THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

On fit uncertainty-reducing interventions in retail supply chains

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Cover:
The comic stripe ironizes how standards proliferate, and with respect to this thesis specifically, is a reference to product size standards. With product size standards, just because a size standard indicates a certain size does not necessarily guarantee that the size is a fit. As such, this thesis looks beyond size standards and deals with fit uncertainty-reducing interventions as a means to achieve product-customer fit.
Source: XKCD (https://xkcd.com/927/)

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Abstract

Fit uncertainty is used in this doctoral thesis to describe the customer's experience of uncertainty about the physical fit of a product when shopping for experience goods. Experience goods are products whose attributes are difficult to ascertain without physical examination. In online retailing, the ability to provide experiential fit information is limited, which poses product flow and inventory challenges for supply chains, including product returns, lost sales, and obsolescence. Thus, product fitting is a critical pre-sales activity for customers to successfully purchase fit-dependent products, and retailers must facilitate the fitting activity in order to reduce unnecessary product handling. To foster improved performance for retail supply chains of experience goods subject to fit uncertainty, this doctoral thesis sets out to explore the effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance.

Fit uncertainty-reducing interventions consist of existing digital product fitting and recommendation technologies. The research designs are included in the five appended research papers. Paper I uses a case survey of retail practices to develop a maturity model of digitalization of product fitting, and it proposes supply chain effects for each of the three maturity levels. Paper II uses three cases, design science, and interventionist research to conceptualize digital product fitting as an intervention that improves product flow and reduces lost sales in retail supply chains for experience goods. Paper III uses case research, quantitative analysis of return transactions, test of an intervention, and mathematical modeling to calculate product return costs associated with fit uncertainty in online retailing. Paper IV uses order and return transactions to investigate how online customers shopping for experience goods seek to mitigate fit uncertainty through different order-placing behaviors, and it assesses the cost implications of the behaviors. Paper V uses order and return transactions to explore the effects of an online apparel-fitting intervention on order performance outcomes and fit uncertainty-mitigating ordering tactics.

This thesis theorizes fit uncertainty-reducing interventions. The use of these interventions to facilitate the product-fitting activity can reduce fit uncertainty, leading to many benefits for the retail supply chain in terms of product flow, such as fewer returns and more sales. This thesis contributes to previous research on end-customer behaviors by focusing on order and return behaviors associated with fit uncertainty. The quantification of existent order and return behaviors is an important theoretical contribution to our understanding of the direct effects of fit uncertainty on retail supply chain performance. This thesis theoretically contributes to returns management and to inventory and assortment planning management; its practical contribution supports retail supply chains of experience goods that are reconsidering how they handle fit uncertainty and the unwanted effects thereof. This thesis provides hands-on knowledge on how the interventions work in real life and how they improve retail supply chain performance. Studying the link between fit uncertainty and retail supply chain performance is important for retailers and manufacturers' understanding of end-customer behavior and for improving product development and assortment planning to ensure availability of products that fit.

Keywords Fit uncertainty, digital product fitting, product recommendation system, product recommender, retail supply chains, experience goods.

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As I am writing this, I am aware of the entire journey. At our first encounter, I remember that Jan asked me if I knew what it meant to pursue a doctorate. I had a silly answer about writing, from which Jan immediately drew the conclusion that I did not know what it meant to pursue a doctorate. But now, now that I have ended this journey, I know exactly its implications. The best part is that I was thrown into the academic jungle, exploring the (to me) unknown apparatus of academia. Being part of an unfamiliar context has triggered curiosity and conversations: the unknown is exciting. I think a word that has permeated our research conversations has been ‘context’; it took several years for pragmatic me to understand what was being referred to, but as I now reach my doctorate, it could be the most important thing I learned from a research perspective, and it is also a word that echoes in my daily reflections. I want to thank you, Patrik and Jan, for your contributions, both in terms of written words and fruitful discussions but also in terms of personal support and public stand-in for me when I grieved my father’s passing. In retrospect, I am so satisfied that I pulled off this doctorate, and I am very pleased with the results: personal development and deepened knowledge, both subject-wise and academia-wise.

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Emmelie Gustafsson

List of appended papers

The thesis is based on the work contained in the following papers:

Paper I

Gustafsson, E., Jonsson, P., and Holmström, J. (2019). "Digital product fitting in retail supply chains: maturity levels and potential outcomes." *Supply Chain Management: An International Journal*, 24(5):574–589.

Paper II

Gustafsson, E., Jonsson, P., Öhman, M., and Holmström, J. (2021). "Swift and even product flows in retail supply chains: the impact of digital product fitting." *Submitted.*

Paper III

Gustafsson, E., Jonsson, P., and Holmström, J. (2021). "Reducing retail supply chain costs of product returns using digital product fitting." *International Journal of Physical Distribution and Logistics Management*, 51(8):877–896.

Paper IV

Gustafsson, E. (2021). "Retail supply chain implications of online customers' order-placing behaviors to mitigate fit uncertainty." *Submitted.*

Paper V

Gustafsson, E., Hjort, K., Holmström, J., and Jonsson, P. (2021). "Effects of virtual fitting technology on online customers' shopping journeys and order performance." *Submitted.*

Contents

1. Introduction

For many types of mass-produced experience goods, such as shoes and apparel, customers want to fit and experience the product by physically trying on the product before selecting it for purchase. In this thesis, *product fitting* is defined as the customer activity of selecting a mass-produced product that physically fits them.

This chapter begins by describing the background of this area of research, elucidating the problem of fit uncertainty in retail supply chains, the different types of interventions aimed at reducing fit uncertainty, and how retail supply chain performance is improved through reduced fit uncertainty. Then, the purpose and the research questions are presented, followed by the conceptual framework, the scope, and finally a short outline of the thesis.

1.1 Fit uncertainty in retail supply chains

The provision of experience goods online poses managerial challenges to retail supply chains, which have to cope with unnecessary product handling, excess inventory, and additional costs due to the effect of fit uncertainty. *Fit uncertainty* denotes the extent to which the customer cannot assess whether a product's attributes match their preference(s) (Hong and Pavlou, 2014), and it arises when the product is an experience good and the customer is as-yet unfamiliar with the product. *Experience goods* are products with attributes that are difficult to communicate from one party to another without physically experiencing them (Nelson, 1970) (e.g., the scent of a perfume, or the fit of footwear). In contrast, search goods are products whose attributes are transferable between parties without the need to experience them physically (Nelson, 1970) (e.g., books and TVs). Online marketplaces are ideal for search goods and digital goods (Alba et al., 1997; Huang et al., 2009), but not for experience goods involving fit uncertainty and requiring physical examination (Dimoka et al., 2012); this leads to a need for research into how fit uncertainty can be reduced for experience goods so as to foster retail supply chain performance.

Fit uncertainty for physical experience goods becomes a serious issue for retail supply chains supplying online marketplaces. Online marketplaces are limited in their ability to provide experiential information, and the customer is unable to experience the products before purchase. In physical stores, customers can touch, feel, and examine products to eliminate fit uncertainty; in the online search for physical fit (i.e., a product that physically fits a customer's body), fit uncertainty hinders efficient operations, due to an overwhelming effect of the product variety on offer and to insufficient communication practices that fail to communicate experiential fit information to the customer (Hong and Pavlou, 2014; Rabinovich et al., 2011; Weathers et al., 2007). For retailers to ensure they can satisfy their customers, they can increase the product variety and provide customers with more choice (Oppewal and Koelemeijer, 2005). Online retailers have the possibility of offering an abundance of product fit information to ameliorate fit uncertainty (Weathers et al., 2007), with the result that customers will likely find products that fit them. However, finding fitting products from among a wide variety of options is difficult for customers, who need to browse large assortments. Fit uncertainty is a problem in physical retail as well: although customers can try on the products before purchase, they are still left browsing the assortment of the retailer. Physical stores lose potential customers when the fitting sizes of appealing products are out of stock. Instead, customers purchase online to obtain the absent variant, shopping for the lowest price and leaving the physical store without compensation for showrooming (Mou et al., 2018).

Consequentially, retailers suffer from lost sales if they are unable to provide fitting products to customers (which is enabled by vast product variety or adapting products to the customers), or from obsolescence if there is no customer fit for the product (the aftermath of having vast product variety) (Wan and Sanders, 2017). As such, product variety both hinders and enables efficient operations of experience goods. For product variety to function as an enabler, several interventions are available that address the problem of losing sales due to the lack of fitting products as well as the risk that unsold products become obsolete. Providing experiential information is key to improving the performance of retail supply chains of experience goods (Hjort et al., 2019; Weathers et al., 2007).

1.2 Fit uncertainty-reducing interventions

Fit uncertainty-reducing interventions, as understood in this thesis, aim to communicate product fit characteristics so as to support customers in decision-making and final product selection of goods with high fit uncertainty. *Fit uncertainty-reducing interventions* are means that reduce fit uncertainty for experience goods; these means, or interventions, entail product fitting and recommendation technologies.

For retailers seeking to support customers in ordering fit-dependent products online, various technology-enabled fit uncertainty-reducing interventions can be applied to the retailers' webshops to make fit more comprehensible for the customers (Miell et al., 2018). In this approach, customers engage with the technology pre-sale, which hopefully alleviates the fit uncertainty concern. These interventions range from the most basic size chart converter to advanced product recommendation systems with algorithms predicting what other customers with similar physical measures purchased (Xiao and Benbasat, 2007; Guan et al., 2016). Size charts facilitate the customer's size selection process; however, just because the size chart indicates a certain size does not necessarily guarantee that that size is a fit. Products' sizes are determined by standards and agreements on standards between brand owners and the factories where the products are produced. Previous literature has shown that products that are size-labeled according to the same size standard differ, despite being labeled as the same size (Jurca and Dzeroski, 2013).

Technologies aimed at reducing fit uncertainty include size and style recommendations, fit visualization, and fit recommendations (Miell et al., 2018). Size and style recommendations are based on questions asked of the customer, which the customer answers to the best of their knowledge. An example of such an application is one where the customer measures a garment that they possess and inputs those measurements into the size tool, which then shows how the size of the product-to-buy relates to the customer's own garment using an overlaying silhouette. Fit visualization interfaces show tension maps for the customer to assess tightness; these interventions typically involve digital readings of the customers and products. Fit recommendation interfaces are based on a virtual try-on, where digital readings of customers and products are combined. Scanning is one established technology used for fit visualization and recommendation interfaces (Guan et al., 2016; Liu et al., 2017). Some product recommendation systems use customer data, such as purchase history and online product browsing data, to recommend products that match the gathered customer data. Such an approach aligns with fit recommendations in the sense that algorithms predict what customers with similar foot shapes purchased and can recommend products that fit according to what has fit others.

Product recommendation applications are an established technology in information systems research and are widely used for marketing purposes (Schrage, 2018). The most relatable application area concerns online retailing (Schafer et al., 2001), but even offline retailing uses recommendation systems for in-store efficiency and sales-pitch purposes (Gustafsson et al., 2019). In this thesis, fit uncertainty-reducing interventions are proposed as a means of improving retail supply chain performance by reducing fit uncertainty, as explained in the following section.

1.3 Retail supply chain performance

In recent decades, retail supply chains have increased the product variety offered to customers in the pursuit of growing sales and gaining market share. Increasing the product variety gives customers more choice, and it is more likely that they will find products that fit their preferences. Here, *retail sales* is conceptualized as a composite that incorporates all dimensions of high and low performance in retail supply chains and that corresponds to manufacturing output (Schmenner and Swink, 1998). If there is no product fit for a customer, the sale is lost. Finding fitting products is difficult for customers, which is seen in reverse product flows for online retailers. Thus, product fitting is a crucial pre-sales activity for customers when shopping.

The main effect of fit uncertainty is on product flow, especially in the reverse flow of products. For experience goods requiring fit, conventional practice involves a supply chain handling large batches and uneven flows of products that sit in inventory for significant periods of time (Şen, 2008), with inventory management as the primary approach to managing the trade-off between lost sales and obsolescence (Bijvank and Vis, 2011). Efficiently providing fitting products to customers is a costly process requiring inventory management and customer service: retail supply chains face trade-offs between cost efficiency and responsiveness in terms of customers' willingness to wait for a product (a delivery lead-time constraint), retailers' ability to stock variety (an inventory-holding constraint), and manufacturers' ability to responsively supply variety (a production-capacity constraint). Inefficiency in reaching customers results in waste and obsolescence, as indicated by retailers' markdowns or even disposals of products.

This thesis draws on large batches, as it is the most cost-efficient production mode. The premise is that manufacturers produce products given their economic profit-maximization rationality (Ketokivi and Schroeder, 2004), striving to achieve low unit costs for the products produced. In order to address lost sales (the customer not finding a fitting product) and obsolescence (the product not being bought by a customer), this research applies fit uncertainty-reducing interventions so as to match fitting products to customers. A product being available in stock does not necessarily mean that the product wanted by the customer is available, only that the assortment offered by the retailer is available. A customer seeking a product that the retailer intentionally does not offer is likely to consider it a service failure, while the retailer does not perceive the situation as lost sales because the product was intentionally excluded from the assortment (Fisher, 2004).

Previous streams of research have dealt with matching supply and demand in terms of end-customers and products. Operations strategy literature has focused on factory-specific capabilities in matching the type of production to the type of product (Schmenner and Swink, 1998; Ketokivi and Schroeder, 2004), while supply chain strategy literature (Fisher, 1997; Pagh and Cooper, 1998; Aftab et al., 2017) has focused on matching product type with supply chain setup. The supply chain strategy stream of research presents solutions for providing customers with fitting products without neglecting production efficiency, including integration of variety within a product (Gilmore and Pine II, 1997), postponement of the assembly point of a product until a customer order comes in (Zinn, 2019), customization of an already mass-produced product (Lim and Istook, 2012), and direct manufacturing (such as with 3D and 4D printing) (Sodhi and Tang, 2017; Patil and Sarje, 2021). The difficulty with mass customization solutions is their aim to produce affordable products with a sufficient degree of product variety and customization such that nearly all customers find what they want (Zipkin, 2001); consequently, these solutions neglect the opportunity to utilize the product variety available in the already-produced product supply. Retail operations literature has focused on matching supply and demand by providing large varieties of products and sizes in-store, but at a risk of obsolescence and high inventory costs in the supply chain (Mou et al., 2018; Ton and Raman, 2010). Later, retail channels came to include omnichannels for providing long-tail assortment (Brynjolfsson et al., 2010; Pereira and Frazzon, 2021).

As elaborated in Section 1.1, product variety enables providing fitting products to customers. Immense product variety poses the challenge of effectively managing the product supply. While the vast product supply is beneficial from a market perspective, as it satisfies customer demand, gains market share, and grows sales, it is detrimental to supply chain performance (Um et al., 2017). High performance in retail supply chains is a difficult-to-achieve combination of cost-efficient operations and sales, driven by product availability and the ability to navigate and find products in the product supply (Randall et al., 2011). Technology-enabled fit uncertainty-reducing interventions recommend products from the already-available product supply on the market, and as such, they achieve maximum sales performance. Here, *cost performance* is considered the retail supply chain's ability to provide products in a cost-efficient way. Given producing companies' economic profit-maximization rationality (Ketokivi and Schroeder, 2004), the available products on the market are produced using high productivity, which enables cost efficiency (Schmenner and Swink, 1998). By matching available fitting products to customers who need or want them, cost performance and sales performance can be achieved simultaneously and without a trade-off between the two.

1.4 Purpose and research questions

This thesis addresses fit uncertainty-reducing interventions as a means of improving retail supply chain performance when the supplied product is an experience good and thus subject to fit uncertainty. The text above makes it clear that fit uncertainty hinders retail supply chain performance, such that supply chains need to cope with unnecessary product handling, excess inventory, and additional costs. Fit uncertainty-reducing interventions aim to alleviate these effects caused by fit uncertainty; as such, the purpose of this thesis is **to explore the effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance**.

To align the research with the purpose, this thesis addresses two research questions. The first research question directs the research on establishing how fit uncertainty affects the performance of retail supply chains supplying experience goods. This research question is important and necessary in order to address the thesis's purpose (i.e., to explore the effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance). The second research question directly relates to the thesis's purpose by directing the research on revealing how fit uncertainty-reducing interventions affect the relationship between fit uncertainty and retail supply chain performance.

The two research questions are formally presented in the subsequent paragraphs, and each is motivated by central arguments from previous literature that are presented before the formulation of the respective research question.

Fit uncertainty pertaining to experience goods has been thoroughly researched in the domain of retailing and information systems, especially from an information-quality perspective (Hong and Pavlou, 2014; Lim et al., 2020). Previous literature has investigated online shopping behavior with respect to fit uncertainty, including the sequence of activities of online searches and online purchases (e.g., Childers et al., 2001; Huang et al., 2009; Kim and Krishnan, 2015), as well as the combinations of online searches and purchases in offline retail stores (e.g., Gallino and Moreno, 2014; Hult et al., 2019; Pauwels et al., 2011). Another stream of research has focused on fit uncertainty for experience goods with respect to negative emotions (Curwen and Park, 2014), self-mending of products and return policies (Gu and Tayi, 2015), vendor choice (Matt and Hess, 2016), and online communication practices (Weathers et al., 2007). However, these have not studied if and how fit uncertainty influences online ordering behavior, nor offered any quantification of retail supply chain performance measures (such as costs caused by additional product handling due to fit uncertainty). Research on how shoppers order experience goods online is still scarce. Such knowledge is important for quantifying the burden that fit uncertainty places on product handling and thus on retail supply chain performance. Knowledge regarding the effects of fit uncertainty on a customer ordering level is necessary when designing a supply chain supplying experience goods; if such knowledge is lacking, the negative effects of fit uncertainty cannot be systematically mitigated, and the positive effects cannot be systematically used in one's favor.

Fit uncertainty arises from the lack of both experiential product information and technology-enabled heuristics that indicate a match between product attributes and customer preferences (Hong and Pavlou, 2014). Previous literature has indicated a lack of research on how to compensate for the lack of physical presence toward customers' perceived information quality and, moreover, how to effectively transfer information on experience attributes from online retailers to customers (Lim et al., 2020) so that more customers find fitting products in the vast product supply (Weathers et al., 2007). Moreover, less attention has been devoted to the effects of fit uncertainty on retail supply chain performance. The literature related to product returns caused by fit uncertainty (Misra and Arivazhagan, 2017; De Leeuw et al., 2016; Saarijärvi et al., 2017) comes the closest to contributing to retail supply chain performance in the research domain of operations and supply chain management, but none of the reviewed research has elaborated on fit uncertainty as a specific hindrance to retail supply chain performance, neither from a factory performance focus nor from a customer order-placing focus.

It is important to understand how fit uncertainty affects retail supply chain performance from an operations and supply chain management perspective in order to efficiently design retail supply chains of experience goods, where fit uncertainty plays a major role in the performance of the supply chain. Matching supply and demand in operations management has thus far offered a strategic choice for companies seeking to align their production with customer demand (Fisher, 1997; Pagh and Cooper, 1998). This choice implies a trade-off between providing customized, customer-specific products and producing the products as efficiently as possible (i.e., a trade-off between cost performance and sales performance) (Thonemann and Bradley, 2002; Randall and Ulrich, 2001; Randall et al., 2011). Previous literature in the domain of operations and supply chain management shows that product variety enables sales, but product variety may also lead to long-tails of products at risk of becoming obsolete and the additional inventory holding of product variety (Wan et al., 2012, 2014; Wan and Sanders, 2017; Um et al., 2017; Ton and Raman, 2010).

Research connecting fit uncertainty and operations and supply chain management is still scarce despite the evident and intuitive effects of the former on retail supply chain performance, such as additional product handling due to customers returning items due to improper fit. Therefore, the first research question targets the relationship between fit uncertainty and retail supply chain performance.

RQ1 How does fit uncertainty affect retail supply chain performance?

With knowledge on how fit uncertainty affects retail supply chain performance, a natural consequent extension of the research is to explore how fit uncertainty can be reduced and how reduced fit uncertainty affects retail supply chain performance. Given that fit uncertainty negatively affects retail supply chain performance (e.g., reverse product flows and additional product handling), it is important to reduce the impact of fit uncertainty on retail supply chain performance.

Previous literature has focused on fit uncertainty-reducing interventions in the aspects of customers' expectations of fit and size (Miell et al., 2018) and the interventions' use, characteristics, and impact on customers' decision processes (Xiao and Benbasat, 2007; Senecal and Nantel, 2004), but it remains unclear how these interventions influence retail supply chain performance. To effectively design and implement fit uncertainty-reducing interventions, further knowledge is needed on how these interventions affect the relationship between fit uncertainty and retail supply chain performance. Therefore, the second research question addresses this issue.

RQ2 How do fit uncertainty-reducing interventions affect retail supply chain performance?

1.5 Scope

This thesis addresses improving retail supply chain performance through fit uncertainty-reducing interventions. The products within the scope of this thesis are of the experience type and involve physical fit uncertainty, meaning that customers are uncertain about how the products physically fit them prior to trying them on. Two typical experience goods that are subject to fit uncertainty are footwear and clothing, both of which are included in this thesis.

