening the package at home, it should be like Christmas Eve*" (Table 1, Interview 4a).

Both managers and owners talked about adding value at the packaging stage, and the importance of having a dedicated staff. They believe in building relationships based on basic personalization capabilities i.e. addressing the customer by their name on a handwritten card, put into the box, wishing the customer good luck with the new garment, and a recommendation to wear the new product with something else bought from the firm. This offers a sense of closeness between the customer and the brand. This kind of personalization is often provided by luxury brands, with the loyalty of their customers being a benchmark for other retailers (Hur et al., 2014). It is still unusual to provide the customers with a product that is not packed in a brown cardboard box.

In addition, to bring extra value to the customers, in terms of personalized order information, when the order is placed, the customer receives a link and can follow the real-time product transportation on his or her mobile phone. The mobile application can help the customer to stay updated concerning their orders, and any new offers that the retailer might have designed for them. In fact, through mobile applications, the retailer can push personalized notifications, provide tailored recommendations on 'what else to buy' or 'what can go with the product they recently bought', and can also track the customers' past purchases. As one of the respondents explains: *"When I get information from the CRM system that this customer bought a pair of jeans last year, I can give her the recommendation to wear this beautiful sweater together with her jeans. This is something a lot of our customers really like; they understand that we really care about them.*" (Table 1, Interview 3b).

Based on this kind of customer relationship management system that focuses on providing the customer additional value all through their shopping process as well as establishing interactions post-purchase, enhances the overall customer experience with the brand. The point of delivery and the moment when the customer opens the package is central to the company and they not only encourage customers to enjoy that moment but also to spread the feeling to others by sharing their experience with their friends. Hence, on every handwritten customer card, the respondent reveal they write, *"Spread the joy to others – take a selfie and contribute to happiness!"* (Table 1, Interview 4b). The way that the firm works seizes the possibility to offer individualized services to enhance the customer experience both during pre- and post-purchase phases including the time of delivery, and builds value for the customer gradually over time.

3.6. Case C – Empirical claims

Case C is a specialized fashion online store focusing on sports and street fashion. It also offers merchandise through brick-and-mortar stores in limited geographical areas. The idea of personalized services stems from the customers having different needs regarding delivery options. *"The demand for individualized offerings is in fact our main challenge"* (Table 1, Interview 5b). Another of the respondents underline the importance of being a good listener *"I believe part of our success is our willingness to talk and listen to our customers"* (Table 1 Interview 6a). The target group is widespread in the Nordic countries but also in other European countries. With different countries having different distribution networks and regulations, the firm chose to invest in its delivery boxes, co-operating with Instagram. The 'Instaboxes' are placed at hot spots in different localities, identified by the customer database in each country.

The delivery service to Instabox is chosen during order placemen i.e. the customer chooses Instabox as the delivery option and identifies the most convenient place to pick up the order. The customer receives an SMS with a tracking link and a pin code, as management in the company discovered that up-to-date information was key "*Customers can wait, but they demand to know for how long and why. Think of a patient in a hospital. Some years ago he/she might have accepted that instruction. Today, they can wait if they know why*" (Table 1, Interview 7a). After the delivery, the customer uses the pin code to unlock the box and pick up the parcel. One of the interviewees says:

> *"We have noticed that our customers are very impatient and they want to have their delivery as soon as possible, but time is not the only variable. They also want their delivery in a convenient place, as most of our customers do not have a car. Therefore, they prefer public places such as the bus station, the mall, or subway station. I think it is necessary to offer a broad spectrum of delivery options, and the possibility to pick an order up at any time, not only during store hours. By using Instaboxes, we can do that"* (Table 1, Interview 5a).

The respondents in company C all believe that adding value at the delivery stage is very important expressed by one of the respondents as "freedom of choosing the delivery options can increase our customers' perceived value and acquire loyal customers" (Table 1, Interview 6b).

4. Foundational premises and discussion

Based on the instances from the cases presented in the above section, the authors now present a model that portrays the essential ingredients required in conceptualizing personalized services during the customer journey in order to provide apparel fulfillment e-commerce. The context of discovery is depicted in figure 2.

