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Object-Interactive Transvections: A Theory for Addressing Persistent Retail Supply Chain Problems

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ABSTRACT

In conventional retail supply chains, the primary objective is to fulfill customer demand by delivering the right product at the right time. However, retailers face persistent problems, including product returns, inventory obsolescence, lost sales, and lost demand. This study investigates how digital product fitting (DPF) can help address these challenges. Using engaged research with three companies incorporating DPF into their operations, we identify four use cases: fulfillment switchover, assortment planning, product design, and networked switchover. Our theoretical foundation is based on transvection theory, which centers on a product's journey through transformation and sorting to meet customer needs—in contrast to conventional supply chain management's focus on efficient processes and resource use. In conceptualizing our empirical findings, we develop a novel *object-interactive transvection* conceptualization that treats both completed and incomplete outcomes as improvable processes. In this conceptualization, digital customer–product interactions enable: (i) a shift from binary fulfillment outcomes to open-ended, customer-specific transvections; (ii) responsive upstream planning that leverages aggregated customer representations; and (iii) digitalized sorting that can be repeated, reversed, and parallelized across nodes. Collectively, these insights reframe static structural choices (match-to-stock vs. customization) as adaptive and interaction-driven operational decisions, and they open new avenues for improving supply chain performance.

1 | Introduction

Purchasing an experience product (such as footwear or apparel) poses challenges for both customers and retailers. For customers, making an informed decision requires some way of experiencing the product (Gustafsson et al. 2019), which means that the customer fits the product before making their final purchasing decision. For retailers, facilitating such experiences presents several difficulties. When the customer cannot find a fitting product, the sale is lost, with the implication that the retailer should have stocked a wider range of variants and sizes (Ketzenberg et al. 2000); conversely, when items in stock are not selected by any customer, they eventually become obsolete, requiring markdowns or removal from inventory. Moreover, until a successful product–customer match is achieved, both parties expend time and effort on managing and returning non-fitting products, which is logistically burdensome—especially for online retailers and their customers (Gustafsson et al. 2021).

Retailers employ various strategies to address the problems of customer fit, with speculation and postponement among the most prominent (Pagh and Cooper 1998). However, the necessary interaction between customer and product, along with the uncertainty of the interactive outcome (Gustafsson et al. 2019), complicates such conventional approaches, making it difficult to achieve a swift and even flow in the retail supply chain (Schmenner 2004). Through our engaged research (Van De Ven 2007; Sternberg et al. 2024), we approach this problem through the lens of object interaction (Wegner 1997), rather than speculation or postponement. We present object interaction as a novel framing in retail logistics research for overcoming the problems of lost sales, obsolescence, returns, and lost demand, whereby we approach the problems as processes to be completed rather than undesirable outcomes to be mitigated.

In our study, we engage with practice at the level of potential solution design (Holmström et al. 2009; Pil et al. 2024) by examining how digital product fitting (DPF) can be used and what types of interactions it enables. The depth of engagement was intermediate, with a focus on design (Sternberg et al. 2024). Specifically, we engaged with practitioners to evaluate and improve different DPF-enabled operational solution designs (i.e., use cases). The aim was not to implement these solution designs in companies but to understand how DPF can be used to address practical problems. Because demonstrated instances are highly informative with regard to what can be replicated, a key element of data collection was describing and interpreting what different retailers have done, for what purposes, and with what outcomes.

Digital product fitting (DPF) refers to technologies that create digital representations of both customers and products to evaluate how well a specific item fits a specific individual. Products can be digitally represented through multiple modes, including 3D scanning or design-based 3D modeling derived from CAD data, technical specifications, or geometry files; likewise, customers can be digitally represented through body or foot scanning, but also through non-scanning approaches, such as algorithmic inferences based on historical fitting and non-fitting products, size profiles, or purchase/return patterns (Gustafsson et al. 2019). The DPF practices used by our engaged companies combine (1) a product representation, (2) a customer representation, and (3) a matching or recommendation algorithm. The specific technologies differ across the firms, but the core principle of DPF remains the same: using digital representations to improve product–customer matching.

In this study, we examined various interactive approaches in emerging practices, with DPF facilitating the completion of previously-incomplete sales processes for experience products. Through our engagement with practice, we found how DPF can transform undesirable retail outcomes into interactive processes that can be completed. This transformation is realized through four use cases of DPF: (1) switching between customization and make-to-stock fulfillment strategies, (2) informing product design, (3) informing assortment planning, and (4) enabling cross-brand sales via a network of shared digital inventory, or platforming (e.g., Hagiu 2014). These uses dynamically reconfigure the retail supply chain to successfully complete product–customer interactions, thereby reducing lost sales, obsolescence, product returns, and lost demand. In developing this interactive digitalized alternative, we challenge the current and prevailing problem framing that is operational in retail supply chain design: the effective management of product variety and flow. Specifically, our objective is to explain how the persistent retail supply chain problems listed above are generated through customer–product interactions involving uncertainty, as well as to show how DPF-enabled operations intervene in these processes. By studying DPF use cases across retail supply chains, we reconceptualize these problems as incomplete object-interactive transvections rather than as static outcomes. This engagement with practice led us to ask a novel empirically-motivated research question: How do lost sales, obsolescence, product returns, and lost demand emerge as object-interactive processes in retail supply chains, and how can these processes be improved through DPF?