With respect to the retail supply chain perspective, retail supply chain frameworks (Lowson, 2001; Randall et al., 2011; Anand and Grover, 2015; Sandberg and Jafari, 2018; Wen et al., 2019; Ge et al., 2019) indicate that the common characteristic of a retail supply chain is its ability to be close to end-customers. Here, the retail supply chain is considered to be both retailer- and customer-centered. In this thesis, the retail supply chain does not include the end-customer perspective per se: the thesis does not consider input from customers in, e.g., how well they think the interventions work, how the interventions could be improved, etc. Instead, this research considers fit uncertainty-reducing interventions applied by retailers from the retailer perspective and includes the interventions' ability to improve product flow. The system studied in this thesis involves product flow activities that are downstream from the manufacturer relating to sales, costs, and delivery lead time. Retailers typically lack control over and insight into the manufacturing process; instead, the retail supply chain is "geared towards the end customer- and market-oriented efforts and capabilities" (Sandberg and Jafari, 2018, p. 1989). Given this context of retailers' lack of insight into manufacturing, it naturally follows that this thesis is concerned with the product flow activities downstream from the manufacturer.

The interventions within the scope of this thesis are the digital means of reducing fit uncertainty for experience goods and consist of digital product fitting and recommendation technologies. This thesis examines interventions intended either for physical commerce or for e-commerce. Interventions intended for physical commerce are typically more accurate in depicting the customer, while interventions for e-commerce are superior in terms of reaching more customers, with more wide-ranging effects if used. Interventions in physical commerce are beneficial for niche products, such as specialty sport products, whereas e-commerce interventions are beneficial for more general retail products. Depending on their level of digitalization, the interventions trigger different supply chain effects. This research incorporates a maturity model that describes the supply chain effects that can be achieved through the use of fit uncertainty-reducing interventions on three digitalization maturity levels. The interventions within the scope of this thesis all aim to reduce customers' experienced fit uncertainty to obtain positive supply chain performance effects in terms of product flow, narrowed down to performance effects in terms of sales, costs, and delivery lead time. In theorizing fit uncertainty-reducing interventions, this thesis incorporates the mechanisms of how the interventions change product flow in retail supply chains. Furthermore, this thesis addresses the interventions' ability to reduce the number of fit-related returns.

With respect to retail supply chain performance, this thesis regards performance dimensions that pertain to product flow, since product flow constitutes the essence of logistics of tangible goods. The retail supply chain performance dimensions that pertain to product flow downstream from the manufacturer and that are studied in this thesis are *sales* (including completed sales and lost sales), *cost* of coping with fit uncertainty (inventory holding, transportation, order picking of returned products, restocking of returned products), and *delivery lead time* (the time from a customer demand arising until the customer has completed the purchase). Although this thesis focuses on these dimensions, other effects flow from these three (e.g., reduced number of returns leads to positive environmental effects with regard to transports, and less obsolescence leads to improved sustainability and less waste). The chosen performance dimensions are common ground for retail logistics and are important in the development of sustainable retail supply chains (Adivar et al., 2019). Furthermore, customers' shopping behaviors heavily impact the performance of retail supply chains, especially in terms of customer order-placing practices seeking to mitigate fit uncertainty, such as ordering multiple sizes with the intention of returning the least-fitting one(s). It naturally follows that this thesis also encompasses customer order-placing behaviors aimed at reducing fit uncertainty.

1.6 Outline of the doctoral thesis

This thesis consists of seven chapters with contents as follows.

Chapter 1: Introduction begins by providing a background of the research area and highlighting the problem of fit uncertainty, the types of available interventions to reduce fit uncertainty, and past research's work on achieving retail supply chain performance through matching supply and demand. After the background, the purpose and the research questions are presented, followed by the scope, and this short outline.

Chapter 2: Frame of reference reviews the previous literature on retail operations with regard to pre-sales and post-sales measures to cope with fit uncertainty and expands the theoretical definition of fit uncertainty-reducing interventions, the types of interventions, and the use of interventions. The chapter then frames the research concerning operations strategy and the theory of performance frontiers, and it reviews previous supply chain strategy research aimed at achieving sales and cost performance.

Chapter 3: Research process and methods begins by describing the research process underpinning the research projects and papers, followed by the research design that has been employed. Then, reflections on the chosen methods in the appended papers are presented, and research quality criteria are reflected upon.

Chapter 4: Synopsis of appended papers provides an overview of how the research papers are linked to the thesis's purpose and research questions, and it summarizes the five appended research papers according to purpose, method, findings, and theoretical contribution.

Chapter 5: Findings presents the results of the appended papers in relation to the thesis's research questions and the three performance dimensions of *sales*, *cost*, and *delivery lead time*.

Chapter 6: Discussion discusses how fit uncertainty-reducing interventions achieve both sales and cost performance, as well as which order and return behaviors emerge from fit uncertainty; it also presents reflections on practical challenges associated with the interventions. The chapter ends by discussing the types of retail channels and products to which the findings apply.

Chapter 7: Conclusions concludes the research by stating the main findings, the theoretical and practical contributions, and recommendations for further research.

2. Frame of reference

This chapter acts as a basis for the theoretical grounding that is conducted in Chapters 6 and 7. This chapter sheds light on three major streams of research: retail operations, operations strategy, and supply chain strategy. It also dives deeper into the central concept of fit uncertainty-reducing interventions. Each second-level section ends by stating the key takeaway for the theoretical grounding in later chapters.

Section 2.1 dives deeper into retail operations with respect to fit uncertainty and the available retailer practices and customer practices to mitigate fit uncertainty, from both a pre-sales and a post-sales perspective. Customers engage in pre-sales activities before making a purchase decision, while post-sales measures compensate for fit uncertainty after the customer has made a purchase decision. Pre-sales measures address fit uncertainty before returns occur, and post-sales measures address the consequences of poor fit after the customer's purchase.

Section 2.2 explains that fit uncertainty-reducing interventions are a specific type of product recommendation system geared toward recommending products based on physical fit. Then, the section provides a theoretical definition of fit uncertainty-reducing interventions by applying the concept of digital encapsulations, followed by an overview of different types of interventions (from the most basic size charts to automatic product recommendation systems). The section ends by describing the use of fit uncertainty-reducing interventions and the value they bring.

Section 2.3 describes operations strategy research with regard to performance capabilities and trade-offs. The theory of performance frontiers was chosen as a structure for describing how trade-offs arise between performance dimensions. Ultimately, retail supply chains seek to pursue sales with the least possible cost and with no or a very short delivery lead time.

Section 2.4 focuses on supply chain strategy research in light of different supply chain setups. It contrasts efficiency (low unit cost) and responsiveness (sales with short delivery lead time) in supply chains, and it dives deeper into the concepts of postponement and mass customization as different means for achieving both responsiveness and efficiency.

2.1 Retail operations: Experience goods and fit uncertainty

The concept of goods being classified as either an experience or search type stems from Nelson's (1970) work on consumer behavior in relation to information. Experience goods are products with attributes that are difficult to transfer from one party to another without experiencing them physically (e.g., how a car feels to drive, the scent of a perfume, or the fit of footwear). In contrast, search goods contain attributes that are transferable between parties without the need to experience them physically (e.g., books and TVs). Klein (1998) adds that experience goods are dominated by attributes that costlier and/or more difficult to obtain knowledge about through information search than through physical product experience.

One stream of research seeks to mitigate fit uncertainty by dealing with *preventing* customers from returning. This stream typically involves the shaping of return policies. Another stream of research deals with *facilitating* the customer fitting process, which typically involves information communication practices that convey fit information to the customer, thereby facilitating the order decision. The following section presents the stream of research that aims to facilitate the fitting process pre-sales; the subsequent section presents the stream of research that deals with post-sales practices aimed at mitigating fit uncertainty.

2.1.1 Pre-sales measures to cope with fit uncertainty

As a way to aid the customer in product fitting of experience goods, size standards are offered for some categories of products that specify or sufficiently model the product from a customer perspective (Bye et al., 2006). A product category with well-developed sizing standards is apparel. As early as the mid-1700s, a demand arose for military uniforms to be mass produced, since these items needed to be available in bulk (O'Brien and Shelton, 1941). However, it was only in the 1940s that ready-to-wear apparel (mass-produced clothing with pre-assigned sizes) started to sell in retail stores; until then, people not in the military had bought custom-made clothing. Thus, the buying behavior of customers shifted from buying tailored garments to buying off-the-shelves in physical retail stores (O'Brien and Shelton, 1941). Upon this shift, people had trouble finding fitting products, since ready-to-wear apparel was based on simple measurements such as height and weight; at this point, the demand for a standard sizing system arose (Zakaria and Gupta, 2014). Nevertheless, sizes are still inconsistent and do not conform to a single standard (Kennedy, 2009); thus, fit uncertainty arises from the lack of experiential product information and the lack of technology-enabled heuristics that indicate a match between product attributes and customer preferences (Hong and Pavlou, 2014).

For physical commerce, retailers provide a large variety of products and sizes to satisfy customer demand, but at a risk of obsolescence and high inventory costs in the supply chain (Brynjolfsson et al., 2010). Shopping involves more information and product fitting for customers, who face a large assortment (Boyd and Bahn, 2009). Physical retail stores usually consist of two areas: a customer-facing area and a backroom area used for receiving products and holding inventory that do not fit on the shelves (Fisher, 2004; Ton and Raman, 2010). Store employees manage the daily operations, which include receiving goods, stocking them, and replenishing the shelves. The employees further assist customers who seek information about the use of a certain product, its location, or its availability (Mou et al., 2018). For physical product fitting in-store, customers can turn to store assistants to request aid in product selection (Mou et al., 2018). Unfortunately, in manually-assisted product selection, store assistants may need to fetch products from behind the counter several times during a customer's product fitting session, and such procedures becomes increasingly ineffective when the demand for assistance increases, such as in a ski rental context when many customers need assistance and the assistance needs to go quickly.

For e-commerce, one pre-sales practice employed by retailers to mitigate fit uncertainty is to convey fit information on their webshops to make fit more comprehensible to the customers. Providing precise information about products on their webshops is a key process through which retailers reduce returns and improve the flow of products (De Leeuw et al., 2016; Hjort et al., 2019).

Pre-sales practices vary in how advanced they are in terms of fit accuracy and ability to check fit to aid the customer's fitting process. A common pre-sales practice is for the customer to acquire product information in order to have a better understanding of the product and to make a more informed order decision; online customer reviews and forums, for instance, might provide useful information (Minnema et al., 2016; Sahoo et al., 2018). Another typical pre-sale practice is to provide size charts so that customers may judge how a particular size will fit them. In terms of more advanced pre-sales practices, buyers can interact with technology prior to their purchase, which should help assuage concerns about fit. Size and style recommendations, fit visualization, and fit recommendations are all technologies aimed at minimizing fit uncertainty (Miell et al., 2018).

However, customers also have their own means of coping with fit uncertainty when no external size and fit technology is available to aid them in product selection. For example, customers can order a loose fit on a regular basis to eliminate uncertainty and returns; alternatively, the customer can order a variety of sizes or substitute products in one transaction. Placing larger orders to reduce fit uncertainty increases return flows in the supply chain while also increasing the likelihood that the customer will find a product that fits.

2.1.2 Post-sales measures to cope with fit uncertainty

The most prominent post-sales measure that retailers use to cope with fit uncertainty is return policies (Hjort et al., 2019). Return policies are easy to implement and change; however, they do not solve the fit uncertainty problem. Return policies can be more or less lenient (Janakiraman and Ordóñez, 2012). Five aspects influence the leniency: time, effort, money, scope, and exchange, all of which affect customers' order and return patterns. Money and effort leniency increase order intention, while scope leniency increases return intention, and time and exchange leniency reduce return intention (Janakiraman et al., 2016). Strict return policies, such as making the return process a hassle for the customer so as to prevent returns, are not favorable when it comes to ordering fit-dependent experience goods, since customers might need to try on the products at home. Lenient return policies promote the customers' fitting process by providing free shipping and returns.

Research has shown that return policies with free returns increase repurchase behavior, customer satisfaction, and profitability (De Leeuw et al., 2016). Other research has argued that free returns do not necessarily benefit the long-term profitability of retailers (Hjort and Lantz, 2016). Providing incentives for customers to keep the ordered products, such as a discount on their next order, reduces returns while maintaining order tendency (Gelbrich et al., 2017). However, a 'keep reward' is also meaningless for products subject to fit uncertainty, since it does not solve the root problem of how the product physically fits. Free returns not only increase customers' order intentions: customers also tend to return goods under such a policy, leading to considerable costs for retailers (Gelbrich et al., 2017).

The retailer's return process includes receiving the customer's return request, processing the return(s), crediting the customer, and analyzing and following up on the return data (Rogers et al., 2002). To avoid returns, retailers should improve return policies and try to gain a better understanding of the sources of returns and customers' reasons for returning. These measures can reduce the number of returns, which in turn will reduce return-related costs and increase customer satisfaction. However, few scholars have empirically studied costs as an effect of fit uncertainty. Ketzenberg et al. (2020) studied return abuse and how different types of returners (abusive, legitimate, and non-returners) exhibit different transactional behaviors. In terms of costs, abusive returners were found to have demonstrably exploitive behavior and cause significant profit losses for the retailer over a long period of time. Ketzenberg et al. (2020) model costs from the perspective of profit losses but do not dive deeper into the subcategories of costs that make up the profit loss.

When customers have the option to self-mend a product to assure a proper fit, the retailer can design a return policy to either promote or suppress self-mending as a fit uncertainty-mitigating mechanism. The retailer benefits from a lenient return policy (lower return charge) if the value of a well-fitting product is low but benefits from a stricter return policy (higher return charge) if the value of the product is high (Gu and Tayi, 2015). The perception of scarcity and the timeliness of orders also influence the return rate; in particular, customers are more prone to return a product when inventory availability information is available to them, and customers who are promised fast delivery are more prone to return compared to slower delivery promises. As such, in order to reduce customers' intention to return, return policies should allow a long return window and not be too punctual on the delivery window (Rao et al., 2014).

Key takeaway: Plenty of research has been conducted regarding return policies as a means of controlling the extent to which customers return. Strict return policies hinder or punish the customer ordering a product subject to fit uncertainty, who needs to put effort into the returning process and even pay a returning charge. On the other hand, lenient return policies promote the customer's fitting process, yet these policies incur costs associated with fit uncertainty and with returns management. As such, a gap persists in alleviating fit uncertainty, as well as in showing the actual effects of fit uncertainty and how fit uncertainty-reducing interventions can improve retail supply chain performance so that sales can prosper while costs decrease.

2.2 Fit uncertainty-reducing interventions

Product selection from among the vast supply of products is challenging for shoppers. Therefore, product recommendation systems have been developed that rely on algorithms and technologies that filter the available data to aid the customer in product selection (Senecal and Nantel, 2004; Marchand and Marx, 2020). Product recommendation systems started to appear in the mid-1990s as a digital sales pitcher that automatically recommended suitable products to customer based on characteristics and preferences contained in their personal profile (Alyari and Jafari Navimipour, 2018; Schafer et al., 2001).

Fit uncertainty-reducing interventions are a certain type of product recommendation system targeting experience goods subject to fit uncertainty. These interventions provide product recommendations with regard to how products physically fit the customer; as such, fit uncertainty-reducing interventions facilitate product selection for this type of fit-dependent product. The following section offers this thesis's theoretical definition of fit uncertainty-reducing interventions.

2.2.1 Theoretical definition

Fit uncertainty-reducing interventions are theoretically defined by applying the concept of digital encapsulation (Holmström et al., 2019) to products and customers. *Digital encapsulation* is a theoretical concept explaining the working principles of real-world solution designs, such as digital twins, product agents, and avatars. With fit uncertainty-reducing interventions, each product and each customer is represented by a digital encapsulation that contains the information needed for selection and fitting (and, in the case of product customization, the information needed for customization). In conventional product fitting, the customer physically fits the product before purchasing it in the retail store or at home in the case of an online order. With fit uncertainty-reducing interventions, any actor who has access to the digital encapsulations can match products and customers digitally. This digitalization has potentially wide-ranging implications for retail supply chains (Chawla and Goyal, 2021), as it means all retail operations, regardless of location, timing, and type of channel (physical commerce or e-commerce), can be customer-close. Production and logistics can thus focus on customer requirements, potentially increasing sales and reducing customer returns and inventory-clearing price discounts.

This conceptualization frames fit uncertainty-reducing interventions as a key to a shift toward digitalized retail operations based on digitally encapsulated products and customers (Hagberg et al., 2016; Walter et al., 2012), as they enable encapsulation-oriented processing between supply chain actors to achieve increasing returns and network effects.

2.2.2 Types of interventions

Many types of fit uncertainty-reducing interventions are implemented in e-commerce and physical commerce; some of the most common ones are listed in this section.

A very basic size and fit tool for e-commerce is size charts, which requires the customer to measure specific body parts and then determine the best size themselves by cross-referencing their measures against the size chart (Miell et al., 2018). Size charts do not contribute to the digitalization of retailing, nor do they provide accurate fit estimations, given that size standards are inconsistent (Kennedy, 2009).

Retailers keen to facilitate the customer's online product selection process invest in more advanced fit uncertainty-reducing interventions. One such intervention is online customer reviews, which allow customers to rate a purchased product so that other customers can gain an understanding of it (Sahoo et al., 2018). As for reducing fit uncertainty, online customer reviews can be specifically designed for size and fit reviews, as in the case of outdoor clothing retailer Revolution Race (https:\revolutionrace.com). After a purchase, customers receive an e-mail asking for their rating of the ordered product, and they include some demographic details along with their size and fit review. In this way, others who are looking to buy that product can see all reviews along with weight and height of each reviewer. This type of software builds on demographic recommender systems (Alyari and Jafari Navimipour, 2018), but automatic recommendations are taken out of the equation; instead, customers inform themselves on how a certain product will fit based on others' reviews.

Another type of intervention is one that provides product fit visualization based on personal reference products (Miell et al., 2018). This type of intervention requires the customer to select a size that they deem will fit, similarly to the customer review intervention. This intervention lets the customer input the measurements of a reference product that they already own; then, the web-based tool visualizes the fit of the browsed product using silhouettes. Such fit recommendation logic is based on the assumption that fit is a subjective measure, but by comparing a product against an already-owned product, the customer should have an informed view of the fit of the browsed product.

As for the most software-advanced fit uncertainty-reducing interventions, these can be based on collaborative filtering techniques (Alyari and Jafari Navimipour, 2018), wherein customers receive fit recommendations based on what other customers with similar body shapes purchased and did not return. Recommendations based on collaborative filtering are associated with the cold start problem (i.e., when a new product enters the assortment): the intervention is unable to provide an accurate fit recommendation when no previous customer has interacted with the product. Such an algorithm can assume that the customer is an average fit the first time they get a fit recommendation. Assuming the customer is an average fit is the highest probability, resulting in the recommended product fitting the customer. If the product does not fit, the system learns, because the customer either returns the product or buys a different size from the recommendation in-store.

To solve the cold-start problem of fit uncertainty-reducing interventions based on others' successful purchases, interventions can provide recommendations solely on personal data and product-level data (Park et al., 2012). In the context of footwear, such an intervention recommends fitting footwear based on the customer's feet from among the products the recommender system has access to. These advanced interventions can use 3D scanning to provide accurate recommendations (Dong et al., 2020). The use of 3D scanning, modeling, and clash detection technologies dates from the 1990s (Tan and Vonderembse, 2006). Fit uncertainty-reducing interventions apply technologies originally developed for mass customization in a novel way: initially, product manufacturers used the technology for customization and make-to-order manufacturing (Piller and Kumar, 2006; Sievänen and Peltonen, 2006); today, physical retailers use 3D scanning to assist in sales of products requiring exceptional fit, such as specialty sports shoes. Additionally, for e-commerce, 3D scanning is possible via phone applications.

2.2.3 Use of interventions

In retail, e-commerce leads the way in digitalizing offerings, selection, purchase, and payment (Grewal et al., 2017; Hwangbo et al., 2018), although physical commerce is increasingly exploring ways to benefit from digitalization (Hagberg et al., 2017; Pereira and Frazzon, 2021). Fit uncertainty-reducing interventions are part of this wider digitalization effort, drawing on the use of digital product and customer encapsulations (Holmström et al., 2019) to select fitting products.

Digital technologies in the form of fit uncertainty-reducing interventions have the potential to transform operations (Chawla and Goyal, 2021). Supply chain integration is a mechanism for translating technological innovation into improved performance (Seo et al., 2014), and the emergence of high-capacity computers and enterprise databases enable integrated redesigns of delivery processes (Jacobs and Singhal, 2017). Order-to-delivery processes that previously required days of information batch processing can be conducted in hours through integrated information processing (Davenport and Short, 1990; Hammer, 1990).

Most recently, digitalization has stimulated interest in mechanisms beyond integration in operations management. Encapsulation-oriented information processing is a novel mechanism that enables performance improvement in operations (Holmström et al., 2019) and the bridging of the physical and the digital through omnichannel retailing (Pereira and Frazzon, 2021; Gao et al., 2020).