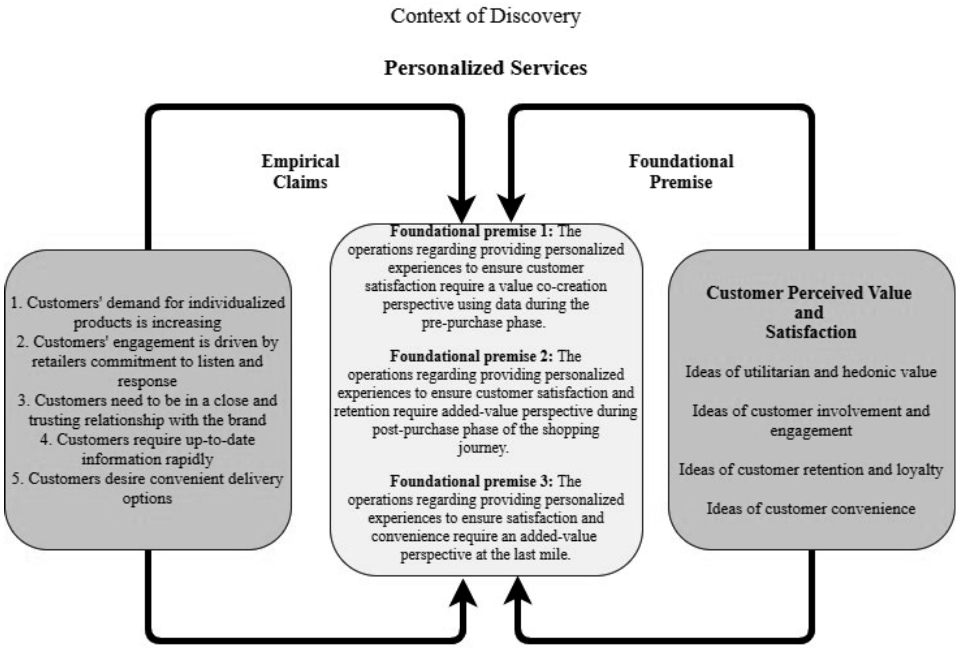

Figure 2. Context of discovery – Personalized services, Empirical claims and Foundational premises

The retail landscape has drastically transformed over the past decade, and the rise of e-commerce is largely accountable for these changes. Although many of today's customers purchase through both traditional stores and online retailers, the shopping experience is very different for each. Making purchasing decisions and getting assistance when needed is more difficult with e-commerce. However, there are many ways to support customers through the online journey and improve fulfillment.

Personalization is the key to provide unique experiences to the customer and improve e-commerce fulfillment, thereby raising the rate at which they translate a potential shopper into a loyal customer, and increase the lifetime value of customers. Nevertheless, so far, most retailers have not gotten as much traction from their personalization initiatives as they could have. Retailers that desire to get ahead and gain a competitive advantage will need to provide truly personalized services throughout the customer journey. By doing so, firms can drive their core business objectives, including building brand value, improving customer engagement, retention, and loyalty.

This is also in line with enhancing perceived value of the customers, who not only expect quality goods and services, but convenience and unique experiences during the entire process from searching for a product to receiving and using it. Considering this, formulating customer-centric strategies becomes a necessity as this will ensure a positive experience or transform a bad one into a good experience, thereby, reinforcing customer loyalty. Hence, propositions from the conceptual model in this study are three.

The first proposition is:

The operations regarding providing personalized experiences to ensure customer satisfaction require a value co-creation perspective using data during the pre-purchase phase.

The second proposition is:

The operations regarding providing personalized experiences to ensure customer satisfaction and retention require added-value perspective during the post-purchase phase of the shopping journey.

The third proposition is:

The operations regarding providing personalized experiences to ensure satisfaction and convenience require an added-value perspective at the last mile.

The conceptual model presented in figure 2 contributes to the theory of increasing customer perceived value using personalized services provided by apparel e-commerce retailers. It should also be considered that the maturity of personalization differs across industries, where the apparel industry is considered to be at a mid-level, there are industries like food and grocery that have achieved higher levels. Even though the case exemplars discussed are from apparel retailers, the model can be generalized for all e-commerce retailers. The idea of providing personalization is also dependent on the current capabilities of the retailer. To enhance customer value, retailers need to find a resort in advanced technologies and analytics in order to address customers' needs. Simply put, retailers need to shift their focus beyond the products and find ways to improve service offerings to gain market advantage, drive sales, and increase value to the customers.