As product variety increases, difficulty in choosing the right product increases, leading to increased need for assistance in physical commerce (Wan et al., 2012) and higher returns in e-commerce (Rabinovich et al., 2011; Abdulla et al., 2019). Here, encapsulation-oriented processing based on fit uncertainty-reducing interventions can be introduced to recommend the available product variety for the customer, reduce the difficulty in choosing, and reduce returns. The practice of directing customer choice through computer-generated recommendations is already widely used for many product categories in e-commerce (Xiao and Benbasat, 2007); through fit uncertainty-reducing interventions, such recommendations can also become available and potentially useful for fit-dependent experience goods and in physical commerce (Hagberg et al., 2017; Walter et al., 2012).

One challenge has been innovating retailing practices that combine reduced inventories with more productive retail operations and efficient resource use (cf. Eroglu and Hofer, 2011). Access to digitally encapsulated products and customers opens up opportunities for different types of sales processes as a means of operational demand adjustment. Together with inventory speculation, discount pricing, and backorders (Hay, 1970), encapsulation-oriented processing presents retailing with new ways to implement pre-orders (Coflerill, 1981), order-and-wait sales (Rajagopalan and Kumar, 1994), customization (Gilmore and Pine II, 1997), and re-orders/subscriptions (Sorescu et al., 2011).

Order-and-wait sales are an early proposal for reducing retailers' inventory levels by offering customers the possibility of purchase to order (Rajagopalan and Kumar, 1994). Through the combination of physical and e-commerce, the practice becomes a solution for mitigating the increase in inventory from increasing product variety (Gao and Su, 2017). The implementation of retail channel integration requires changes in retail store operations, logistics, and supply chain operations (Mou et al., 2018; Oh et al., 2012). Digital encapsulations of products and customers, which enable more flexibility in the timing of delivery processes, also enable processes combining physical and online retail channels (Pereira and Frazzon, 2021).

Having access to digital customers, manufacturers benefit from increased knowledge about the customer base and can pursue more fit-driven manufacturing operations, such as enhanced product development and customization. Distributors and retailers can pitch products to end-customers; for example, long-tail products that risk becoming obsolete and which customers may have difficulties finding can be pitched to the end-customers who benefit from them.

Key takeaway: Drawing on previous research on fit uncertainty-reducing interventions, this thesis considers fit uncertainty-reducing interventions in terms of how these interventions affect retail supply chain performance. The potential use of fit uncertainty-reducing interventions to further innovate ways of improving retail supply chain performance remains largely unexplored by academic research. Previous research has focused on fit uncertainty-reducing interventions in terms of technology development (Hwangbo et al., 2018), customers' expectations of fit and size (Miell et al., 2018), and the interventions' uses, characteristics, and impact on customers' decision processes (Xiao and Benbasat, 2007; Senecal and Nantel, 2004), mostly from an information systems perspective; however, it is unclear how these interventions promote retail supply chain performance. A more thorough understanding of how these interventions influence the link between fit uncertainty and the performance of the retail supply chain is needed in order to successfully design and execute measures that reduce the effects of fit uncertainty on retail supply chain performance.

2.3 Operations strategy: Performance capabilities and trade-offs

Early research on operations strategy includes Skinner's (1974) article on the focused factory. Skinner (1974) introduced factory focus, which suggests that factories should focus on their core competencies and competitiveness to stop compromising trade-offs within the factories. Operations strategy literature has largely dealt with competitive priorities in manufacturing and the inter-relationships of competitive objectives, such as cumulative capabilities (Boyer and Lewis, 2002; Ward et al., 1998; Swink et al., 2005; Cai and Yang, 2014). The term *capabilities* is loosely defined in literature, but it is interpreted here as resources that enable specific performances. These streams of research suggest that strategic use of resources leads to market competitiveness and factory performance.

This thesis argues that factory-specific capabilities should remain focused in order to achieve economies of scale in the supply chain. The following section lays out the theory of performance frontiers, a well-established theory in operations strategy research, and comprehensively describes performance capabilities and trade-offs in manufacturing, although the trade-off reasoning holds for supply chains as well.

2.3.1 Performance frontiers

The theory of performance frontiers captures the essence of performance; it addresses what factory performance is and how it relates to cumulative capabilities and trade-offs (Schmenner and Swink, 1998). The theory builds on two fundamental principles: the law of trade-offs and the law of cumulative capabilities, both of which have their origins in manufacturing.

The law of trade-offs holds that the performance dimensions of quality, flexibility, delivery, and unit cost cannot be achieved all at once.

The law of cumulative capabilities holds that improvements in some manufacturing capabilities, such as quality, are fundamental and facilitate improvements in other manufacturing capabilities, such as flexibility, delivery, and unit cost.

At first glance, the two laws appear to be in contradiction, yet they are not. For the law of trade-offs, a factory may be regarded as a technologically constrained entity. The choices made by the factory regarding technologies define the constraints on the production capabilities. In the short run, the constraints cause trade-offs to arise among the performance dimensions (Schmenner and Swink, 1998; Skinner, 1996); however, in the long run, factories that concentrate their efforts on attaining excellence in one or a few selected performance dimensions will outperform factories that concentrate their efforts on reaching excellence in several performance dimensions at the same time (Skinner, 1974).

According to the law of cumulative capabilities, increases in performance dimensions are most effective if they are pursued in a certain sequence (e.g., quality is considered a forerunner to cost reduction) (Cai and Yang, 2014). The law of cumulative capabilities asserts that some performance dimensions drive other performance dimensions, which holds for a factory in the long run. The two laws are not in contradiction: the law of trade-offs concerns the overall performance of a factory at a specific point in time, while the law of cumulative capabilities concerns a factory's performance over time.

The two laws are combined in the theory of performance frontiers. A performance frontier is defined as "the maximum performance that can be achieved by a manufacturing unit given a set of operating choices" (Schmenner and Swink, 1998, p. 108). Economics theory is used to describe the performance frontier as a production frontier. "A production frontier is defined as the maximum output that can be produced from any given set of inputs, given technical considerations" (Schmenner and Swink, 1998, p. 108). In terms of a performance frontier, the *output* constitutes all performance dimensions, such as quality, flexibility, delivery, and cost, while *technical considerations* constitute the choices that influence the design and operations of a factory (Skinner, 1996).

Furthermore, there are two types of performance frontiers. The first is an asset frontier, which is made up of investments, such as machines and information technologies. The second is an operating frontier, and it concerns the production decisions that can be made given the range of assets available (Schmenner and Swink, 1998). The asset frontier may be defined as a factory's maximum performance, but the operating frontier is defined as the greatest performance possible based on how the management decides to operate.

2.3.2 Performance frontiers applied to retail supply chains

The theory of performance frontiers has its origins in operations strategy literature; however, in this thesis, the scope of performance frontiers is broadened to apply to retail supply chains rather than manufacturing facilities. According to Vastag (2000), who expands the theory of performance frontiers to encompass a between-firm scope beyond the original within-firm scope, such an expansion is plausible.

The term 'performance frontier' is redefined in this thesis in order to encompass supply chains, as opposed to the definition by Schmenner and Swink (1998). Here, the performance frontier is defined as the maximum performance that a retail supply chain can achieve, given a set of operating choices (cf. definition by Schmenner and Swink (1998, p. 108): "A performance frontier is therefore defined as the maximum performance that can be achieved by a manufacturing unit given a set of operating choices.")

Table 2.1 illustrates how the theory of performance frontiers is applied to this research, wherein the setting for performance frontier theory is at the level of the retail supply chain. Here, retail supply chain operations (or how conventional retail is conducted now) are the operating frontier. The asset frontier is renamed the *utilization frontier*, which means that all available product supply is used to meet market mediation performance.

Table 2.1: Performance frontiers theory applied to the research context.

	Performance frontier in manufacturing	Performance frontier in retail supply chains using fit uncertainty-reducing interventions
Context	Manufacturing plant	Retail supply chain
Operating frontier	Plant operations	Retail supply chain operations
Asset frontier	Plant design and investment	"Utilization frontier" Physically available product supply
Cost	Production cost within the plant	Cost related to the degree of product variety
Performance	Plant performance	Responsive market mediation performance

The law of trade-offs stipulates that none of the performance dimensions (quality, flexibility, delivery, unit cost) can be achieved simultaneously. However, Schmenner and Swink (1998) contend that higher levels of the performance dimensions *can* be concurrently achieved if the operating frontier is moved closer to the asset frontier (here, the utilization frontier), which can only be accomplished through the use of technology that radically improves the current operating frontier.

Key takeaway: The important performance dimensions in this thesis are sales, costs, and delivery lead time, and the argumentation is that with the use of fit uncertainty-reducing interventions, no trade-offs need to be made between the dimensions to improve any of the other dimensions. Given that there is already product supply available on the market, maximum sales performance can be achieved together with short delivery lead time, and given that companies strive for high productivity in the manufacturing of products, the available products on the market are produced using high productivity, i.e., low unit cost. The issue of interest for theory is digitalization-enabled performance improvement through the use of fit uncertainty-reducing interventions.

2.4 Supply chain strategy: Supply chain setups

This section dives deeper into the logistics stream of research on matching supply and demand through different supply chain setups.

2.4.1 Designing for efficiency or responsiveness

The practical problem addressed in this thesis is the uneven and slow product flow in retail supply chains for products that require physical fitting. Designing the right type of supply chain for the product supplied is essential to achieving supply chain performance and has been a major focus of research in recent decades. Omnichannels have drawn research interest (Adivar et al., 2019; Pereira and Frazzon, 2021), and as e-commerce and return rates have increased, reverse supply chains and circularity have also become important topics (Hultberg and Pal, 2021; Rau et al., 2021). No uniform supply chain strategy is applicable to all types of products; the supply chain strategy must match the specific characteristics of the product type supplied and the product family (Christopher et al., 2006).

Notably, numerous supply chain strategy frameworks are used to match product type to supply chain type (Fisher, 1997; Pagh and Cooper, 1998; Christopher et al., 2006; Wagner et al., 2012; Collin et al., 2009). Fisher (1997) distinguishes between functional and innovative products, which are termed standard and special products by Christopher et al. (2006). Both frameworks describe the demand type for these products as either stable (for functional and standard products) or volatile (for innovative and specialty products). If the product supplied is of a functional character with predictable demand, then an efficient supply chain is the best choice (Fisher, 1997). Innovative products require a responsive supply chain, which can quickly respond to demand and minimize the stockouts, price reductions, and obsolescence that are otherwise involved in unsuccessful innovative products (Fisher, 1997). Market mediation is also challenging for long-tail products, which are prone to becoming obsolete (Brynjolfsson et al., 2010). Table 2.2 presents the characteristics of efficient supply chains and of responsive supply chains.

Table 2.2: Efficient vs. responsive supply chain characteristics.

	Efficient supply chains	Responsive supply chains
Primary purpose	Supply predictable demand efficiently at the lowest possible cost	Respond quickly to unpredictable demand in order to minimize stockouts, forced markdowns, and obsolete inventory
Manufacturing focus	Maintain high average utilization rate	Deploy excess buffer capacity
Inventory strategy	Generate high turns and minimize inventory throughout the chain	Deploy significant buffer stocks of parts or finished goods
Lead-time focus	Shorten lead time as long as it does not increase cost	Invest aggressively in ways to reduce lead time
Approach to choosing suppliers	Select primarily for cost and quality	Select primarily for speed, flexibility, and quality
Product-design strategy	Maximize performance and minimize cost	Use modular design in order to postpone product differentiation for as long as possible

The concepts of 'lean' and 'agile' are sometimes related to efficient and responsive supply chains; while lean manufacturing focuses on continuous material flows, reduction of lead times, and cost reduction (Hines et al., 2004; De Treville et al., 2004; Christopher et al., 2006), agile manufacturing promotes the flexibility to be able to switch quickly between production processes, so as to be able to cope with volatility in demand (Christopher et al., 2006). Lean and agile supply chain designs are alternative notions of the responsive and efficient supply chains proposed by Fisher (1997). The market winner for lean supply chains is cost, whereas the market winner for agile supply chains is service level or availability (Mason-Jones et al., 2000). The 'leagile' supply chain is a combination of lean and agile, and it arose as an attempt to combine the two in order to establish a cost-efficient supply chain with the ability to adopt to volatility in demand.

Global trends and requirements have led the supply chain strategy field to include sustainability to a larger extent than before, and sustainability is more often included as a performance dimension in the designing of supply chains (Adivar et al., 2019). Sustainability research in retail deals with such topics as 'sharing economy' and 'circularity.' Regarding sharing economy, certain products can be shared between people, such as household appliances, which promotes sustainability and use rate of the products but to the detriment of retailers who lose sales. General clothing and footwear, which are more hygiene- and fit-sensitive, might not be fit to be shared. Regarding circularity, a growing trend in the footwear context is the 4D printing of shoes using recycled plastics (Patil and Sarje, 2021). The goal with circularity is that products at an end-of-life stage should be given new life instead of being treated as burn waste, as can be seen in recycling plastic-made shoes. Reverse logistics is an important part of designing retail supply chains to promote efficiency and sustainability. Concerns about attaining a circular economy have fueled efforts to improve resource-use efficiency by employing a variety of waste management strategies, such as reuse and recycling (Van Engeland et al., 2020; Kahhat and Navia, 2013).

In terms of these concepts and their relation to the type of product studied in this thesis, fashion goods are commonly referred to as innovative, due to their volatile demand, short life cycles, and sometimes seasonality, but some goods (such as basic garments) last several seasons and have a stable demand (Christopher et al., 2006). Here, we see a product type (clothing) that can be either standard or special, depending on the product characteristics. The product characteristic of importance in this thesis is 'fit', and here, another distinction can be made: some products require exceptional fit, such as professional ice hockey skates, whereas others (e.g., ballerina flats) require only decent fit. As such, a product requiring exceptional fit is regarded as a specialty product, while a decent-fit product is regarded as a standard product, but not in the context of demand.

Not only are the nature of demand and the type of product relevant to supply chain strategies, but also replenishment lead time has been proposed as an important factor influencing the choice of strategy (Christopher et al., 2006), due to its impact on responsiveness (Sandberg and Jafari, 2018). As clarified in the section on scope, this thesis regards the delivery lead time as lasting from the customer demanding the product to the product being in their possession.

2.4.2 Postponement

Companies often make a choice to have either an efficient supply chain or a responsive supply chain (Pagh and Cooper, 1998; Collin et al., 2009), but it is also possible to have two differentiated supply chains for different purposes or to combine the two types.

The concept of postponement was developed by Alderson (1950), who described how products could be differentiated by postponing form, identity, and inventory location to the latest possible time in order to attain supply chain efficiency. Bucklin (1965) later explained the postponement concept in terms of risk and uncertainty costs associated with the products supplied, which later frameworks build on (Fisher, 1997; Pagh and Cooper, 1998; Christopher et al., 2006; Collin et al., 2009). By postponing certain activities (e.g., logistics and distribution, manufacturing activities) until the customer demand arises, cost efficiency can improve (Pagh and Cooper, 1998). Manufacturing activities for apparel goods are not easily postponed, due to their construction. For apparel, manufacturing postponement may involve dying textiles (Aftab et al., 2017; Zinn, 2019), while footwear consists of more parts than apparel (e.g., tongue, sole, laces). Factors such as part commonality and product modularity impact whether and how postponement can be performed (Aftab et al., 2017).

For apparel and footwear production, the dominant production strategy is speculation, which is defined as “the converse concept of postponement, which holds that changes in form, and the movement of goods to forward inventories, should be made at the earliest possible time to reduce the cost of the supply chain” (Pagh and Cooper, 1998, p. 14). Economies of scale can be achieved with this method, but they entail decentralized inventories. For fit-dependent experience goods, stocking all sizes of a product in a decentralized manner enhances the responsiveness of the supply chain, since customers can access the available inventories at retail stores. However, when customers are unable to find a fitting size, the inventory can be considered phantom inventory (Ton and Raman, 2010), meaning that fitting products are available but inaccessible to the customer.

With manufacturing postponement, final manufacturing operations are performed downstream in the supply chain, after the items have been logistically differentiated (Pagh and Cooper, 1998). The order point is set before the final manufacturing activities, since the final operations are executed upon customer order. Manufacturing postponement is a good option when it is critical to keep inventory close to customers, as this type of postponement allows for a greater choice of differentiated products while also reducing inventory. However, the cost and the complexity associated with customer orders increase, and economies of scale decline.

It is not only possible to postpone manufacturing activities; postponement literature also notes that logistics activities can be postponed (Zinn, 2019). For logistics postponement, finalized products are directly dispatched to customers from a consolidated inventory at a central warehouse. In this process, manufacturing operations are triggered by inventory levels, while logistics operations are triggered by customer orders. Postponement of logistics activities is linked to better on-time delivery, lower inventory costs, shorter and more predictable delivery lead times, and more consistent transportation costs. Because the inventory is centralized, high in-stock availability can be achieved with lower inventory levels. However, due to faster transit routes and smaller package volumes, shipment prices may be greater (Pagh and Cooper, 1998). The literature has begun to examine postponement of reverse logistics activities, and research now points to solutions that are both commercially and environmentally viable (Rau et al., 2021).

Postponement may entail frequent shipments of smaller quantities over longer distances if inventory is kept upstream. Thus, postponement is beneficial for goods that are insensitive to transportation costs and sensitive to inventory costs (i.e., high-value goods with large product variety), which are usually not mainstream apparel and footwear products. One inhibitor of the use of postponement is that of lead time: when order to delivery lead time is an important aspect, postponement is not desirable (Van Hoek, 2001). Postponement enables supply chains to customize products to specific customer requirements (Van Hoek, 1998). In terms of costs from four perspectives (distribution costs, production costs, inventory costs, and obsolescence costs) (Elrod et al., 2013), postponement reduces inventory holding, warehousing, and obsolescence costs (Fisher, 1997; Elrod et al., 2013). (Obsolescence costs are related to outdated inventory and often cannot be completely eliminated, but they can be managed and mitigated (Elrod et al., 2013).) Increasing the need for customization reduces the opportunity to take advantage of economies of scale, but using a mass customization approach is a viable middle-of-the-road option in terms of cost efficiency.

2.4.3 Mass customization

Mass customization has been a widely-known and -accepted concept in manufacturing since it first arose in 1987 (Davis, 1987). It promised advantages in its attempt to combine economic efficiency with a sufficient degree of customization to satisfy customer demand. However, mass customization has failed to ultimately deliver what was once expected of it (Zipkin, 2001; Gilmore and Pine II, 1997). The flaw lies in the *sufficient* degree of customization. Fit uncertainty-reducing interventions enable companies to pursue their operations goals by letting them focus on economies of scale, and mass customization enables a sufficient degree of economies of scale (Piller and Kumar, 2006).

Sufficient (i.e., "good enough") is not always good enough from the perspective of customer value. Managers discovered that customer value was not examined thoroughly enough before mass customization was employed as a production strategy (Gilmore and Pine II, 1997). The result is a trade-off between sufficient customer value and sufficient production economies, one that is not ideal for either of the two aspects (Heikkilä, 2002). Early manufacturing strategy literature was focused on factory performance; later, the supply chain became the focus of performance; still later, Brown and Bessant (2003) pointed out that little attention had been devoted to investigating the manufacturing strategy applied to other paradigms, such as agility and mass customization. Brown and Bessant (2003) argues that if companies attempt to become agile and adopt a mass customization approach to manufacturing, they risk losing the contribution of factory-specific manufacturing strategies.

For fit-dependent products, the mass customization methods of modularity and postponement (e.g., assemble-to-order, configuration, and add-ons) have been seen as possible approaches to overcome the efficiency vs. responsiveness dilemma (Berger and Piller, 2003; Squire et al., 2009). 3D technologies supporting some fit uncertainty-reducing interventions have been used for this type of mass customization (Piller and Kumar, 2006; Sievänen and Peltonen, 2006); however, their implementations have been largely disappointing, with retailers unwilling to invest time and effort in the customization process and customers unwilling to pay a price premium for the customized product. Customization practices trade off superior fit for longer delivery lead time, while traditional retail trades off instant delivery for a lesser degree of fit and an increased risk of the customer not finding a fitting product.

However, mass customization ignores the possibility of fully utilizing the available product variety that already exists. This opens up a new way to approach the conundrum of combining production cost efficiency, individual customer needs, and fast delivery: researching fit uncertainty-reducing interventions.

Key takeaway: Classical supply chain strategy frameworks (Fisher, 1997; Pagh and Cooper, 1998) are oriented around the nature of demand, but this thesis adds the dimension of *fit* to the supply chain strategy discussion. Previous attempts of achieving both cost-efficiency and responsiveness include postponement practices and mass customization, but these lead to trade-offs between sales, costs, and delivery lead time. The addition of fit to the supply chain strategy discussion means that experience goods with size and fit characteristics need not require customized production to assure fit; instead, fit uncertainty-reducing intervention technologies can be used as an add-on to efficient supply chain setups so that responsiveness capabilities (in terms of short delivery lead time) can be achieved.

3. Research process and methods

To explore the effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance, this research has taken on a mixed-method approach involving both qualitative and quantitative data analyses. This chapter provides an overview of the research journey and process, explains the research design, reflects on alternative methods for the appended papers, and ends with a discussion on research quality.

Section 3.1 describes the research process, which provides context for the research with regard to the sequence of papers and research projects. The section sheds light on my role in the research projects and papers, and on research collaborations.

Section 3.2 describes the research design, dividing it into two phases. The first phase was the qualitatively exploratory phase, in which Papers I and II were conducted. These papers conceptualized digital product fitting as a fit uncertainty-reducing intervention, proposing effects and in which contexts the effects apply and elaborating on the mechanisms that enable the effects in terms of the theory of swift, even flow. The second phase was the quantitatively exploratory phase, which included Papers III–V. This phase focused on quantifying the actual effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance.

Section 3.3 provides an overview of the methods used in the appended papers, as well as some thoughts on alternative methods.

Section 3.4 discusses the research quality in terms of validity measures, practical relevance, and reliability.

3.1 Research process

This PhD project began in August 2016 and spans two research projects. The formulation of the first research project, digital model driven physical retail and supply chain management (DM-retail), was set upon the starting date. The Swedish Retail and Wholesale Council financed DM-retail until the writing of the licentiate thesis. The second research project, Platform-based digital shoe retail (Digital Retail), was a continuation on DM-retail following its tracks but focusing on e-commerce operations, financed by Vinnova together with the Swedish Retail and Wholesale Council. Figure 3.1 shows the research process as a time line.

3.1.1 Digital model-driven physical retail and supply chain management

DM-retail was conducted to report how a new technology, digital encapsulation, had the potential to transform traditional retailing. The starting point of the research was physical retail stores' advantage in interacting with the customer to create accurate models of needs and requirements. This advantage differs with the type of product, ranging from minor for search goods (e.g., books and music) to indispensable for experience goods (e.g., apparel

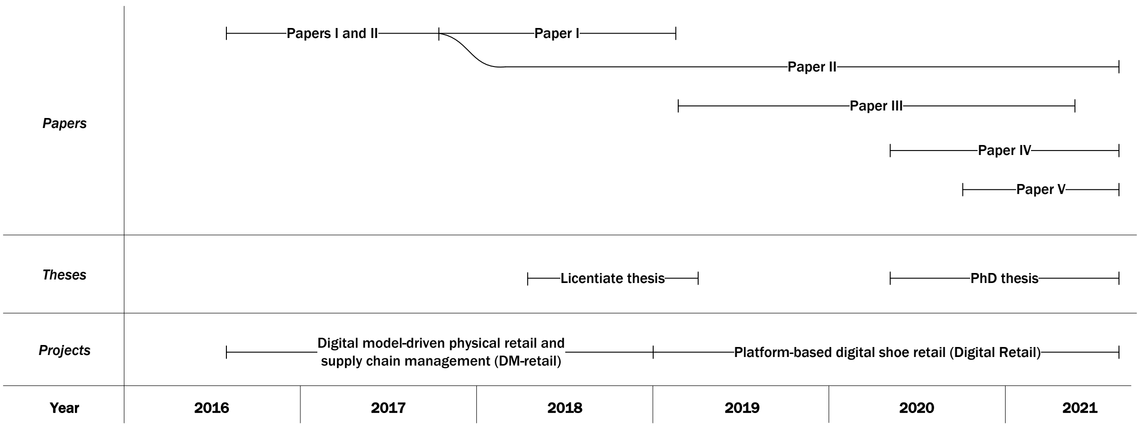

Figure 3.1: Timeline of the research process.

and footwear); the difference can be explained in how effectively the customer demand can be encapsulated without the physical presence of the customer. Therefore, DM-retail focused on experience goods subject to fit uncertainty, specifically apparel and footwear. The project aimed to identify and describe opportunities (prerequisites, enabling mechanisms, and potential outcome) of different actors in the retail supply chain (physical retailers, e-retailers, brand owners, logistics service providers, and technology suppliers) to introduce digital encapsulations of customers and products in ways that enabled more value-adding and efficient ways of operating.

The research project formally stood alone from external parties, which gave me full control over which parties to study. On the empirical side, DM-retail's starting point led to an investigation of which fit uncertainty-reducing interventions existed in real-life retail operations. The investigation focused on products subject to fit uncertainty, where the majority of interventions pertained to clothing and footwear. The review of interventions led to contact with the companies using them. Principally, I engaged with three of the companies, which were deemed the most 'mature' in this respect (i.e., their operations were permeated by the fit uncertainty-reducing intervention).

In parallel to investigating real-life fit uncertainty-reducing interventions, I reviewed the literature spanning operations and supply chain management and retail operations. The purpose of the two parallel streams of review was to establish the novelty and originality of fit uncertainty-reducing interventions in improving retail supply chain performance. There is literature on fit uncertainty-reducing interventions, but there is no academic documentation in operations and supply chain management literature of these interventions as a way to manage supply and demand.

In April 2017, the first study was finalized and presented as a paper at the NOFOMA conference in Lund, Sweden. The paper's assigned reviewers suggested that the paper scope be split in two, to which we (the paper authors) agreed. The resulting Paper I focused on a maturity model and the supply chain effects of fit uncertainty-reducing interventions as an initial conceptualization of matching supply and demand in retail supply chains, and Paper II focused on extending the theory of swift, even flow to the retailing domain through the use of fit uncertainty-reducing interventions.

The review of real-life interventions led to the understanding that there is no single uniform intervention, but rather more and less mature/advanced fit uncertainty-reducing interventions. For Paper I, I collected all data and wrote the main parts of the paper under the supervision of my co-authors. The maturity model idea was coined by my supervisor Professor Jonsson. The authors took turns working on the paper, and it was improved jointly. I was responsible for data collection and analysis, but I discussed problems as they arose with my co-authors; for instance, the coding of cases was solely carried out by me, but it was extensively discussed among all three authors to assure coding consistency. For Paper II, I originally coined the idea of using digital models of products and customers to bypass the responsiveness/efficiency trade-off, and I was responsible for collecting and analyzing data. As the paper progressed, my supervisor and co-author Professor Holmström mainly fine-tuned the paper's contribution to involve the theory of swift, even flow. The co-authors took turns working on the paper.

Paper I took a slightly different form after the split; it also came to include the contextual factors of fit uncertainty-reducing interventions. Paper I was presented at the 2018 edition of the NOFOMA conference. The two papers were worked on in parallel and were submitted to journals in summer 2018. Paper I was successfully accepted and was published in March 2019, but Paper II required some more empirical work, which led to the merging of Paper III in Gustafsson (2019) with Paper II. Paper III in Gustafsson (2019) consisted of a case study of two cases that used fit uncertainty-reducing interventions, with a focus on the mechanisms driving the supply chain outcomes and which contextual factors influenced those mechanisms. I was responsible for data collection, data analysis, and writing this paper. I started writing the licentiate thesis in summer 2018, with a focus on elaborating on how fit uncertainty-reducing interventions can shift the performance frontier in retail supply chains. Paper II came to include this performance frontier synthesis.

3.1.2 Platform-based digital shoe retail

As 2018 turned to 2019, DM-retail ended and Digital Retail started. I co-authored the Digital Retail project application with Professor Jonsson, Professor Holmström, and the industry people with whom I have engaged throughout the PhD project.

The project aimed to develop a platform for digital product fitting across a network of retailers in order to revolutionize existing retail channels. This was done using the latest 3D scanning technology. The effect goal was to save money, time, and the environment through better inventory management and demand knowledge, fewer transports, and above all adjusting production to demand. The project's two objectives were: 1) to practically develop and test a prototype of a shoe-and-feet matching database for multiple retailers, both a technology and a business model; and 2) to evaluate the effects of digital product fitting on supply chains and business models.

DM-retail stood alone from external parties, but Digital Retail included two of the companies I had previously studied: Dress Shoe Customizer and Ski Boots Networker. Digital Retail was an extension of DM-retail, but with a focus on online retailing. The first paper conducted within the project, Paper III, included a test of the applicability of a fit uncertainty-reducing intervention in fashion shoe e-commerce. I designed the study and gave directions on how the test should be conducted. Ski Boots Networker provided the fitting technology (3D scanner) used in the test and also scanned the studied retailer's shoes on the inside. The participants' feet were then matched against the scanned shoes in the database. Dress Shoe Customizer was responsible for setting up the test, and the case retailer representative was responsible for conducting and leading the test. Paper III resulted in a product return costs model and in estimations on what a fitting technology might cost for its implementer to break even by the first year of operation. I was responsible for data collection (other than the data collected from the test) and for setting up the cost model, performing the calculations, and writing the paper. Paper III was presented at the 2020 edition of the NOFOMA conference, after which the continued work resulted in it being published in summer 2021.

The second paper within Digital Retail, Paper IV, involved studying customer ordering behavior. This paper does not analyze fit uncertainty-reducing interventions, but it still fits the thesis's purpose of researching fit uncertainty and its effect on retail supply chain performance. The ordering behaviors discovered in this research are related to fit uncertainty, and the paper models customer service time and supply chain cost implications associated with these behaviors. I was responsible for all parts of the paper, from the Paper Idea to writing it; I turned to my supervisors when something needed to be discussed and for broadening my scope and seeing the paper's weak points.

Paper V uses a similar analysis as Paper IV, but it concerns ordering behaviors when fitting technology is present. Both Papers IV and V draw from archival databases containing transaction data on customers' placed orders and returns. Professor Hjort is the first author of this paper; we first met at a fundraiser hosted by The Swedish Retail and Wholesale Council, where Professor Hjort told Professor Jonsson and me that he had an archival database from a clothing company who had implemented a fitting technology and suggested that we become research collaborators. A few years later, we entered into collaboration and submitted the paper to the 2021 edition of the NOFOMA conference. Professor Hjort holds the ownership of the data and was also responsible for the interviews that were conducted; my role in the paper was to analyze the data. The writing of the paper was shared among the co-authors.

3.2 Research design

At the very beginning, this research set out to explore how retail could benefit from the use of digital technologies, just as the construction industry uses computer aided design (CAD) to model buildings. As such, the research design was centered on the research phenomenon's innovative and nascent nature. A question asked early in the commencement of this research was how retail could be improved, and the subsequent question was what hinders retail supply chain performance. An assessment of both real-life practices and the literature revealed that products subject to physical fit uncertainty would benefit from being digitally encapsulated, since customers and products could then be matched and find each other in the vast product supply.

This research has assessed both real-life practices and the literature throughout the process until the end of writing the report. This thesis is centered on its purpose and research questions, all of which emerged against the backdrop of assessed practices and the literature, together with the conceptual framework presented in the introductory chapter. In keeping with the general research process toward a doctorate, this process has not been linear but rather has taken different turns; still, the goal of mitigating the operational consequences occurring from fit uncertainty in retail supply chains has remained the strict point of focus when reexamining the research questions, the methods used, and the theoretical framework.

Table 3.1 provides an overview of the appended papers' characteristics that justify the applied research designs. The research design in this thesis was flexible, in that data collection methods and analysis methods evolved over time. The research design began as qualitatively exploratory, and then it evolved to being quantitatively exploratory.

Table 3.1: Overview and characteristics of the appended papers for justification of applied research designs.

Paper	Research phenomenon	Qualitative/ quantitative	Phenomenon's stage of existence	Unit of analysis	Unit of observation	Sampling strategy	Number of cases
Paper I	Digital product fitting as a fit uncertainty-reducing intervention	Qualitative	Nascent	Retail supply chain performance outcomes resulting from use of fit uncertainty-reducing interventions	The cases' use of fit uncertainty-reducing interventions	Theoretical	13
Paper II	Digital product fitting as a fit uncertainty-reducing intervention	Qualitative	Nascent	Mechanisms of how fit uncertainty-reducing interventions change product flow in retail supply chains, and constraints to swifter and more even flow	The cases' use of fit uncertainty-reducing interventions	Theoretical	3
Paper III	Product returns arising from fit uncertainty, and a fit uncertainty-reducing intervention to reduce fit-related returns	Both	Nascent (intervention) and mature (returns)	Retail supply chain costs associated with product returns and how a fit uncertainty-reducing intervention influences fit-related product returns	The case company's e-commerce operations	Convenience	1
Paper IV	Customers' order-placing behaviors for a typical experience product	Quantitative	Mature	Retail supply chain product flow activities and customer lead time associated with customers' order-placing behaviors to cope with fit uncertainty	Transaction data on customer orders and returns	Convenience	1
Paper V	The effect of a fit uncertainty-reducing intervention on customer orders and returns	Quantitative	Mature	The use and effects of a fit uncertainty-reducing intervention on customer orders and returns	Transaction data on customer orders and returns	Convenience	1

The transition from qualitative to quantitative research occurred because the phenomenon's stage of existence went from nascent to mature. In the qualitatively exploratory phase of the research, the research phenomenon (fit uncertainty-reducing interventions) had not been examined at all from the perspective of matching supply and demand and the potential effects this bring for retail operations and operations and supply chain management; thus, case research and design science were combined in order to understand and conceptualize fit uncertainty-reducing interventions. In the quantitatively exploratory phase, the understanding I gained of the interventions and associated effects meant that I was better prepared to further explore the actual effects of fit uncertainty and fit uncertainty-reducing interventions. In addition to this background, the research phenomena of customer orders and returns were mature, and quantitative data existed in form of order and return transactions, which called for quantitative yet exploratory analyses.

3.2.1 Qualitatively exploratory phase

During the first half of the research, when the research in Papers I and II was conducted, the research design was qualitatively exploratory. Both these papers regarded the same research phenomenon (namely, digital product fitting as a fit uncertainty-reducing intervention), since they both stem from the same stream of research described in the research process section. Design science research combined with case research was selected, due to the research phenomenon's nascent nature. Nascent indicates that the fit uncertainty-reducing intervention did not exist to its fullest extent, and the exploratory nature of the research indicates that speculations and guesses were necessary to conceptualize the phenomenon as a concept for matching supply and demand in operations and supply chain management.

Current theory in operations and supply chain management has yet not provided a way to bypass the cost-sales performance trade-off. Research in the field typically deals with balancing the trade-off; however, improvements in one come at a cost of lower performance in the other. The conceptualization process undertaken in Papers I and II was highly iterative and required going back and forth with the literature pertaining to how to solve the trade-off and which digital modeling practices were available to solve it. Here, it was beneficial to use case research in combination with design science, to fully understand the conceptualized fit uncertainty-reducing intervention.

Typical descriptive research relies on historical data to establish the existence of the research phenomenon; in other words, it relies on the past. The drawback of studying the pre-existing is that reality is studied in light of historical data and what has already happened. Until the writing of Paper II, my research had a more pragmatic approach and studied the current implementations of emerging fit uncertainty-reducing interventions. The implementations partly represent the concept of the fit uncertainty-reducing intervention, which is why it was beneficial to extract knowledge from such implementations in order to understand the implications before they happened.

In order to understand implications before they happened, Papers I and II used a qualitatively exploratory stance to generate theory (Barratt et al., 2011). Here, an exploratory approach allows rational thinking to generate theory (Barratt et al., 2011; Lee et al., 2011). In this process, I logically came up with a possible solution (i.e., fit uncertainty-reducing interventions) to a problem (i.e., fit uncertainty), which in later research phases was supported by empirical evidence. In this exploratory research, I used established concepts and frameworks that are useful in describing the research phenomenon of fit uncertainty-reducing interventions. In the beginning, I conceptualized fit uncertainty-reducing interventions, and later I showed their effects using transactions data. This research is an attempt to theorize fit uncertainty-reducing interventions by detailing them through different maturity levels, usages, mechanisms, and effects. The theorization builds on concepts and frameworks that describe the phenomenon. This research generates theory by being phenomenon-driven, but this does not limit its ability to contribute to already-existing theories, such as the theory of swift, even flow, which is detailed in Paper II.

For Paper I, the research was highly iterative (Dubois and Gadde, 2002); it began with reviewing customization practices and digital encapsulation practices in order to first come up with a satisficing solution to the trade-off problem. Then, I searched for real-life implementations of such solutions. No such solutions were found among the surveyed implementations, but the footwear industry had related practices of encapsulating feet using 3D scanning. Therefore, the conceptualization process was characterized by *cherry-picking* both theoretical solutions to efficiently and responsively providing fitting experience goods as well as technology used in real-life implementations. Design science research enabled the search for a satisfactory solution to a practical problem (Lee et al., 2011) that fit uncertainty-reducing interventions aim to solve. Looking for the satisfactory solution, rather than the optimal solution, is beneficial when studying something new that has not been researched, as this allows for early development that can be further researched once the initial conceptualization has been established, such as in Papers I and II.

3.2.2 Quantitatively exploratory phase

Paper III started the transition toward the quantitative part of this thesis. When the conceptualization in Papers I and II was in place, the research could start addressing the actual effects of fit uncertainty and of fit uncertainty-reducing interventions. Paper III investigated two research phenomena: the first phenomenon was product returns arising from fit uncertainty, and the second phenomenon was how a fit uncertainty-reducing intervention can reduce fit-related returns. The phenomenon of product returns was deemed mature, since there are many available reverse product flows to study. The intervention phenomenon was regarded as nascent in its existence, since the fit uncertainty-reducing intervention under study was the first of its kind to be applied to the product in this context (the paper tested the functionality of a 3D scanning-based product recommendation system for fashion shoes).

The different maturities of the research phenomena in Paper III called for different methods to address the units of analysis (Golicic and Davis, 2012), which were retail supply chains' costs of product returns and how these costs could be reduced by applying a fit uncertainty-reducing intervention. The cost part of the analysis allowed for a quantitative approach, where mathematical modeling was used to calculate costs arising from product returns. The input parameters stemmed from the qualitative part of the research: the case study of a retailer selling fashion shoes.

The retailer was selected based on convenience, which allowed the extraction of details that were necessary for testing the intervention in the retailer's natural environment. The main reason for settling for a convenience-selected case was that the retailer consented to conduct the intervention test, which was administration-heavy and required the retailer to dispatch 48 pair of shoes to the intervention provider, who scanned the shoes on the inside. The dispatching meant that many products were unsaleable during the time of scanning, and much engagement was required from the company for the test of the intervention to succeed. Consequently, convenience sampling seemed to be the most viable option at the time.

The research phenomenon in Paper IV was customers' order-placing behaviors when ordering a typical experience product subject to fit uncertainty (in this study, shoes). The phenomenon was deemed mature, since huge amounts of data on e-commerce shoe sales are available. However, only journalistic pieces were found to address customers' ordering behaviors: no reviewed scholarly research had quantified the occurrence of the order behaviors. The phenomenon's existence called for quantitative analysis to fill that gap in the literature.

The research phenomenon in Paper V was the effects of an online fitting technology for apparel on order performance outcomes and on fit uncertainty-mitigating ordering tactics. The phenomenon was deemed mature, since several retailers use or have used the technology and the technology provider is still in operation. Additionally, much research has delved into customers' purchase and return behaviors, so the field of knowledge is mature, but a gap still persists, as scant research has studied the effectiveness of technologies designed explicitly to reduce returns (Gelbrich et al., 2017). The phenomenon's existence called for quantitative analysis to fill that gap in the literature.

Papers IV and V differ from the other papers in terms of case descriptions. The case descriptions in the papers were described with sufficient details for understanding the research phenomena, not for generating theory on its own. The research phenomena in these two papers allowed for a quantitative analysis of historical transaction data of customer orders and returns. Both these papers used convenience sampling of cases from which to extract data; this is convenient, especially since it is difficult for a researcher to gain access to company data without contacts who can deliver the data.

3.3 Reflections on research methods

This section gives an overview of the methods applied in the appended papers as well as reflections on alternative methods. Table 3.2 shows the applied methods in the five appended papers.

All five papers are based on some form of case research. As explained in the research process section, Papers I and II were split after a reviewer's suggestion. Paper I used a case survey, a method for surveying a larger quantity of cases at the expense of the level of detail in the studied cases (Larsson, 1993); as such, secondary data from the cases' websites constituted the main source of data, which was complemented with interviews in some cases as well as direct observation of fit uncertainty-reducing interventions in some cases. Due to the paper split, a natural overlap of data can be seen in Papers I and II, since both papers emerged from the same research study.

Paper II used multiple cases to explore different uses of fit uncertainty-reducing interventions; the data collection methods constituted interviews, direct observations of fit uncertainty-reducing interventions, and secondary data from the cases' websites. The cases in Paper II were chosen from the more mature cases in Paper I.

Table 3.2: Research methods applied in the appended papers.