4.1. Towards building a future research agenda

This study proposes a theoretical framework for apparel e-commerce fulfillment during pre-purchase, post-purchase, and the last mile of the customer journey. The theoretical framework is built on satisfaction through personalized services as the principle of middle-range theory, which bridges customer perceived value theory with empirical evidence. It is suggested that per the theoretical and empirical findings, the perspective of the retailers should shift beyond the product to services. This is in line with the firms competing at a global level, striving to bring a competitive advantage that can sustain the increasing customer demands. Adding a personalized service perspective to the e-commerce business strategy will support managers by providing unique experiences and increase overall value to the customer. A fine-tuned and unique shopping experience can go a long way in ensuring customer satisfaction and building loyalty in new and returning customers. Regardless of various changes in the industry, it remains evident that personalizing customer service in a way that improves fulfillmen will always be relevant for a successful customer experience strategy.

The focus of the study was to build a conceptual model around the idea of providing personalized services. There are some limitations to the study, one of them concerning verifications from the case studies. Even the most detailed narratives are usually a simplification of what were told, and even though the transcripts from the cases were rich, the authors chose to present few quotes and took them of the context of the narratives. It is therefore likely that a revisiting of the data would reveal other issues and aspects of the data. However, as the study focuses on conceptualization and is theory-driven, this limitation was deemed appropriate. One of the future directions would be to undergo more in-depth empirical research supporting the model suggested.

Competing Interest

No competing interests were disclosed.

References

Amed, I., Berg, A., Kappelmark, S., Hedrich, S., Andersson, J., Drageset, M. and Young, R. (2017), *The State of Fashion 2018*, available at: https://cdn.businessoffashion.com/reports/The_State_of_Fashion_2018_v2.pdf (accessed 29 December 2018).

Arslanagic-Kalajdzic, M. and Zabkar, V. (2017), “Is perceived value more than value for money in professional business services?”, *Industrial Marketing Management*, Vol. 65, pp. 47–58.

Banica, L. and Hagiu, A. (2016), “Using big data analytics to improve decision-making in apparel supply chains”, *Information Systems for the Fashion and Apparel Industry*, pp. 63–95.

Behnam, M.., Sato, M.., Baker, B.J.., Delshab, V. and and, M. (2020), “Connecting customer knowledge management and intention to use sport services through psychological involvement, commitment, and customer perceived value”, *Journal of Sport Management*, Vol. 1, pp. 1–13.

Bilgihan, A., Kandampully, J. and Zhang, T. (Christina). (2016), “Towards a unified customer experience in online shopping environments: Antecedents and outcomes”, *International Journal of Quality and Service Sciences*, Emerald Group Publishing Ltd., Vol. 8 No. 1, pp. 102–119.

Bonetti, F.., Pantano, E.., Warnaby, G. and Quinn, L. (2020), “Augmented Realities: Fusing Consumers’ Experiences and Interactions with Immersive Technologies in Physical Retail Settings”, *International Journal of Technology Management.*, Vol. 13 No. 3–4, pp. 260–284.

Botsman, R. and Rogers, R. (2010), “Beyond zipcar: Collaborative consumption”, *Harvard Business Review*, Vol. 88 No. 10, p. 30.

Brodie, R.J., Saren, M. and Pels, J. (2011), “Theorizing about the service dominant logic: The bridging role of middle range theory”, *Marketing Theory*, Vol. 11 No. 1, pp. 75–91.

Cao, L. and Li, L. (2015), “The impact of cross-channel integration on retailers’ sales growth”, *Journal of Retailing*, Vol. 91 No. 2, pp. 198–216.

Chi, T. and Kilduff, P.P.D. (2011), “Understanding consumer perceived value of casual sportswear: An empirical study”, *Journal of Retailing and Consumer Services*, Pergamon, Vol. 18 No. 5, pp. 422–429.