Paper	Method	Data analysis	Data sources
Paper I	Case survey	Cross-case and within-case	Secondary data from cases' websites, interviews, direct observations
Paper II	Multiple case study	Cross-case and within-case	Interviews, direct observations, secondary data from cases' websites
Paper III	Single case study, quasi-experiment-like test, mathematical modeling	Within-case	Archival database with return transactions, test data, interviews, and direct observations
Paper IV	Single case study	Within-case	Archival databases with order and return transactions
Paper V	Single case study	Within-case	Archival databases with order and return transactions

Paper III used a rather intricate method, in that multiple methods were used to arrive at the paper's final results (Golicic and Davis, 2012). The Paper Is based on a single case from which experiment parameters were taken and further used in the mathematical modeling of product return costs. It is perhaps an overstatement to describe the performed test of a fit uncertainty-reducing intervention as an experiment, since the test was not constructed according to a rigorous experiment design. The obtained case data was an archival database with return transactions; interviews and direct observations led to a case description. Mathematical modeling was then applied to determine the cost calculations.

Paper IV used a single case for which an archival database containing order and return transactions was used. The paper shows customer order-placing behaviors when no external size or fit uncertainty-reducing intervention is available to assist them. Paper V used the same type of analysis as the preceding paper, but it contributes order-placing behaviors when an external fit uncertainty-reducing intervention is offered to assist the customers in size selection.

In line with the purpose of the thesis (i.e., to explore the effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance), several methods can be applied. The following sections present methodological reflections about alternative methods in the papers. For more details on how data collection and data analysis were performed, I refer the reader to the appended papers.

3.3.1 Paper I

Paper I used a case survey (Larsson, 1993; Yin and Heald, 1975) of 13 retail cases and three technology-developing companies to identify potential retail supply chain performance effects of fit uncertainty-reducing interventions. As case survey is a less-frequently used method, I will elaborate on its characteristics. Unlike in-depth case research, which examines a few cases, case survey research surveys a larger number of cases in order to attain stronger analytical generalizability (Yin, 2014; Larsson, 1993). The purpose of using a case survey in this paper was to develop propositions for potential supply chain outcomes. Case survey research differs from ordinary case research because case characteristics are emphasized instead of in-depth analysis of the cases themselves (Larsson, 1993). The case survey method is an efficient way to learn about already-existing case studies. However, as technology-enabled fit uncertainty-reducing interventions are emerging, nascent in nature, and thus not previously documented in research literature through case studies, the paper uses a variety of secondary and primary sources instead.

Case research of multiple cases is a viable approach that could have been applied to this paper; however, the paper's conceptual nature would likely not have benefited from engaging more in-depth with the cases. Above all, the choice to conduct a case survey instead of a multiple-case study was based on the priority of covering a larger domain of cases (Larsson, 1993). Mathematical modeling and simulation could have addressed and quantified various relationships between fit uncertainty-reducing interventions and outcomes; however, such methods rely on a more thorough understanding of a phenomenon in order to model it (Karlsson, 2016). These methods would be suitable when more research has been carried out in the area and as a continuation of Papers I and II. Survey research could have benefited Paper II by involving actors who could benefit from the use of fit uncertainty-reducing interventions (e.g., manufacturers, brand owners, and retailers). Survey research was often discussed as a viable option to test the proposed outcomes; however, surveys need to be extremely clear in order to be fully understood by the respondents (Forza, 2002). Since I was not studying any specific fit uncertainty-reducing intervention at the time, it would have been difficult to describe the intervention such that survey respondents would understand it; therefore, it was more suitable to construct outcome propositions based on the covered literature and then analytically test the propositions (Yin, 2014) against identified retail practices in a case survey.

3.3.2 Paper II

Paper II sought to conceptualize and explore fit uncertainty-reducing interventions by studying three types of interventions; therefore, exploratory methods of case research in combination with design science constituted the core methods (Voss et al., 2002; Holmström et al., 2009). Cases are often chosen if they exhibit interesting characteristics, such as being unusually revelatory, extreme exemplars, or offering research opportunities (Yin, 2014). Case research with a few cases is suitable when describing the existence of a phenomenon (Siggelkow, 2007). The research phenomenon here, digital product fitting as a fit uncertainty-reducing intervention, is emergent in nature and is still rare in the industry, which is why little empirical data is available to study. Thus, the case selection approach in Paper II was taken to study technologically mature applications so as to conceptualize digital product fitting as a fit uncertainty-reducing intervention matching supply and demand in retail supply chains.

Survey research could address both the customer perspective and the supply chain perspective of the intervention; however, the number of companies that use technology to reduce fit uncertainty is too limited for a survey to be successful (Forza, 2002). Additionally, reaching out to customers to investigate their interactions with and responses to using product-fitting technology is of limited interest in this paper, since the thesis focuses on exploring the technology, not the customer use of it.

Mathematical modeling and simulation could address and quantify the various effects of fit uncertainty-reducing interventions; however, these methods do not add to the conceptualization of fit uncertainty-reducing interventions. Mathematical modeling and simulation would benefit the research when there is quantitative data to analyze (Karlsson, 2016). These methods are relevant in later papers, when the understanding of fit uncertainty-reducing interventions is more thorough. Experiments are perhaps the best alternative to design science, as they make it feasible to study something that does not yet exist in practice. It would have been possible to conduct experiments at the sites of the users of fit uncertainty-reducing interventions; however, experiments rely on a thorough understanding of the phenomenon under study (Karlsson, 2016). Action research is also closely linked to design science (Coghlan, 2011), but it places a stronger emphasis on the company where the research is carried out. Papers I and II were part of a research project that stood alone from external parties, meaning there was no evident party to engage with, which allowed fit uncertainty-reducing interventions to be conceptualized using fragments of several case companies' implementations.

Fit uncertainty-reducing interventions exist in different forms depending on the level of digitalization employed by the company, as shown in Paper I. Paper II conceptualizes a fit uncertainty-reducing intervention based on the practices of three cases. The resulting generic design (typical design science output; see, e.g., Holmström et al. (2009) and Van Aken et al. (2016)) that Paper I produces is of a conceptual nature; in other words, it does not fully exist in practice, but the cases exhibit its core: recommending products based on digital encapsulations of products and customers. From the above arguments, it seems that the methods of case research in combination with design science used at this stage of knowledge in this area were appropriate for addressing the paper's purpose.

3.3.3 Paper III

Paper III used a mixed-methods approach (Golicic and Davis, 2012). It estimated costs arising from product returns associated with fit uncertainty. The paper builds on a single case, chosen because the case offered research opportunities and is considered a typical internet retailer (Yin, 2014). The case study led to a return process flow chart as a basis for estimating product return costs. Alternative approaches could include studying multiple cases' return processes, but such processes often follow a typical structure, as seen in Rogers et al. (2002). Instead of creating a possible amalgam of a return process by combining several retailers' return processes in a flow chart, the paper draws its conclusions from a typical retailer and is clear regarding the return activities that are present in the studied case. The case exhibited typical characteristics of an e-retailer and was sufficient for the purpose of mapping the returns process; with some modifications, the return costs model can easily be adapted to another context.

A quasi-experiment-like test was set up to test how well the fit uncertainty-reducing intervention under study could handle fashion footwear. Fashion footwear has difficult shapes for digital modeling, and it constitutes a fair share of footwear purchases on the internet. A quasi-experiment, like an ordinary experiment, seeks to evaluate interventions in a controlled environment, but with the difference that quasi-experiments do not use random sampling (Lonati et al., 2018), which means that each participant in the sample has equal chance of being part of the experimental group. I intentionally describe the test as *quasi-experiment-like*, because the participants in the test were not randomly recruited, nor was the design a proper experiment design; the test was simply a *test*.

Unlike proper experiments, quasi-experiments often involve real-life interventions in their natural setting, unlike ordinary experiments, which are often conducted in a constructed setting (Lonati et al., 2018; Bendoly et al., 2006). As such, the quasi-experiment-like test involves higher external validity than most properly conducted experiments. On the other hand, the internal validity of the test is questionable, since the participants were not recruited randomly and there is a potential of bias, since the participants were employed by the case retailer. Thus, an alternative approach to the quasi-experiment-like test would have been a true experiment.

3.3.4 Paper IV

Paper IV uses a quantitative analysis to explore the occurrence of customers' order placing behaviors when they shop shoes online. The analysis focuses on order placing behaviors that indicate fit uncertainty in the customers' ordering behavior. The data stemmed from a single retailer that was conveniently selected for its willingness to share transaction data on customer orders and returns.

A viable alternative way of describing customers' order behaviors implies the studying of multiple cases. A multiple case study approach would imply improved generalizability of the results. However, studying the occurrence of the ordering behaviors for several retailers would add an interesting cross case analysis to the paper. The paper's purpose, however, was not to compare the ordering behaviors, but to dive deeper into an within case analysis. If comparing the ordering behaviors between cases, it would likely have fallen out that some factors affect the ordering behaviors more, such as; shipping and return policies, price of the products, etc. Such study is legitimate to conduct when more is known about the research phenomenon (Voss et al., 2002), e.g., knowing that there are ordering behaviors related to fit uncertainty.

Another alternative method to explore ordering behaviors related to fit uncertainty is the survey method. Since the research phenomenon, ordering behaviors related to fit uncertainty, is known to, perhaps not all e-commerce shoppers, but many, the respondents of the survey would understand questions related to the phenomenon (Forza, 2002). Questions in a survey would address customers' ordering behavior when ordering an experience product subject to fit uncertainty online. That way, it would be possible to indicate to what extent different ordering behaviors exist. However, the analysis of actual transaction data yields a truer result since it represents actual customer orders and returns, compared to a survey which rely on customers judgement when they answer the survey. On the other hand, a survey would be more accurate compared to the quantitative analysis in the sense that it would be possible to ask the customers if an intended order practice is the result of fit uncertainty. Both methods have pros and cons, and a combination of the two could have been desirable. Considering that the research phenomenon involved describing the occurrence of ordering behaviors related to fit uncertainty, the decision landed on adopting a quantitative analysis of order and return transactions.

3.3.5 Paper V

Paper V had a similar research approach to Paper IV, but in Paper V, the customer use and the effects of a fit uncertainty-reducing intervention constituted the unit of analysis. Since the research phenomenon is nascent in nature, the number of possible cases is limited; thus, due to the few available cases that have implemented a fitting tool, the studied case was selected through convenience sampling as the result of a research collaboration initiated by Professor Hjort, who coauthored Paper V.

Studying multiple cases that have implemented fitting tools would have added to the generalizability of results (Yin, 2014; Voss et al., 2002); however, the same reasoning holds as given for Paper IV. Investigating several cases with fitting tools would have led to a discussion on the differing characteristics of the cases, such as product price, type of product, etc. In contrast, the purpose of Paper V was to investigate the customer use of the fit uncertainty-reducing intervention and its effects on customer orders and returns. The quantitative analysis matched the purpose in terms of quantifying various aspects of the use and the effects of the fit uncertainty-reducing intervention.

The survey method could also have been used to address the paper's purpose (Forza, 2002). The survey would have needed to include questions whose answers could indicate how customers would use the intervention. However, conclusions from such a data analysis would address a possible indication of future usage of the intervention, since the conclusions could not rely on historical data.

An experiment was a viable option to the quantitative analysis of customer order and return transactions. To address the paper's purpose, the experiment would have involved setting up reality-like scenarios demonstrating a fitting tool on a webshop. It would then have been possible to control the variables studied, such as how the participants in the experiment would have reacted to different levels of fit (Bendoly et al., 2006). For instance, if the fitting tool yields that the fit of a product is 50 percent, would the participant order that product or order a size that was consecutive to the recommended size? An experiment would also be appropriate for use in evaluating the technology acceptance model (Gefen et al., 2003). However, this thesis does not go in-depth into the user aspects of fit uncertainty-reducing interventions but is instead concerned with the effects the fit uncertainty-reducing interventions have on the relationship between fit uncertainty and retail supply chain performance. Therefore, it seemed that the quantitative analysis of customer order and return data was best suited for studying the effects of the fit uncertainty-reducing intervention in its natural setting.

3.4 Research quality

This section assesses the research quality of the thesis. Some time ago, logistics research was dominated by quantitative methods, wherein the quality of the research is predominantly judged according to the traditional four research quality criteria: construct validity, internal validity, external validity, and reliability (Halldórsson and Aastrup, 2003; Yin, 2014). The influence of these research quality criteria has continued; even when researchers in logistics started conducting qualitative-oriented research, the criteria continued to be applied (Ellram, 1996). Naturally, not all research quality criteria are useful for all types of research, as Yin (2014) notes (e.g., the criterion of internal validity might not perfectly align with qualitatively exploratory research). However, I use the traditional research quality criteria of construct validity, internal validity, external validity, and reliability because researchers can generally relate to these. In this quality discussion, I use these terms, but I also refer to alternative research-quality concepts that fit this thesis. In addition, two more measures of research quality are relevant for this research, as they cover research quality of design science research: pragmatic validity and practical relevance (Van Aken et al., 2016).

3.4.1 Practical relevance

Practical relevance is not limited to design science research, but I believe it is an essential quality measure for research that is not 'fundamental research'. In the framework by Hevner et al. (2004), relevance entails that the research is driven by business needs, and it indicates how the research phenomenon is a valuable contribution to solving a significant field problem (Van Aken et al., 2016). In the framework by Hevner et al. (2004), rigor entails that the research phenomenon should be assessed with regard to applicability and generalizability and that it is anchored in existing knowledge and methodologies. In an attempt at rigor, Paper I anchors the concept in the literature pertaining to matching supply and demand in the supply chain strategy domain, such as matching product type to the right type of supply chains (Fisher, 1997), postponement and speculation (Pagh and Cooper, 1998), and mass customization (Gilmore and Pine II, 1997). Paper II anchors the research phenomenon in the existing operations strategy theory of swift, even flow (Schmenner and Swink, 1998).

The practical relevance of the conceptual development in Papers I and II is established from both theoretical grounding in operations and supply chain management literature as well as interaction with real-life cases. The research problem of efficiently manufacturing products to specific customer needs has been researched in various ways through operations management practices. Reality shows that the research problem is still a pressing issue in current retailing, indicating a need for research. Papers III–V are driven by a strong business need to improve return rates for products subject to fit uncertainty. E-commerce continues to grow, and with sustainability permeating society today, the number of returns need to be reduced, not only from an environmental perspective but also to make the business environment more sustainable regarding retailers' operating costs, etc. Therefore, the practical relevance is high.

3.4.2 Pragmatic validity

Here, pragmatic validity refers to the strength of the evidence claiming that the fit uncertainty-reducing interventions will produce the desired results (Van Aken et al., 2016). Therefore, the value of the research to the academic domain of operations and supply chain management is significant, since it contributes a new research phenomenon instead of merely adding to an already-existing phenomenon. However, such a statement is not 100 percent correct, because Papers I and II studied existing fit uncertainty-reducing interventions and the parts thereof in order to be able to understand how the conceptualized fit uncertainty-reducing intervention can be developed, be implemented, and yield value.

Studying the non-existent raises the issue of research quality and rigorousness. Pragmatic validity is acknowledged as a limitation in this thesis, since the concept of digital product fitting as a fit uncertainty-reducing intervention has not been field-tested according to the premises provided in its definition in Paper I (i.e., matching supply and demand in retail supply chains). The concept was tested in a closed system in Paper III, within the boundaries of the retailer and its products. The concept as a whole, i.e., matching customers to products in an open system regardless of brands and actors, does not yet exist in reality. Therefore, it cannot be established whether the open system concept will generate the proposed supply chain performance effects.

The drawback of studying a nascent research phenomenon is the scant empirical data available to support it, but this is also what adds to the research's originality. A dearth of available empirical data poses validity threats to the research, especially the question of whether the research holds true if there is little evidence to support it. Here, "bits and pieces" of real-life practices and literature-derived practices were put together conceptually to form a solution to the research problem. These "bits and pieces" are fragments of fit uncertainty-reducing interventions and their effectiveness in solving the research problem; each is established in the literature, but what is not yet established is the combined use of them, which Papers I and II contribute.

Paper II provides evidence for the concept in a closed supply chains (the supply chain of the case *Skates Stocker*) that transfer the digital customer encapsulations to upstream actors to bring product development closer to the end-customers, as explained in an interview. The digital customer encapsulations also act as decision support for steering inventory to retailers, since the demand planning function knows which sizes and skate models the customers scan for.

Finally, although the pragmatic validity is questionable, rigor was attempted by way of paying attention to the transparency of reasoning on both the richly described research design and the analysis of data when defining the concept (Ketokivi and Choi, 2014). This was especially important for Paper II, which is the most conceptual paper of the appended papers, but is equally important in Paper I, since case survey research is not as common as, e.g., single- or multiple-case studies.

3.4.3 Construct validity

Construct validity involves "identifying correct operational measures for the concepts being used" (Yin, 2014, p. 46). To assure research quality through construct validity, Yin (2014) suggests using multiple sources of evidence and that all the evidence converges. Tracing empirical data in time achieves convergence, which often necessitates that the data are stored and accessible over time.

Papers I, II, and III used interviews as a source of data. For this reason, careful attention was paid to securing the empirical data through voice-recordings, transcriptions, case descriptions, and saving e-mail correspondence. Papers I through III also used secondary data on company websites for triangulation purposes (Voss et al., 2002). In addition, key informants reviewed drafts of the research, which is one way to ensure construct validity (Yin, 2014). All cases in Paper II reviewed the findings at different points in time over the duration of the research. The research process for Paper II was highly iterative, and the cases presented their views on the paper's findings and thereby helped refine them. Paper II is the result of a longitudinal multiple-case study. Longitudinal research enables researchers to follow the business's progression, which can yield insight into causal relationships. This type of longitudinal research was fruitful for gaining insight into the relationship between fit uncertainty and retail supply chain performance.

For Paper III, which developed a model on retail supply chain costs, construct validity was established by basing the costs and supply chain performance measures on the findings in the preceding Papers I and II.

Papers III, IV, and V relied on archival databases containing historical customer order and return transactions. To ensure construct validity, the original databases were stored as backups, and the analyses were performed on duplicates of the databases.

3.4.4 Internal validity

Internal validity is the extent to which causal relationships can be established (Voss et al., 2002). Yin (2014) suggests that internal validity is not applicable to exploratory research. This is understandable, since case study analyses are the least standardized analyses, since there are few, if any, formulas to follow (Yin, 2014). Voss et al. (2002) suggest that cross-case analyses increase internal validity.

Both Paper I and Paper II used cross-case analyses. The coding of cases is essential to cross-case analyses. To ensure coding consistency, I discussed the cases and the coding with the co-authors. The discussion helped maintain both consistency and a perspective on the case coding.

Paper III, which involved the quasi-experiment-like test, suffered from internal validity issues, mainly due to the participants being employees at the case company; as such, bias could not be eliminated. However, whether the results were internally valid or not, the test yielded valuable learning outcomes. For instance, a pilot run would have been beneficial to discover the technology's difficulty in adapting to the type of footwear tested. Additionally, the software used deep learning algorithms to learn the fit of shoes; for these algorithms to learn, they require data, and the better they are, the more data they need in order to improve even more. The cold start problem for this test would have been inevitable. As for the modeling part of the paper, the method relied on internal validity between the theoretical constructs (i.e., the performance measures), and that adds to the internal validity of that part of the paper.

Papers IV and V used within-case analyses to explore order and return behaviors. The internal validity is higher in these two papers than in Papers I, II, and III, since it is possible to determine causal relationships in the data studied. Of course, there can always be factors that intervene and influence the relationship studied, but the quantitative data enable higher internal validity compared to the other papers.

3.4.5 External validity

External validity involves "defining the domain to which a study's findings can be generalized" (Yin, 2014, p. 46). External validity is similar to pragmatic validity, but the difference is that external validity concerns the generalizability of results, whereas pragmatic validity is concerned with whether the research produces the anticipated results. External validity can only be valid if the pragmatic validity is valid. The pragmatic validity is acknowledged as a limitation in this thesis, and thus so is the external validity. If external validity is important when conducting a research project, then case research is not ideal, as it is not the best method to ensure generalizability. Multiple case studies are a better base for generalizing the findings compared to single-case studies (Eisenhardt and Graebner, 2007), but the problem remains.

The means taken to ensure external validity in the case research papers (Papers I, II, and III) include using replication logic in the selection of cases (Papers I and II) and using existing theory and drawing on analytical generalizability (Yin, 2014) to generalize the findings (Papers I, II, and III). The cost model developed in Paper III is clearly described so that potential users of the model can determine which parameters fit or do not fit their operations or context. In my opinion, the model is most simplistic and easy to adapt when it is anchored in a real case and not nested in a user manual, where the model and all ingoing parameters are described in generic terms.

All cases in Papers I through V share some common characteristics (e.g., they sell products requiring fit, and they sell mass-produced products). Thus, the results should be applicable to companies that also share these characteristics.

Papers IV and V study customer orders and returns when the product is an experience good subject to fit uncertainty, but ordering and returning practices can also be studied from other perspectives than fit uncertainty; for example, the same ordering behaviors identified in Paper IV could be identified for other product types.

3.4.6 Reliability

Reliability involves "demonstrating that the operations of a study, such as the data collection procedure, can be repeated, with the same results" (Yin, 2014, p. 46). To ensure reliability, or repeatability, Yin (2014) suggests using study protocols and a study database. Protocols enable the research to be repeated, and these should be stored and accessible. Case study protocols were used in all papers, and all data have been stored.