Colgate, M. and Stewart, K. (1998), “The challenge of relationships in services - a New Zealand study”, *International Journal of Service Industry Management*, Vol. 9 No. 5, pp. 454–468.

Cronin Jr, J.J., Brady, M.K. and Hult, G.T.M. (2000), “Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments”, *Journal of Retailing*, Vol. 76 No. 2, pp. 193–218.

Croxton, K.L. (2003), “The order fulfillment process”, *International Journal of Logistics Management*, Vol. 14 No. 1, pp. 19–32.

Davis-Sramek, B., Mentzer, J.T., Stank, T.. and Davis-Sramek, B., Mentzer, J.T. and Stank, T.P. (2008), “Creating consumer durable retailer customer loyalty through order fulfillment service operations”, Vol. 26 No. 6, pp. 781–797.

Dumitrescu, L. and Vinerean, S. (2010), “The glocal strategy of global brands”, *Studies in Business and Economics*, Vol. 5 No. 3, pp. 147–155.

Fazal-e-Hasan, S.M., Ahmadi, H., Mortimer, G., Grimmer, M. and and Kelly, L. (2018), “Examining the role of consumer hope in explaining the impact of perceived brand value on customer–brand relationship outcomes in an online retailing environment.”, *Journal of Retailing and Consumer Services*, No. 41, pp. 101–11.

Fogliatto, F.S., Da Silveira, G.J.C. and Borenstein, D. (2012), “The mass customization decade: An updated review of the literature”, *International Journal of Production Economics*, Elsevier, Vol. 138 No. 1, pp. 14–25.

Giri, C., Jain, S., Zeng, X. and Bruniaux, P. (2019), “A Detailed Review of Artificial Intelligence Applied in the Fashion and Apparel Industry”, *IEEE Access*, Vol. 7, pp. 95364–95384.

Grewal, D., Iyer, G.R., Krishnan, R. and Sharma, A. (2003), “The Internet and the price–value–loyalty chain”, *Journal of Business Research*, Vol. 56 No. 5, pp. 391–398.

Hagberg, J., Sundstrom, M. and Egels-, N. (2016), “The digitalization of retailing: an exploratory framework”, *International Journal of Retail & Distribution Management*, Vol. 44 No. 7, pp. 694–712.

Harrison, A. and Hoek, R. Van. (2008), *Logistics Management and Strategy: Competing through the Supply Chain*, 3rd ed., Pearson Education.

Holbrook, M.B. (1994), “Nature of customer value – an axiology of services in the consumption experience”, *In Rust, R.T. and Oliver, O.R. (Eds), Service Quality: New Directions in Theory and Practice*, Sage, Thousand Oaks, CA.

Holbrook, M.B. ed. (1999), “Consumer value: a framework for analysis and research”, *Psychology Press*.

Holt, D.B., Quelch, J.A. and Taylor, E.L. (2004), “How global brands compete”, *Harvard Business Review*, Vol. 82 No. 9, pp. 68–75.

Hur, W., Kim, M. and Kim, H. (2014), “The role of brand trust in male customers’ relationship to luxury brands”, *Psychological Reports*, Ammons Scientific Ltd, Vol. 114 No. 2, pp. 609–624.

Kohli, A.K. and Jaworski, B.J. (1990), “Market Orientation: The Construct, Research Propositions, and Managerial Implications”, *Journal of Marketing*, SAGE Publications, Vol. 54 No. 2, pp. 1–18.

Kolyperas, D.., Maglaras, G. and Sparks, L. (2019), “Sport fans’ roles in value co-creation.”, *European Sport Management Quarterly*, Routledge, Vol. 19 No. 2, pp. 201–220.

Kotler, P. (1968), *Marketing Management: Analysis, Planning and Control*, Prentice-Hall, New York, NY.

Kumar, V.., Dalla Pozza, I. and Ganesh, J. (2013), "Revisiting the satisfaction–loyalty relationship: empirical generalizations and directions for future research", *Journal of Retailing*, Vol. 89 No. 3, pp. 246–262.

Levitt, T. (1960), "Marketing myopia", *Harvard Business Review*, pp. 45–56.