To ensure reliability in this thesis, special attention was paid to describing the research processes in the papers with great detail and transparency (Ketokivi and Choi, 2014), especially when the methodological approach is less well-known, as in Paper I. Another important aspect of reliability is maintaining a case study protocol (Yin, 2014). As stated in the section on construct validity, all collected data and the analyses thereof were stored in a database. In addition, Papers I, II, and III, which all involved interviews, have the interview questions appended to them. For Paper III, the replicability of the test is made possible through the explicitly stated design of the test. As for the cost model part of the paper, the assumptions made are explained in the paper, and all notions and equations are explained for replicability purposes.

For Papers IV and V, to ensure that the data collection procedure can be repeated and is likely to arrive at the same results, the papers describe the content in the datasets so that another researcher would be able to gather all necessary data to complete the analysis and arrive at the same conclusions. Furthermore, the papers clearly define the ordering and returning behaviors that were identified, making it feasible for another researcher to analyze the data with respect to these behaviors.

4. Synopsis of appended papers

This chapter summarizes the five appended research papers in terms of their purposes, methods, findings, and theoretical contributions. Figure 4.1 shows how the thesis's purpose fits with the research questions and the appended papers.

Paper I addresses the overarching purpose of the thesis, to explore the effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance, by conceptualizing *digital product fitting* as a fit uncertainty-reducing intervention and proposing supply chain effects that result from fit uncertainty-reducing interventions. Paper II aligns with the overarching purpose by further conceptualizing the digital product-fitting intervention to improve product flow and reduce lost sales, elaborating on which mechanisms yield the effects. Paper III addresses the overarching purpose by illuminating how reduced fit uncertainty could improve retail supply chain costs resulting from product returns. Paper IV aligns with the overarching purpose by quantifying the occurrence of customers' order-placing behaviors as a means of coping with fit uncertainty. Such order-placing behaviors affect the supply chain and are key for understanding the effects of fit uncertainty on retail supply chain performance. Paper V addresses the thesis's purpose by examining the customer use of a fit uncertainty-reducing intervention and the effects of the intervention on customer orders and returns. Understanding how customers use the intervention is important for further fit uncertainty management in retail supply chains.

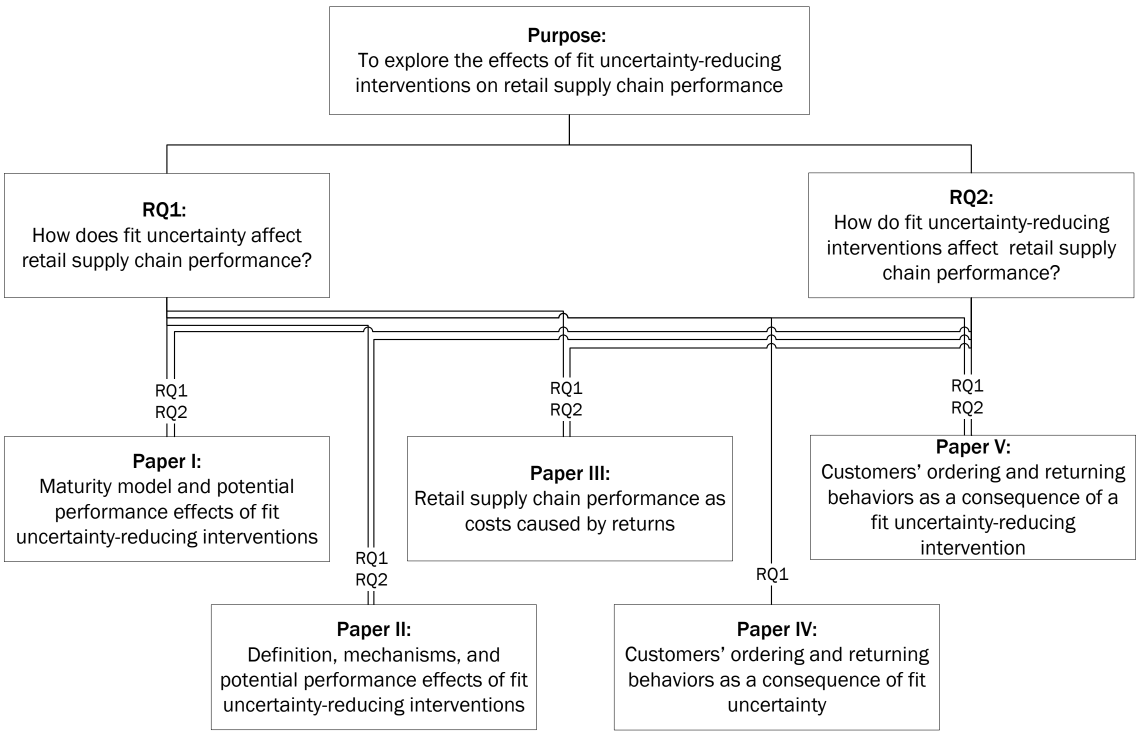

Figure 4.1: How the purpose, research questions, and papers fit together.

4.1 Paper I

Gustafsson, E., Jonsson, P., and Holmström, J. (2019). “Digital product fitting in retail supply chains: maturity levels and potential outcomes.” *Supply Chain Management: An International Journal*, 24(5):574–589.

Purpose. The paper identifies the supply chain outcomes of fit uncertainty-reducing interventions in retail supply chains. The interventions comprise fit recommendation systems in retail that use digital encapsulations of products and customers to match product supply to customer requirements. The paper explores and indicates the potential of the interventions to improve both responsiveness to customer requirements and the utilization of existing variety in mass-produced products.

Method. The paper uses the case survey method (Larsson, 1993) to review 13 retail cases and three technology-developing companies in order to develop a maturity model of product fitting that specifies three levels of digitalization and potential outcomes for each level. The proposed outcomes are based on empirical data from the case survey combined with a review of academic literature.

Findings. Fit uncertainty-reducing interventions influence outcomes in four established supply chain management areas: material flow efficiency, customer relationship management, assortment planning, and product development. The interventions potentially improve material flows through more efficient in-shop operations and product handling; they potentially improve customer relationship management through relationship-based sales and targeted benefit offers; they potentially improve assortment planning through fact-based assortment decisions; and they potentially improve product development through a focus on customer requirements (taken from fitting sessions) and streamlining customer information to the producers. Fit uncertainty-reducing interventions are most relevant for products where the final product configuration is difficult to make to order, the product and customer attributes are easily measurable, and tacit knowledge of customers and products can be formalized using digital encapsulations. Advanced fit uncertainty-reducing interventions using digital encapsulations are ideal for supply chains using automated matching in any type of retail channel that supplies speculatively mass-produced products.

Theoretical contribution. The theoretical contribution is a maturity model of digitalization of product fitting. The paper combines streams of research on digitalization in retail supply chains (Plomp and Batenburg, 2010; Pereira and Frazzon, 2021; Chawla and Goyal, 2021), supply chain maturity models (Lockamy and McCormack, 2004; Hellweg et al., 2021), and supply chain performance (Wan et al., 2014) to extend knowledge on how to bypass the problematic trade-off between product variety (sales) and efficiency (costs and delivery lead time) in supply chains, enabling simultaneous sales increase and operational efficiency. Established supply chain configuration frameworks (Fisher, 1997; Pagh and Cooper, 1998) distinguish between efficient and responsive supply chain designs; this paper complements established frameworks by making efficient supply chain design more responsive through the use of a fit uncertainty-reducing intervention.

4.2 Paper II

Gustafsson, E., Jonsson, P., Öhman, M., and Holmström, J. (2021). “Swift and even product flows in retail supply chains: the impact of digital product fitting.”

Purpose. The paper extends the theory of swift, even flow in order to guide technology-enabled fit uncertainty-reducing interventions to improve product flow and reduce lost sales in retail supply chains for experience goods.

Method. The paper uses case research (Voss et al., 2002), design science research (Holmström et al., 2009), and interventionist research (Oliva, 2019) in combination. It examines the effect of the case companies' fit uncertainty-reducing interventions on the theory of swift, even flow. Using three longitudinal case studies, the paper sheds light on the mechanisms of how the interventions change flow in the retail supply chains, as well as the constraints to swifter and more even flow.

Findings. The findings are threefold: first, the paper theoretically examines the mechanisms through which the conceptualized digital product-fitting fit uncertainty-reducing intervention changes retail supply chain management; second, the paper operationalizes the key design constructs of the conceptualized fit uncertainty-reducing intervention; and third, the paper extends the theory of swift, even flow to performance improvements in digitalized retail supply chains. Engaging with the case companies, whose operations are suffused with fit uncertainty-reducing interventions, the paper observes the mechanisms through which the interventions affect performance and identifies the combination of digitalization, network-building, and object-oriented information processing that operationalizes the design of fit uncertainty-reducing intervention-based retail operations. The swift and even flow-based analysis identifies how the conceptualized fit uncertainty-reducing intervention provides the means to simultaneously increase sales and reduce costs. The intervention triggers improved sales performance by moving beyond the bottleneck of local inventory, narrowing the discrepancy between customer demand and available supply, concentrating the value-adding tasks of each supply chain member, improving the customer-perceived product fit, and redesigning tasks to utilize science-based methods.

Theoretical contribution. The paper contributes to theory by extending the manufacturing theory of swift, even flow (Schmenner and Swink, 1998; Vastag, 2000) to the retail supply chain domain, elaborating how fit uncertainty-reducing interventions can eliminate or reduce the bottleneck of fit uncertainty with regard to product flow.

4.3 Paper III

Gustafsson, E., Jonsson, P., and Holmström, J. (2021). "Reducing retail supply chain costs of product returns using digital product fitting." *International Journal of Physical Distribution and Logistics Management*, 51(8):877–896.

Purpose. Fit uncertainty that arises due to inadequately presented fit information on webshops causes unnecessary costs in retail supply chains. The costs are apparent in the extent to which experience goods are returned due to poor fit after being ordered online. This paper calculates product return costs associated with fit uncertainty in e-commerce and further tests the ability of a fit uncertainty-reducing intervention to reduce fit uncertainty for fashion shoes.

Method. The paper uses a mixed-methods approach (Golicic and Davis, 2012). It combines a single case study (to map a returns handling process), a quantitative analysis of returns data (to estimate the frequency of and reasons for returns), a test of a fitting technology (to observe how well such technology functions for fashion footwear after being developed for other types of footwear), and mathematical modeling of product return costs (to understand fit uncertainty and returns as cost carriers for retail supply chains). The model incorporates product handling costs, tied-up capital, inventory holding costs, transportation costs, and order-picking costs.

Findings. The findings indicate that the return cost of a product in the studied case is 5 EUR (17 percent of the products' prime cost). The most frequent cause of return for products in the study is fit-related: the products were reported as being too small or too large for 55 percent of the returns. The fitting technology could reduce fit-related returns by 25–80 percent, depending on how well it is calibrated to the product. Fashion footwear with shapes that are difficult to measure could be less appropriate for the type of technology tested, and other ways of representing the footwear (i.e., not the scanning that was tested in this paper) could be necessary.

Theoretical contribution. The paper reveals how fit uncertainty impacts product return costs in e-commerce and how a fit uncertainty-reducing intervention used pre-sales can reduce fit uncertainty. Theoretically, it contributes to understanding how customers interact with and use pre-sales interventions for virtual fit verification to reduce fit uncertainty. It also contributes to the stream of research dealing with avoidance practices to offset returns in online retailing, identifying the important role of the pre-sales fitting activity of virtual fit verification; in contrast, previous research only focused on conveying fit information (De Leeuw et al., 2016; Hjort et al., 2019; Miell et al., 2018).

4.4 Paper IV

Gustafsson, E. (2021). "Retail supply chain implications of online customers' order-placing behaviors to mitigate fit uncertainty."

Purpose. The inability to physically try on products in e-commerce prior to purchase can cause product returns and repetitive product handling that slow down product flow. The paper investigates how online customers shopping for experience goods seek to mitigate fit uncertainty through different behaviors around placing orders, and it assesses the cost implications of these behaviors.

Method. The paper uses a quantitative analysis of order and return transactions (Bradlow et al., 2017) from a retailer that sells a typical experience good: shoes. The data span two years and contain 190,000 order and return transactions. The data were analyzed for how customers place orders when the product is subject to fit uncertainty and how these practices affect the supply chain in terms of customer service time, inventory holding costs, order-picking costs, return handling costs, and transportation costs.

Findings. Findings indicate four order-placing behaviors used by online customers to mitigate fit uncertainty: 1) customers who are confident in their size ordering many different shoes of identical size; 2) customers ordering consecutive sizes in a sequence of orders, returning those that are too large or small from the previous order; 3) customers reordering a fitting pair of shoes shortly after the first order; 4) customers ordering multiple consecutive sizes of a shoe in the same order. The supply chain consequences of the identified ordering behaviors on product flow and customer lead time are considerable. Large orders from customers confident in their size reduce lost sales and handling due to bad fit. Dealing with a poor fit by placing consecutive orders for different sizes slows down product flow and increases customer lead time. Ordering multiple consecutive sizes in the same order counterintuitively reduces handling for the retailer while effectively mitigating fit uncertainty and reducing delivery lead time for the customer. However, to solve the root problem of customers being unable to experience fit-dependent products in the pre-order stage, technological fit uncertainty-reducing interventions are needed.

Theoretical contribution. The paper theoretically contributes the phenomenon of customer order-placing behaviors as a means to cope with fit uncertainty to the online fit uncertainty literature (Hong and Pavlou, 2014; Dimoka et al., 2012). It further adds the product flow consequences of these behaviors to the product return literature (Rogers et al., 2002; Hjort et al., 2019), specifically the product flow consequences of customer service time, inventory, order picking, return handling, and transportation.

4.5 Paper V

Gustafsson, E., Hjort, K., Holmström, J., and Jonsson, P. (2021). "Effects of virtual fitting technology on online customers' shopping journeys and order performance."

Purpose. Against the backdrop of scant literature examining the effectiveness of return-reducing interventions, this paper empirically investigates the effect of a fit uncertainty-reducing intervention on order performance and on fit uncertainty-mitigating ordering tactics in an apparel and e-commerce context.

Method. The paper uses a quantitative analysis of order and return transaction data (Bradlow et al., 2017) from a retailer that sells a typical experience good, apparel, and has implemented a fit uncertainty-reducing intervention for its webshop. The data span half a year and contain 128,000 order and return transactions. The data was analyzed according to order performance (i.e., sales and returns).

Findings. The paper finds that the use of the intervention is associated with both increased order sizes and more returns. For customers who order multiple sizes as a fit uncertainty-mitigation tactic, the use of the intervention reduced returns. Surprisingly, the use of the intervention increased fit-related returns while reducing returns related to dissatisfaction with the product or model.

Theoretical contribution. The paper contributes to a stream of research investigating pre-sales measures to mitigate product returns from a customer journey perspective (Lemon and Verhoef, 2016). For e-commerce, an important distinction among the means to experience fit is whether fitting is available pre-sales or only post-sales. Few research studies have examined the effectiveness of technologies designed explicitly to reduce return rates (Walsh and Möhring, 2017). This paper contributes to the scant literature on pre-sales technologies (Bechwati and Siegal, 2005; Minnema et al., 2016) by evaluating a specific fit uncertainty-reducing intervention in terms of order performance.

5. Findings

This chapter presents the findings of the appended papers in relation to the thesis's research questions. Section 5.1 reports the findings related to the first research question (RQ1: How does fit uncertainty affect retail supply chain performance?), and Section 5.2 reports the findings related to the second research question (RQ2: How do fit uncertainty-reducing interventions affect retail supply chain performance?).

Both research questions involve *retail supply chain performance*. This term refers to performance dimensions related to product flow, as elaborated in the thesis's scope in the introductory chapter. Thus, Sections 5.1 and 5.2 are structured according to these performance dimensions: *sales*, *costs*, and *delivery lead time*.

Table 5.1 shows the findings described in Sections 5.1 and 5.2 with respect to the performance dimensions of sales, costs, and delivery lead time. The first column shows the performance dimension that the findings relate to, the second column shows the findings in relation to the first research question, and the third column shows the findings in relation to the second research question.

5.1 How fit uncertainty affects retail supply chain performance

This section reports the findings related to the first research question: How does fit uncertainty affect retail supply chain performance?

5.1.1 The effect on sales

Papers I and II indicate a trade-off between inventory spoilage and lost sales. A prerequisite for customers to find fitting products is that retail supply chains provide fitting products. However, retail supply chains cannot know that the products they provide fit the customers; thus, providing a vast product supply enables sales of fitting products. The provision of a vast product supply runs the risk of inventories becoming obsolete, but provision of a narrow product supply runs the risk of lost sales. In Paper II, a case informant from the case Skates Stocker explained that there is a hockey player that uses skates with a very large size, and these skates are primarily sold only to that particular player. Retailers note that there is a demand for that large size and stock one pair of skates in that size; the problem is, 12 retailers do the same, and as a result, there are 12 skates of that size in the supply chain. This is an example, and a finding, from Paper II that illustrates the trade-off between lost sales and obsolescence: retailers stock up on inventory to secure potential sales, but the stock may remain unsold.

Paper IV finds that fit uncertainty leads to lost sales; in some cases, the effect stems from customers' ordering behavior. Lost sales due to poor fit amounted to 4.7 percent of customer orders. A high degree of single-item orders indicates a customer behavior of hazarding a guess at fit to avoid the hassle of returning. The same single-item ordering behavior was observed in Paper III. Another ordering behavior used by customers is ordering multiple consecutive sizes in an order, as identified in Paper IV. This behavior indicates that the

Table 5.1: Findings.

Performance dimension	The effect of fit uncertainty	The effect of fit uncertainty-reducing interventions
Sales	Large inventories to secure potential sales	Increased sales through narrowing the discrepancy between customer demand and available supply
		Transparency in how sales are lost and won on the store floor, enabling supply chain and assortment planning for higher sales without increasing inventory holding costs
	Lost sales due to lack of fitting products and/or lack of fit communication practices	Increased sales, since the interventions have a sales pitching effect and customers trust the interventions' recommendations
	Increased sales when customers do not return ill-fitting products	Lost sales when fit uncertainty-reducing interventions are unsatisfactorily calibrated
Costs	Large number of returns to be handled	Reduced number of returns
		A reduction of 20–40 percent in the return cost, depending on what the intervention is capable of reducing
	Increased tied-up capital and inventory holding costs due to customers needing to evaluate the fit of the products post-order	Decreased inventory holding costs and tied-up capital, because fewer products are in customers' evaluation loops
		Decreased inventory costs by using fit uncertainty-reducing interventions for dynamic switchover of delivery between physical inventory and make-to-order
	Increased transportation costs for sending an order associated with returns to the customer, as well as the subsequent return transportation	Decreased transportation costs due to fewer returns
	Increased order-picking costs through increased number of picks that will be returned and re-stocked	Decreased order-picking costs due to fewer orders placed erroneously by customers
Delivery lead time	Retailers' use of customization	Customization can be used to finalize the fit of a product without increasing delivery lead time
		A partial and dynamic move toward more speculative production and the use of the intervention for matching-to-stock instead of matching-to-production design
	The order-placing practice of ordering a product, returning it, and ordering another product increases the delivery lead time for the customer	
	The order-placing practice of ordering multiple products in one order and potentially returning some products is unaffected in terms of delivery lead time, given that the customer kept the fitting product(s)	

customer is uncertain which size to order, so they order both/all and return the least fitting. Interestingly, in half of all the identified instances of this practice in the dataset, the customer decided to keep both sizes. The effect on sales is significant, given that the retailer upsold without making an effort to do so.

5.1.2 The effect on costs

Local inventory in stores acts as a bottleneck to product flow resulting from fit uncertainty, as indicated in Paper II. Local inventory in stores is considered essential for retail supply chains to cope with fit uncertainty, as it offers customers the ability to test products prior to purchase so as to eliminate fit uncertainty. However, fit uncertainty also accounts for expenditures in retail supply chains, as shown in Paper III, which reports costs arising from fit uncertainty from an e-commerce perspective, namely: returns handling costs, tied-up capital, inventory holding costs, transportation costs, and order-picking costs.

Fit uncertainty causes goods to be returned, since e-commerce customers struggle to evaluate the fit of a product pre-purchase. Returns handling involves the receiving of the returns, quality inspection, and restocking of the returns as saleable goods on the shelves. Returns caused by fit uncertainty accounted for 55 percent of all returns for the studied case retailer in Paper III, 47 percent of all returns for the studied case retailer in Paper IV, and 48 percent of all returns for the studied case retailer in Paper V. The customers who returned the products marked them as too small or too large. Given that approximately half of all returns are fit-related, the returns handling costs for such returns are significant. Paper III showed that the return cost in the studied setting amounted to 5 EUR per product, and the returns handling accounted for the largest cost caused by fit-related returns (and all returns in general).