Lin, F. and Shaw, M.J. (1998), "Reengineering the order fulfillment process in supply chain networks", *International Journal of Flexible Manufacturing Systems*, Vol. 10 No. 3, pp. 197–229.

Mark Abraham, Kerckhove Van, Robert Archacki, Josep Esteve González and and Stefano Fanfarillo. (2019), "The Next Level of Personalization in Retail", *BCG*, available at: https://www.bcg.com/publications/2019/next-level-personalization-retail.aspx (accessed 31 May 2020).

Medini, K. (2015), "Customer order fulfilment in mass customisation context - an agent-based approach", *International Journal of Simulation and Process Modelling*, Vol. 10 No. 4, pp. 334–349.

Mollá-Descals, A., Frasquet-Deltoro, M. and Ruiz-Molina, M.E. (2011), "Internationalization patterns in fashion retail distribution: implications for firm results", *The Service Industries Journal*, Vol. 31 No. 12, pp. 1979–1993.

Piercy, N.F. (1995), "Customer satisfaction and the internal market", *Journal of Marketing Practice: Applied Marketing Science*, Emerald, Vol. 1 No. 1, pp. 22–44.

Roy, S.K., Balaji, M.S., Sadeque, S., Nguyen, B. and and Melewar, T.C. (2017), "Constituents and consequences of smart customer experience in retailing", *Technological Forecasting and Social Change,* Vol. 124, pp. 257–270.

Shang, X., Liu, X., X., G., C., C., Ma, Y. and and Nyberg, T.R. (2013), "Social manufacturing cloud service platform for the mass customization in apparel industry", *Proceedings of 2013 IEEE International Conference on Service Operations and Logistics, and Informatics*, Ieee, pp. 220–224.

Sheth, J.N., Newman, B.I. and Gross, B.L. (1991), "Why we buy what we buy: a theory of consumption values", *J. Bus. Res.*, Vol. 22, p. 159.

Suryadi, N., Suryana, Y., Komaladewi, R. and Sari, D. (2018), "Consumer, Customer and Perceived Value: Past and Present", *Academy of Strategic Management Journal*, Vol. 17 No. 4, available at: https://www.abacademies.org/articles/consumer-customer-and-perceived-value-past-and-present-7393.html (accessed 27 April 2020).

Tam, J.L.M. (2004), "Customer Satisfaction, Service Quality and Perceived Value: An Integrative Model", *Journal of Marketing Management*, Vol. 20 No. 7–8, pp. 897–917.

Verhoef, P.C., Kannan, P.K. and Inman, J.J. (2015), "From Multi-Channel Retailing to Omni-Channel Retailing. Introduction to the Special Issue on Multi-Channel Retailing.", *Journal of Retailing*, New York University, Vol. 91 No. 2, pp. 174–181.

Walsh, J. and Godfrey, S. (2000), "The internet: A new era in customer service", *European Management Journal*, Elsevier Ltd, Vol. 18 No. 1, pp. 85–92.

Wang, C. and Zhang, P. (2012), "The evolution of social commerce: The people, management, technology, and information dimensions.", *CAIS*, Vol. 31 No. 5, available at: http://myweb.cmu.ac.th/somkeit.n/Phd/2.Tax online/The Evolution of Social Commerce.pdf (accessed 4 March 2019).

Xuan Nguyen, N., Nguyen, D.T., Suseno, Y. and Bui Quang, T. (2020), "The flipped side of customer perceived value and digital technology in B2B professional service context", *Journal of Strategic Marketing*, Routledge, pp. 1–21.

Yang, Z. and Peterson, R.T. (2004), "Customer perceived value, satisfaction, and loyalty: The role of switching costs", *Psychology and Marketing*, Vol. 21 No. 10, pp. 799–822.

Zauner, A., Koller, M. and Hatak, I. (2015), "Customer perceived value—Conceptualization and avenues for future research", *Cogent Psychology*, Vol. 2 No. 1, p. 1061782.

Zeithaml, V.A., Berry, L.L. and Parasuraman, A. (1996), "The Behavioral Consequences of Service Quality", *Journal of Marketing*, Vol. 60 No. 2, pp. 31–46.