Fit uncertainty causes tied-up capital. Tied-up capital is the cost of ordered products being in the customer's evaluation loop, and it is based on lead time from when the product is dispatched to the customer until it is received again by the dispatching unit. Here, the evaluation loop is the key effect of fit uncertainty, and the evaluation loop for online shopping replaces the evaluation phase that otherwise takes place in a physical store when customers test products. The inventory holding costs are the tied-up capital cost multiplied by the inventory interest rate. Inventory holding is an effect of fit uncertainty in the sense that each size requires an inventory of its own, and customers' evaluation loops theoretically raise the safety stock (or violate the safety stock if the evaluation loops are unaccounted for), as indicated by Paper II. Paper IV reports various ordering behaviors that are linked to fit uncertainty; depending on the type of ordering behavior, the customer may take up shorter or longer evaluation loops, which affects inventory holding costs.

Transportation costs arise as an effect of fit uncertainty when ordered products are returned due to fitting issues. Transportation costs are the costs of sending an order associated with returns to the customer, as well as the subsequent costs for the return transportation. Since the distribution of single-item orders differed across the cases in Papers III, IV, and V, transportation costs may vary. The most transportation-heavy ordering behavior a customer can engage in is to order one item, return it, and order another; as indicated in Paper IV, this behavior accounted for three percent of the orders in the dataset.

Order-picking costs are determined by the number of delivered items and are an estimate of the costs for picking items that are returned (i.e., picks that have been executed to no avail). Therefore, fit uncertainty affects order-picking by increasing the number of picks that will be returned and restocked. The order-placing behavior that accounts for the highest order-picking costs is the customer ordering products in sequence (order, return, order again). These sequenced orders account for two separate order compilations (compiling the first order and compiling the second order), as shown in Paper IV.

5.1.3 The effect on delivery lead time

Sending parcels back and forth between the retailer and the customer affects delivery lead time for e-commerce sales, as identified in Paper IV. The ordering behavior that stands out in terms of delivery lead time is the one where the customer places orders in sequence. This practice involves two sequential delivery cycles (one delivery cycle for the customer to receive the first order, and another to receive the final order). Orders with consecutive sizes in the same order deliver a fitting product to the customer in one delivery cycle. Paper IV reveals that transportation is the costliest product flow activity, so sending parcels back and forth significantly burdens the retail supply chain.

Fit uncertainty induces retailers to add customization elements to their operations, as indicated in Paper II. In that context, fit uncertainty increases delivery lead time compared to the product being sold directly off-the-shelf, as customers have to wait for a considerable amount of time (sometimes several weeks) for delivery of purely customized products.

In contrast to traditional off-the-shelf retail, which holds large inventory levels so as to deliver products to customers instantly, Ski Boots Networker in Paper II uses in-store customization for the final fit of the product; in that way, customization can be used without increasing delivery time.

5.2 How fit uncertainty-reducing interventions affect retail supply chain performance

This section reports the findings in relation to the second research question: How do fit uncertainty-reducing interventions affect retail supply chain performance?

5.2.1 The effect on sales

Paper II finds that fit uncertainty-reducing interventions act as a means to increase sales by narrowing the discrepancy between customer demand and available supply. The conceptual effect that fit uncertainty-reducing interventions have on sales is further elaborated in Papers I and II. These papers conceptualize digital product fitting as a fit uncertainty-reducing intervention, recommending fit as a result of matching digitally encapsulated products and customers. These digital encapsulations contain the information needed for selection and fitting, and, in the case of product customization, the information needed for customization. Fit uncertainty-reducing interventions potentially improve sales because customers are directed to products that fit them. Paper I presents a maturity model of the digitalization of product fitting based on real-life operational fit uncertainty-reducing interventions. This maturity model is based on technological maturity and supply chain maturity; the former involves how advanced the intervention's technology is, and the latter involves streamlining fit information between supply chain actors.

Traditionally, reducing lost sales involved increasing inventory so that more models and sizes were available (i.e., increasing product variety). In both physical retail and e-commerce, increased product variety makes it more difficult for customers to find fitting products without assistance. Despite the presence of a large variety of products, this variety is often not efficiently available to the customer. Through fit uncertainty-reducing interventions, customers can efficiently assess fitting products from among a large variety. However, increased product variety also entails higher inventory holding costs and poses a risk of obsolescence at the end of the season. A representative from Skates Stocker explained that their use of the fit uncertainty-reducing intervention enables them to clearly see how sales are lost and won on the store floor, enabling supply chain and assortment planning for greater sales without increasing inventory holding costs. In reference to the 12 special sizes example in Section 5.1.1, the intervention that Skates Stocker uses enables the supply chain management function to see the distribution of players' scanned sizes and can match these to their retailer orders when stocking up on skates for the season to come. Skates Stocker can then advise its retailers which sizes to stock. This exemplifies customer-close supply chain management, reducing lost sales on the retail level while at the same time reducing product variety and inventory holding on the supply chain level.

One case in Paper I uses a scanner to recommend insoles to running shoes. The case informant explained that the scanner serves as a sales pitch to customers, and they subjectively estimated that seven out of ten customers buy the insoles. Ski Boots Networker in Paper II also indicated this positive sales effect; the retailer estimated that nine out of ten customers buy the insoles, and moreover, friends and family coming along to the store also buy a pair of insoles.

Paper I further proposes that fit uncertainty-reducing interventions benefit sales because new product development according to customer needs can be followed up with a direct sales pitch to the customers who would potentially benefit most from the new product. For example, if a supplier develops an exceptionally wide shoe that is a particularly good fit for a previously-unserved segment of customers, benefit sales means this segment is now directly informed about the new product and its benefits. This type of reverse matching denotes that the customer encapsulations are searched to recommend fitting products, and it shows which customers might be interested in certain products based on size, form, and previous purchases. Such a fit uncertainty-reducing intervention is ideal for end-of-season clearance and pitching new products. Paper V also shows that fit uncertainty-reducing interventions increase order size, i.e., have a positive sales effect.

5.2.2 The effect on costs

The effect of fit uncertainty-reducing interventions on returns handling costs remains unknown, given that the interventions under study in Papers III and V suffered from calibration issues. Paper V indicated an increased return rate when the intervention was used by customers, but this was a direct effect of the calibration issue. Although empirical support is lacking for the interventions studied in the appended papers, the theoretical effect of fit uncertainty-reducing interventions is to reduce fit uncertainty and, as such, reduce the number of returns caused by fit uncertainty, as proposed in Paper I. A reduction in number of returns leads to lower costs associated with returns (i.e., inventory holding costs, tied-up capital, transportation, and order-picking costs). Inventory holding costs and tied-up capital decrease because fewer products remain in customers' evaluation loops. Transportation costs decrease due to a reduced return rate. Order-picking costs decrease because fewer erroneously placed orders are placed by customers. Paper III shows that a possible return cost reduction for the studied case ranges from 1.1–2.2 EUR (20–40 percent of the return cost), depending on the reduction rate that the fit uncertainty-reducing intervention is capable of achieving.

Paper IV shows that customers employ different ordering behaviors to cope with fit uncertainty; thus, fit uncertainty-reducing interventions are needed to alleviate the customer concern of fit uncertainty. These interventions serve a purpose in helping customers decide which size to order, with the consequence of a lower number of orders wherein the customer orders consecutive sizes and a lower number of orders wherein the customer places sequential orders of consecutive sizes. If fit uncertainty-reducing interventions can influence customer ordering behavior, they can have a positive effect on order-picking costs, such that fewer erroneously ordered items are picked.

Traditionally, to achieve manufacturing efficiency and instant delivery of off-the-shelf products, retail supply chains relied on make-to-stock and manual matching to the inventory available in the retail store. This traditional off-the-shelf retail is superior to order-and-wait retail in terms of the unit cost and delivery speed tradeoff but is inferior in terms of fit and risk of inventory obsolescence. Paper II shows that fit and sales can be improved simultaneously, as inventory and costs are kept low by using fit uncertainty-reducing interventions to implement a dynamic switchover of delivery between physical inventory and make-to-order.

5.2.3 The effect on delivery lead time

Conventionally, customized fit comes with higher production cost and longer delivery lead time, but through the use of fit uncertainty-reducing interventions, fit is improved without costlier production or longer delivery lead times, as indicated in Papers I and II.

Using customization, Dress Shoe Customizer in Paper II trades off superior fit for longer delivery lead time (as opposed to traditional retail, which trades off instant delivery for a lesser degree of fit and customer uncertainty around not finding a fitting product). In scaling up, Dress Shoe Customizer explained that a fit uncertainty-reducing intervention offers a way to move toward more cost-efficient batch production without sacrificing product fit. When sales volume increases, their intervention facilitates a partial, dynamic move toward more speculative production and the use of the intervention for matching-to-stock instead of matching-to-production design (shoe last). This dynamic switching between matching-to-stock and customization can be introduced so as to increase sales volume without trading off delivery and cost on the supply chain level. This intervention-enabled dynamic switchover is an example of turning a previously static choice (match-to-stock *or* customization) into a dynamic decision (match-to-stock *and* customization).

6. Discussion

This thesis explores the effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance. This chapter elaborates on the thesis's contributions. Figure 6.1 presents the parts of discussion.

Section 6.1 expands our conceptual understanding of how to make better use of existing product variety in retail supply chains. A key contribution is an alternative way to simultaneously achieve both sales performance and cost performance in retail supply chains, without a trade-off between the two. The streamlining of fit information is the primary mechanism that enables retail supply chain performance improvement.

Section 6.2 highlights the contribution of identifying ordering and returning behaviors and ascertaining how these emerge from fit uncertainty. If the physical fitting activity is made a pre-sales activity instead of a post-sales activity, retail supply chain performance can be improved, especially in terms of fewer product returns. Such reformulation of the fitting activity involves retailers' operating procedures, such as selling and returning policies.

As detailed in Chapter 5, fit uncertainty-reducing interventions affect retail supply chain performance, but that relationship depends on the customer's usage of the intervention, which is discussed in Section 6.3. In turn, the intervention usage depends on the intervention's accuracy and on how the customer interprets the provided fit information. The customer's use of the intervention also depends on their willingness to use it, in terms of the effort they need to expend either in engaging with the intervention pre-sales or in engaging with the post-sales aftermath of not using the intervention, such as returning.

Section 6.4 delineates the transferability of this thesis's findings in terms of type of retail channel and type of product to which the findings apply. The findings apply to two application areas: physical commerce and specialty products, and e-commerce and general products.

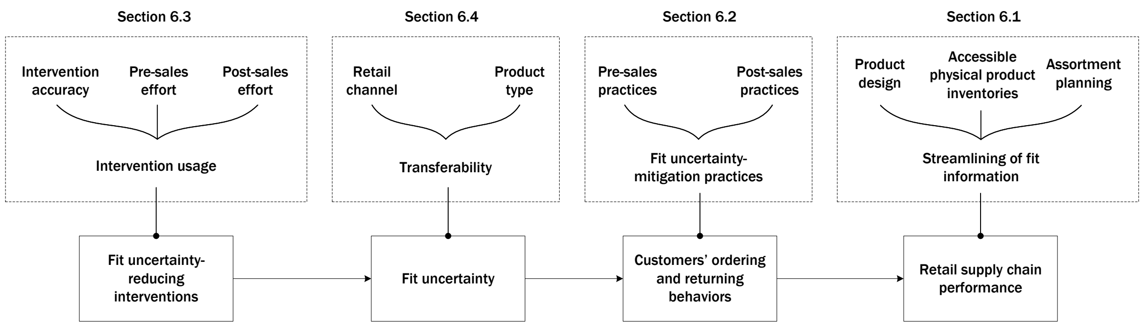

Figure 6.1: Discussion model.

6.1 How fit uncertainty-reducing interventions change the cost-sales performance trade-off

The conceptualization of the digital product-fitting intervention in Papers I and II contributes to and builds on previous research on supply chain strategy frameworks, in particular how to design for cost-effectiveness and responsiveness in supply chains. Well-established frameworks in the field of supply chain strategy include Fisher (1997) and Pagh and Cooper (1998). The findings of this thesis show how the use of fit uncertainty-reducing interventions in retail supply chains does not force a choice between speculation and postponement (Pagh and Cooper, 1998), or between efficiency and responsiveness (Fisher, 1997), in the design of the supply chain. Instead, the findings demonstrate how these interventions allow for efficiency and responsiveness to be combined, reducing the need to modify products in order to achieve the objectives of mass customization (Gilmore and Pine II, 1997; Piller and Kumar, 2006), i.e., the interventions allow physical efficiency and responsiveness capabilities to be combined in the *same* supply chain. Research has indicated that focusing on either manufacturing efficiency or customer responsiveness is not relevant to improving practice in settings where both cost and responsiveness are important for supply chain competitiveness (Schonberger and Brown, 2017). This investigation of fit uncertainty-reducing interventions in retail supply chains supports this view. Implementing technology to digitalize product fitting changes the trade-off between cost and responsiveness in the retail supply chain, making many of the benefits of customization available without increasing costs.

The mechanism for retail supply chain performance improvement is fit information being streamlined to actors upstream from the retailer (Gao et al., 2020). More specifically, fit information (which includes information regarding both customers and products) enables removal of the product flow bottleneck of inaccessible local inventory, and it lets retail supply chain actors specialize and improve their operations, such that brand owners can focus on developing better-fitting products and retailers can better plan assortments.

In traditional retail, where no fit uncertainty-reducing intervention is used, the *product flow bottleneck* is represented by a shortage of inventory to close sales (Mou et al., 2018; Ton and Raman, 2010). To close a sale without a fit uncertainty-reducing intervention, there must be room for the product to be physically tested, either at a physical retail store or, in the case of e-commerce, in the customer's own home. When the physical store lacks a fitting product, the result is lost sales; when the customer finds that a product ordered via e-commerce is a misfit, the result is lost sales and return flow inefficiencies. In traditional retail, sales are constrained by the available inventory of physical products. Phantom inventory is inventory that is inaccessible to customers (Ton and Raman, 2010); inventory of experience goods subject to fit uncertainty with imprecise size labels is phantom inventory until the customer can try on the products. In e-commerce, mislabeled assortments from which the customer can buy risks not only lost sales, but also greater return flow and logistics costs (Abdulla et al., 2019).

Increasing the local inventory in which customers can find fitting products increases the chance of closing sales, and fit uncertainty-reducing interventions enable navigation within larger assortments. Digitalizing the product-fitting activity through the use of fit uncertainty-reducing interventions removes the flow bottleneck of locally available inventory, increases the likelihood that customers will find fitting products, and as such reduces phantom inventory and costs due to imprecise size labels. Such costs include costs associated with reverse logistics in terms of returns of ill-fitting products (transports and return handling), as well as tied-up capital and inventory costs for holding inventory and making it accessible to customers.

Sales can be increased by growing the network of actors sharing the digital encapsulations of customers and products. An expanding network enabling wide use of the encapsulations offers a platform for retail supply chain actors to *specialize and improve their operations* (Holmström et al., 2019). It allows different supply chain actors to focus on a limited set of unique tasks and collaborate within a wider network to improve both efficiency and customer-perceived quality (fit). The role of the retailers can be focused on creating customer encapsulations, assisting in sales, and delivery. The role of the brand owners can be better focused on designing products with improved fit and adjusting and planning assortments accordingly. The principles of factory focus (Skinner, 1974; Ketokivi and Salvador, 2007) are encouraged for retail supply chains supplying experience goods subject to fit uncertainty. Combining factory focus (i.e., producing the goods to a low unit cost, or mass production) with fit uncertainty-reducing interventions achieves the same goal as customization but at a fraction of the cost associated with a customized product. Furthermore, by making product fit explicit and visible to both the retailer and customers, fit uncertainty-reducing interventions affect how product quality is perceived (Nonaka et al., 1996).

Streamlining the fit information enabled by fit uncertainty-reducing interventions potentially leads to continual adaptation of assortments, pricing, and targeted product designs (Grewal et al., 2011, 2017; Roggeveen and Sethuraman, 2020), bringing upstream actors' decision-making closer to customers. The sharing of digital encapsulations in a network allows both retailers and suppliers to recognize the variability of customer demand and the available supply. This offers a strategic opportunity to move the whole supply chain toward customer-close operational decision-making. For example, the sequence of the combination of speculation (cost efficiency) and postponement (responsiveness) can be fluid, rather than a fixed decision. Fit uncertainty-reducing interventions can be deployed in a speculation-first or postponement-first manner, as they do not necessitate a choice between the two (Pagh and Cooper, 1998). The determinants of the combination order can be found on an operational level. Fit uncertainty-reducing interventions can be deployed first so as to fully utilize available product variety and to reduce the need for customization; this was the primary purpose of using the interventions in the established retailers studied in this thesis. However, the interventions can also be deployed after customization, enabling companies to incrementally take advantage of speculation as customer demand is growing; this sequencing enables a dynamic combination of customization with make-to-stock.

The use of fit uncertainty-reducing interventions in retail supply chains changes the trade-off between cost and responsiveness, achieving many of the benefits of customization at a lower cost. This thesis's findings indicate a shift in the performance frontier in retail supply chains, with fit uncertainty-reducing interventions changing the trade-off between cost and responsiveness (Schmenner and Swink, 1998). With fit uncertainty-reducing interventions, retail sales are not constrained by the inventory of physical products but are instead enabled by digitalized products and customers. They further reduce phantom inventory (Ton and Raman, 2010) and increase the timing flexibility of delivery processes, increasing opportunities for switching between selling from inventory and customizing products; this achieves some of the fit-related benefits of mass customization (Piller and Kumar, 2006) without forfeiting the cost benefits of mass production.

6.2 Quantification of prevalence of fit uncertainty-related order and return behaviors and associated costs

A key contribution in this thesis is the quantification of the prevalence of ordering and returning behaviors associated with fit uncertainty, particularly whether the availability of fitting pre- or post-sales impact customers' ordering and returning behaviors.

In the pre-sales stage, the customer browses for fit-dependent products, either in a physical store or in a webshop. In the physical store, the customer is able to try on (i.e., fit) products prior to purchase, which mitigates fit uncertainty and the risk of needing to return due to poor fit. In e-commerce, unfamiliarity with a product and/or brand causes fit uncertainty, and physical try-on is only available post-sales (i.e., after delivery). Customers seek solutions to reduce fit uncertainty or take a chance that the product will fit, resulting in the different ordering behaviors described in Paper IV. Problematic customer shopping processes are those in which customers order goods that do not fit and have to return them. Even more troublesome is the customer's anticipation that the ordered item would fit, yet it does not, resulting in unmet expectations and a bad shopping experience. Despite the fact that research suggests lenient return policies in order to alleviate bad customer experience of the shopping process (Janakiraman et al., 2016), the post-sales activity of returning remains a burden for customers and is ineffective in improving return rates.

Research on post-sales measures of coping with fit uncertainty regards return policies as a means of controlling the extent to which customers return items. As stated above, such research recommends lenient return policies to alleviate bad customer shopping experiences (Janakiraman and Ordóñez, 2012), but post-sales returns remain a hassle for customers, even if the items are easily returned. Strict return policies aim to prevent returns (Janakiraman et al., 2016), but these are directly ineffective and unhelpful for experience goods subject to fit uncertainty, as these require physical fitting. Strict return policies are understandable from the perspective that customers can abuse lenient return conditions (Ketzenberg et al., 2020; Lantz and Hjort, 2013; Gelbrich et al., 2017). While lenient return policies promote the customer's fitting process, these policies incur costs associated with fit uncertainty and with returns management.

This thesis quantifies actual order and return behaviors as a direct effect of fit uncertainty. Knowing how customers cope with fit uncertainty, as can be seen in their order and return behaviors, is an important aspect for understanding and for further relieving customers' fit uncertainty concerns. Order and return behaviors could be important input for storage assignment policies in warehouses in terms of *where* to store products (e.g., if goods should be stocked according to size or according to model). These behaviors are further useful in leading both practitioners and academic scholars to realize the effect that fit uncertainty has on retail supply chain performance and to pursue actions and research to mitigate fit uncertainty.

This thesis complements existing research on alleviating fit uncertainty before it becomes a post-sales matter; as such, it contributes to pre-sales measures of coping with fit uncertainty by exploring the effects of fit uncertainty-reducing interventions. The considerable effect that these interventions have on the customer shopping process is that the fitting activity can occur pre-sales instead of post-sales (see Figure 6.2), and as such, the fitting activity can occur at the first point of fit uncertainty. This move is essential for the interventions' return-reducing effect and for counteracting return-induced logistics costs (Abdulla et al., 2019; Rogers et al., 2002).

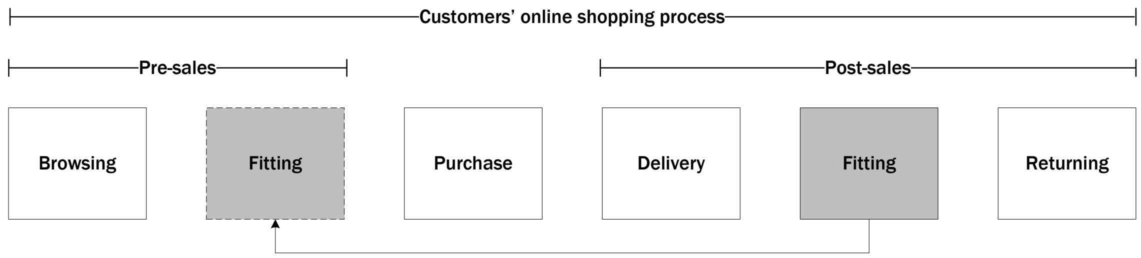

Figure 6.2: Customer shopping process.

A significant contribution of this thesis is the quantified cost effects of fit uncertainty on retail supply chain performance. This thesis agrees with previous research that fit uncertainty causes a large share of returns in e-commerce (Misra and Arivazhagan, 2017), but it dives deeper into the costs underlying returns. Ketzenberg et al. (2020) model return costs, but from a profit-loss perspective. This thesis complements the sales perspective of Ketzenberg et al. (2020) by diving deeper into the costs that constitute loss of profit. These quantified costs indicate that actions are needed to reduce fit uncertainty and its incurred costs. Above all, the thesis quantitatively and empirically underpins the costs that previous research only points out as an evident effect (Gelbrich et al., 2017). A strength of the thesis is that the effects of fit uncertainty are made explicit through the quantification of cost effects and through the prevalence of order and return behaviors, both with and without fit uncertainty-reducing interventions. Additionally, revealing customers' ordering and returning behaviors due to fit uncertainty and the concurrent costs is important input for practitioners forming e-commerce selling policies. Retailers should consider promoting an overordering customer behavior (i.e., ordering consecutive sizes in one order) for customers who choose between two sizes.

6.3 Reflections on usage and practical challenges of fit uncertainty-reducing interventions

Undoubtedly, fit uncertainty is a pressing issue for retail supply chains, but few retailers use a fit uncertainty-reducing intervention, and even when it is present, customers do not use it, as indicated in Paper V. This section discusses intervention usage from the aspects of intervention accuracy, customers' post-sales efforts, and pre-sales efforts.

6.3.1 The intervention's accuracy

The precision, or accuracy, of the intervention is very important for recommending fitting products, but in practice it is perhaps not feasible for the technology to recommend the correct products all the time. The question, then, is how to best display and communicate fit.

As an example, one intervention uses scanning data of customer feet and matches these to a database of shoes that have been scanned on the inside. The technology is very precise, but the results are difficult for customers to interpret. Fit is displayed as two bars, each representing one of the customer's feet. Interpreting the fit is easy when both bars are filled to the top with green: it is clearly a very good fit, according to the technology. Since each foot is seldom an identical copy of the other, differing fit between the feet and the shoes are common: in a scenario where both bars are yellow and half-filled, or when one bar is filled green and the other is one-fourth filled red, the fit is not as obvious to interpret. In a physical store with sales assistants, the customer can be assisted in interpreting the recommendations. However, being assisted is not possible in e-commerce, where the customer is left to interpret the recommendations by themselves unless supervised by a virtual assistant (Hanna et al., 2020; Roggeveen and Sethuraman, 2020). It is plausible that virtual assistance with regard to fit will be possible when that type of technology has been developed further (Grewal et al., 2017).

Another intervention also uses scanning data of customer feet, but it matches these data against a transactions database and recommends shoes based on what other customers with similar foot shapes bought and did not return. Such application is easier for the technology supplier, who need not scan the shoes on the inside. However, the technology has the cold start problem; it cannot accurately recommend products when data on previous purchases are scarce. Moreover, fit is not pre-programmed in the technology; instead, fit is established through a combined assessment of how customers deemed fit, based on if they returned or not. A lower level of accuracy may be easier for the customer to interpret; for instance, displaying shoe fit as one measure instead is likely easier to interpret than the more complex option of two types of fit (one measure for each foot).

Another intervention lets the customer input measures of a product (e.g., a garment) that they already own. The customer then browses the retailer's online assortment, and for products that they consider ordering, the intervention shows an overlaying silhouette on the considered product. The customer can then judge the fit of the product based on their experience of fit in relation to a known garment. The fit accuracy of such an intervention is rather low, as it does not say anything about the fit: it is up for the customer to judge the fit based on the product comparison.

The difficulty with fit is that it is a subjective measure, and the customer may disagree with the technology's definition of fit: for example, a customer may view a loose fit as a good fit, whereas the technology is programmed to recommend tighter fit. In physical commerce, product recommendation systems can function as a sales pitch, and sales assistants can convince the customer that the recommended product is the best choice. E-commerce does not offer this opportunity, so the consequence of an erroneous product recommendation is far more severe in the e-commerce context than in physical commerce. Retailers are frightened that the technology will worsen the customer experience, as being recommended a product where the customer disagrees on the fit is worse than the customer ordering a product and realizing that it fits poorly when testing it at home. Flawless functionality of the intervention is important for the retailer, since it is a prerequisite for the retailer to pursue sales: a systematic error in the intervention's algorithm would cause returns and dissatisfied customers.

Nevertheless, even with flawless functionality, the retailer cannot steer the outcome of how the customer uses the intervention. The customer may interpret a 100 percent fit as a non-fit, and such an outcome would be dreadful for the retailer, since the customer would lose trust in them.

6.3.2 Customer pre- and post-sales efforts

Using an intervention does not occur without effort. A customer who is unwilling to invest time in using the intervention pre-sales will risk spending time in post-sales activities, such as returning ill-fitting products. In contrast, a customer who is willing to invest time in using the intervention pre-sales improves their chances of avoiding spending time on post-sales activities and further product browsing.

In physical commerce, if the customer invests time in using the fit uncertainty-reducing intervention, a product will be selected more quickly, since the customer is directed to products that will fit (Heller et al., 2019). In contrast, if the customer is unwilling to invest time in using a fit uncertainty-reducing intervention, they will spend more time searching and fitting products to find a product that fits. Product selection without a fit uncertainty-reducing intervention makes it more difficult for customers to find suitable products without assistance, in both physical commerce and e-commerce (Wan et al., 2012). Even though a huge number of products may be accessible, the customer does not always have access to all of them (Grewal et al., 2012; Ton and Raman, 2010). A fit uncertainty-reducing intervention benefits both parties: from a customer journey perspective (Lemon and Verhoef, 2016), the customer requires fewer fitting sessions to find fitting products; from the retailer's perspective, sales assistants can spend less time on assisting the customer while simultaneously recommending better fitting products to the customer. In e-commerce, if the customer is unwilling to use a fit uncertainty-reducing intervention, they risk having to return ill-fitting products, not only inducing costs for the retailer but also causing a worse customer experience journey for themselves.

The challenge for the retailer is to influence the customer to use the intervention, such as by providing monetary incentives like a ten percent discount on the order or free return if the product does not fit (Gelbrich et al., 2017). In physical commerce, the retailers studied in this thesis pointed out that customers seem reluctant to use the interventions, which could indicate that customers feel they need to complete the purchase if they invest time in using the intervention.

6.4 Transferability: The types of retail channels and products to which the findings apply

The findings of the thesis mostly apply to experience goods that are subject to fit uncertainty and that are wearable. Typical goods include footwear and clothing, but other types of products that require physical fitting may benefit from this research as well, such as jewelry. Four of the five research papers in this thesis have focused on shoes, with the fifth paper focusing on clothing. Consequently, the findings are applicable to these experience goods, in their respective contexts: *retail channel* (physical commerce or e-commerce) and *type of product* (specialty/niche products or general products). *Specialty products* are experience products for which the customer values exceptional fit, since fit affects the performance of the product and hence the customer's performance when using it. *General products* are experience products for which fit is of lesser importance for the customer compared to specialty products. The findings apply to two application contexts: physical commerce and specialty products, and e-commerce and general products. These application areas are discussed in the following sections.

6.4.1 Physical commerce and specialty products

Ice hockey skates, ski boots, and running shoes are examples of specialty products, since the fit of the products have clear implications for the performance of the user, and it was among these products that fit uncertainty-reducing interventions were used in physical commerce.

One finding was that interventions supported the sales pitch and convinced the customer that the recommended product was the correct choice. This finding is applicable to physical commerce, where sales assistants can use the interventions to make their point and to convince the customer that the recommended product is the correct choice. Additionally, sales assistants can use the intervention to demonstrate how another size and product model would fit and can take the customer's preferences into consideration. This thesis shows no indication of the sales pitching effect in e-commerce; the reason this finding is limited to physical commerce is that the (studied) interventions are operated by a sales assistant and the technology itself is very accurate and presents detailed information to the customer. The obstacle to achieving the sales pitching effect in e-commerce is that the intervention is ill-suited to convey detailed information from an information-processing customer perspective. Interventions applied in physical commerce can extract data that is difficult to extract from an e-commerce intervention, such as pressure point data. More advanced interventions in physical commerce can distinctly show problematic fit areas and also recommend insoles to alleviate the fit problem.

This reality leads to another findings area applicable to physical commerce: customization. Customization practices used by the retailers we studied included heating and forming the products according to the customer's desires during the customer's shopping visit. Such final customization means that the customer can take the products with them at the end of their visit. It seems that final customization is limited to physical commerce. A prerequisite for physical commerce to secure potential sales is that each retailer stocks all variants in their assortment. The findings around how sales are lost and won on the store floor in combination with customization capabilities apply to products for which customization is possible and are limited to physical commerce.

6.4.2 E-commerce and general products

Fashion shoes and clothing are examples of general products. Here, fit is important, but less than that of specialty products. The findings that apply to e-commerce and general goods are those pertaining to the performance dimension of costs, since the findings stem from analyses of e-commerce operations. The calculated performance measures are based on e-commerce operations, but they are valid measures for physical commerce as well, albeit with a different framing. For instance, transportation costs need not represent transports associated with returns, but could instead focus on transports between stores; if a store is missing a variant demanded by a customer, the variant could be sent to that store from another store in the retail chain.

Findings on ordering behavior are limited to e-commerce, but similar shopping behaviors are likely present in physical commerce, along with behaviors that span both e-commerce and physical commerce (such as browsing and fitting products in the physical store and then ordering online, see, e.g., Balakrishnan et al. (2014)). Such shopping behavior can be seen as abusing the physical retail channel, but perhaps it is not abuse: offering the possibility to try the products in the physical store could be part of the retailer's strategy to cope with fit uncertainty in the online channel.

The identified customer shopping behaviors need not be limited to footwear and clothing, as studied in this thesis. Furniture is also a product subject to fit uncertainty, and it often costs more than footwear and clothing, providing an incentive for customers to examine it physically prior to purchase. Additionally, furniture is bulky, making a potential return costly for the customer. The shopping behavior of browsing and testing in-store and then ordering online is a plausible scenario for furniture shopping. That said, the shopping behavior and cost findings in this thesis are applicable to goods that are subject to fit uncertainty and that fall within the delivery boundaries of pick-up points.

In terms of product flow, and especially the reverse product flow appearing when customers return products after ordering online, the supply chain cost models produced in Papers III and IV are not limited to experience products subject to fit uncertainty, but can be applied to any product subject to being returned. Such cost models can, with some modification, also be used in a forward flow fashion.

7. Conclusions

This chapter concludes this thesis's theorization of fit uncertainty-reducing interventions. The research encompasses a definition of the interventions and the mechanisms that enable more efficient product flows (Paper II), different maturity levels and expected supply chain effects (Paper I), and quantified analyses of the effects of fit uncertainty and interventions on retail logistics performance dimensions (Papers III, IV, and V).

Section 7.1 highlights the main findings (i.e., fit uncertainty-reducing interventions are a matter of digitalization maturity, and local inventory is a bottleneck to product flow as a result of fit uncertainty). Customer order-placing and -returning behaviors are direct effects of fit uncertainty that disrupt product flow in retail supply chains, carrying negative supply chain effects and causing increases in the following costs: returns handling costs, tied-up capital, inventory holding costs, transportation costs, and order-picking costs. Fit uncertainty-reducing interventions can be used to clearly streamline fit information from retailers to supply chain management functions, including such information as how sales are lost and won on the store floor, thereby enabling better inventory management and assortment planning. For the interventions to yield positive performance effects, they need to be well-calibrated.

Section 7.2 elaborates on the theoretical and managerial contributions of the research. This thesis theoretically adds to supply chain strategy literature by elaborating on how to design efficient and responsive supply chains through the use of fit uncertainty-reducing interventions. It also theoretically contributes to retail operations literature by expanding returns management literature through the quantification of the existence and prevalence of customers' order-placing and -returning behaviors. Practitioners should consider this thesis's findings when shaping return policies for fit-dependent products.

Section 7.3 concludes the chapter by addressing streams of future research, especially the requirements for the interventions in order for customers to use them, how to best communicate fit online, and how return policies interplay with fit uncertainty and customers' shopping behaviors.

7.1 Main findings

By analyzing fit uncertainty in retail supply chains, this research has quantified the effects incurred by fit uncertainty on retail supply chain performance and shown how fit uncertainty can be reduced through technological interventions. The interventions involve fit recommendation systems in retail that use digital encapsulations of products and customers to match product supply to customer requirements. Fit uncertainty-reducing interventions do not conform to a single maturity level; instead, such interventions have been used to define a maturity model of digitalization of product fitting. The technological maturity levels vary in terms of how the matching is performed so as to recommend fitting products to the customer, how much information the digital encapsulations contain, and how much information is actually used for product fit recommendations. The dimension of supply chain maturity spans the maturities of integration among supply chain actors.

This thesis has theorized that local inventory in physical stores acts as a bottleneck to product flow as a result of fit uncertainty. Local inventory is a prerequisite for retail supply chains to manage fit uncertainty, as it provides customers the ability to test products before purchase in order to eliminate fit uncertainty. However, fit uncertainty incurs costs for retail supply chains. The quantified effects shown in this thesis consist of costs pertaining to returns caused by fit uncertainty. This thesis has revealed that fit uncertainty causes the following costs to increase: returns handling costs, tied-up capital, inventory holding costs, transportation costs, and order-picking costs.

Certain customer ordering and returning behaviors are also a direct effect of fit uncertainty and disrupt product flow in retail supply chains, carrying negative supply chain effects with them. Dealing with a poor fit by placing sequential orders for different sizes slows down product flow and increases the delivery lead time to the customer. Ordering multiple consecutive sizes in the same order counterintuitively reduces handling for the retailer while also effectively mitigating fit uncertainty and reducing lead time for the customer. However, technological fit uncertainty-reducing interventions are still needed to address the root problem of customers not being able to experience fit-dependent products before they order.

Another main finding is that interventions need to be well-calibrated. The slightest miscalibration causes negative systemic effects for the retail supply chain. Interventions suffering from calibration issues cause returns, not reduce them. This thesis has further found that fit uncertainty-reducing interventions are most relevant for products where both the product attributes and the customer attributes are easily measurable and where tacit knowledge of customers and products can be formalized using digital encapsulations.

7.2 Theoretical and managerial contributions

Contributing to the supply chain strategy literature, this thesis theoretically adds a way to achieve both efficient and responsive supply chains. This contribution relates to previous work on achieving the benefits of customization with the efficiency of mass production. Established supply chain design frameworks (Fisher, 1997; Pagh and Cooper, 1998) differentiate between efficient and responsive supply chain designs. Mass customization literature focuses on combining efficiency and responsiveness, but a trade-off between customization benefits and mass-production efficiency persists. This thesis supplements the established frameworks by making the efficient supply chain design more responsive using fit uncertainty-reducing interventions. The interventions do not force a choice between designing physical efficiency and responsiveness capabilities in supply chains (Fisher, 1997); on the contrary, the interventions enable the combination of efficiency and responsiveness capabilities in the same supply chain, such that both sales and costs can be improved simultaneously.

This thesis contributes to the retail operations literature pertaining to experience goods, and more specifically to previous research on order and return behaviors (Ketzenberg et al., 2020; Lantz and Hjort, 2013; Gelbrich et al., 2017), by focusing on behaviors associated with fit uncertainty. It quantifies the prevalence of order and return behaviors directly ensuing from fit uncertainty that influence retail supply chain performance, especially with regard to order-picking costs, transportation costs, and product handling costs. These quantified costs are also a contribution to the returns management literature (Rogers et al., 2002;

Hjort et al., 2019) that is focused on the effects of activities related to returns handling. In a wider perspective, the costs associated with order and return behaviors add to the retail supply chain performance literature (Anand and Grover, 2015; Fleisch and Tellkamp, 2005; Adivar et al., 2019).

The most critical element in retail supply chains is to collect demand data, disseminate it, and make it visible and usable in the upstream actors of the supply chain. This thesis has shown how fit uncertainty-reducing interventions can be used to clearly streamline fit information from retailers to supply chain management functions, including such information as how sales are lost and won on the store floor, adding fit information to the visibility literature (Gao et al., 2020; Barratt and Oke, 2007; Williams et al., 2013). This streamlining enables supply chain and assortment planning for higher sales without increasing inventory holding costs, and it gives rise to new business models for the industry wherein all products belong to the customers that they fit. Some business models have stepped away from the mass-production approach and instead entered customized production, but they are often unsuccessful due to the cost-inefficiency of producing products that way.

A contribution to both practice and theory is that this research enables the industry to continue drawing on mass production to enable cost efficiency while maintaining the fit benefits of customization through the use of fit uncertainty-reducing interventions, since finding a fitting product in the available product supply is as good a fit as a customized product can provide. The interventions also facilitate long-tail assortment management (Brynjolfsson et al., 2010; Walter et al., 2012; Rabinovich et al., 2011), as long-tail items can be pitched to customers who need them, which reduces the risk of these products becoming obsolete. Data collection on the product and the customer levels facilitates supply chain visibility of the data and enables more accurate steering of retail supply chain operations in terms of assortment planning and distribution (i.e., what products to stock and where to stock them). Streamlining fit information to upstream supply chain actors offers advantages for conducting availability improvements and for having healthy stock levels.

Practitioners should consider this thesis's findings when shaping return policies for experience goods subject to fit uncertainty. If fit uncertainty is left unresolved by the seller, customers come up with their own ways of coping with fit uncertainty; this is reflected in their shopping behavior, which can have more or less impact on returns-handling operations. In the case that the retailer, for any reason, is uninterested in implementing a fit uncertainty-reducing intervention, their return policies could still be shaped to facilitate the customer's product selection process. Instead of strict return policies that aim to prevent customers from returning items, policies should encourage customers to order multiple products in the same order, since that type of order carries less negative impact on the retailer's performance compared to the type of order where customers order one item, return it, and order a new product.

7.3 Further research

This research clearly shows the effects of fit uncertainty and fit uncertainty-reducing interventions on retail supply chain performance. It also raises the question of how customers perceive fit uncertainty. The scope of the thesis has been the product flow downstream from manufacturing, but it remains unclear what the actual effects of fit uncertainty-reducing interventions are on the product flow upstream in the supply chain. This section dives deeper into two streams of potential further research: the customer perspective, and the supply chain perspective.

This thesis has determined that fit uncertainty and fit uncertainty-reducing interventions affect customers' shopping behaviors, but further research is needed on what is required from a fit uncertainty-reducing intervention for customers to use the intervention. Here, Davis's (1989) technology acceptance model could be of use.

There are interventions available that are aimed at reducing customers' perceived fit uncertainty when shopping experience products online, but few seem to have become a success; why? What is required from a fit uncertainty-reducing intervention for customers to successfully use it? How should fit be communicated online, given that it is a subjective measure? For instance, some interventions let customers input the size of a shoe or garment they already own, and based on that input, the intervention shows the fit of the considered product as a percentage in relation to the already-owned item. High percentages, such as 90–100 percent, may convince the customer to purchase that size, and low percentages, such as 0–30 percent, may convince the customer that the product is not fit for them, and therefore the percentage dissuades the customer from purchase. What happens in the middle range, such as 40–60 percent fit, is interesting from a research perspective.

Involving customers and getting their perspective on fit is a promising avenue of research that could greatly improve the technological development of fit uncertainty-reducing interventions. In the above example, what percentages represent good and bad fit? If the customer knows that a product is a 60 percent fit, is that helpful to their decision-making process on which size to order?

Furthermore, return policies also interplay with fit uncertainty and shopping behavior. Further research is needed to determine the relationship between return policies and customers' shopping behaviors concerning experience goods. An experiment could be carried out to observe how customers' shopping behavior changes given different return policies. Such an experiment could also yield insight into which customer segments would use and would not use the interventions, and the common characteristics for these segments.

This thesis has shown that fit uncertainty affects customers' shopping behaviors, which leads to effects on the supply chain. What has not been examined in this thesis are the effects on product flow activities upstream of the manufacturer. An interesting avenue of research would be to dive deeper into the effects that streamlining has on product development. This thesis has touched on product development from a qualitative perspective, but less so from a quantitative perspective. Therefore, it is suggested that further research measure the effects of fit information on, e.g., the number of models and variants in the offered assortment, whether batch sizes and production volume change, etc.

This thesis has theorized that fit uncertainty-reducing interventions could lead to improvements around lost sales and obsolescence, but further research is required to quantify the extent to which these improvements are present; from that point, it will be possible to prove if and how fit uncertainty-reducing interventions affect these aspects.

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