The remainder of the paper is structured according to the elements of engaged research (Sternberg et al. 2024). Section 2 presents the problematic situation by identifying the persistent problems in retail supply chains for experience products. Section 2 further expounds on the area of concern by reviewing literature on retail supply chain design and operations (including mass customization, omnichannel retailing, adaptive systems, and flow-oriented supply chain design), and it identifies where this body of knowledge falls short in resolving the persistent problems. Section 3 describes the methodological approach and empirical engagement through three iterative cycles of engaged research. Section 4 introduces the theoretical framing, drawing on and extending transvection theory to structure the analysis of customer–product interactions in retail supply chains. Section 5 details how DPF is deployed in practice and presents the four identified use cases. Section 6 articulates the study's contributions, including: contribution to solving the problem, by showing how DPF-enabled operations address persistent retail supply chain problems; the contribution of a new theoretical framing through the development of object-interactive transvections; and contribution to the literature through the reframing of mass customization, omnichannel retailing, and supply chain design around customer–product interactions rather than ex ante specifications. Section 7 concludes the paper by discussing the identified use cases, comparing insights from established theoretical perspectives with those offered by our new theoretical framing, and highlighting how the novel object-interactive transvection supports the identification of new improvement actions in the retail supply chain.

2 | Retail Operations of Experience Products

Retail operations for experience products are characterized by high demand uncertainty, heterogeneous customer needs, and limited pre-purchase information (Mou et al. 2018). Unlike search products, the value and suitability of experience products cannot be fully assessed prior to use; as a result, retailers must make inventory, assortment, and replenishment decisions under conditions wherein demand is both difficult to predict and only partially observable. Over time, this has given rise to a set of persistent operational problems that recur across product categories and retail formats, despite substantial advances in forecasting, optimization, and supply chain coordination (Aastrup and Kotzab 2010). These persistent problems are: lost sales, inventory obsolescence, product returns, and lost demand. While these problems (apart from lost demand) are well-documented, they are typically addressed through narrow-scope solutions rooted in optimization and inventory theory. The introduction of DPF creates possibilities to address them collectively through novel combinations of operational processes and digital customer–product interactions.

2.1 | Persistent Problems in Retail Supply Chains for Experience Products

2.1.1 | Lost Sales

Lost sales occur when retailers are unable to sell the product selected by the customers, most commonly due to stockouts (Sanchez-Ruiz et al. 2018). The consequences of lost sales extend beyond immediate revenue loss: customers become dissatisfied when they encounter a stockout, which damages store image and weakens customer loyalty (Zinn and Liu 2001; Sanchez-Ruiz et al. 2018). In addition, in their response to a stockout, customers may substitute products, delay purchases, or decide to buy the product elsewhere (Emmelhainz et al. 1991; Zinn and Liu 2001). Such customer responses confound the fulfillment process and complicate demand forecasting (Subramanian and Harsha 2021). The persistence of demand uncertainty, complicated by customer responses to stockouts, has made the problem of lost sales difficult to eliminate despite significant managerial and analytical efforts (Grewal and Levy 2007; Aastrup and Kotzab 2010).

Lost sales due to stockouts in retail are often represented as a trade-off with obsolescence due to excess inventory (Fisher 1997). Addressing the problem of lost sales through inventory theory relies on modeling and optimization such as that in the newsvendor model, which balances the cost of holding excess inventory against the cost of stockouts (Khouja 1999; Berk and Gürler 2016); however, this approach does not explicitly incorporate lost sales. Modeling approaches that directly address and incorporate lost sales are scarce, as they are analytically and computationally more complex than backorder-based models (Bijvank and Vis 2011; Subramanian and Harsha 2021).

Additionally, retailers deploy a variety of strategies to mitigate stockouts, including improved ordering and stocking policies, enhanced store operations and shelf replenishment, inventory monitoring, and replacement mechanisms (Emmelhainz et al. 1991; Ehrenthal and Stölzle 2013). These efforts are often supported by technologies ranging from point-of-sale analytics and RFID to deep reinforcement learning-based decision models (Dehaybe et al. 2024). More advanced modeling approaches combine mitigation strategies, including multi-sourcing, regional supplier diversification, reserved inventory, and alternative shipment options (Suryadi and Rau 2023).

Despite recent advances in demand forecasting and efficient store operations, lost sales are primarily treated in the literature as an outcome of stockouts, rather than a process to be managed. While DPF has been suggested as a potentially effective technology for mitigating lost sales (Gustafsson et al. 2021), the literature lacks investigation into how its deployment affects lost sales operationally and through which mechanisms.

2.1.2 | Inventory Obsolescence

Inventory obsolescence leads to products that can no longer be sold, at whatever node of a supply chain they are held. Such obsolescence can occur for different reasons, with products reaching the end of their lifecycle due to perishability or physical deterioration (Teunter 1998), technological evolution (Arthur 2009), or because they have passed their fashion season or other predetermined marketing time period (Fisher et al. 2001; Rajan and Wang 2016). Products with short shelf lives, rapid technological cycles, or strong fashion sensitivity (such as food, consumer electronics, and apparel) are particularly prone to obsolescence. This challenge persists as a result of uncertain demand and long supplier lead times, leading retail distribution centers to hold excess inventory as a buffer against variability (Rajan and Wang 2016; Mou et al. 2018). Beyond direct financial losses, inventory obsolescence has broader societal implications (including resource waste and environmental harm), making it a critical issue for sustainability (Sharma and Sharma 2024).

Retailers use several strategies to mitigate inventory obsolescence. These include replenishment solutions—such as vendor-managed inventory and automated replenishment systems (Kaipia and Tanskanen 2003; Govindan 2013)—as well as warehouse practices like first in first out (FIFO) to prioritize older stock (Rajan and Wang 2016; Ramdasi and Shinde 2021). Furthermore, improved demand forecasting using AI and machine learning aims to reduce forecast error and overstocking (Sharma and Sharma 2024), while product segmentation and assortment decision-making seek to manage seasonality and demand substitution patterns (Rajan and Wang 2016). For suppliers, mass customization and postponement strategies can be developed to delay final product differentiation so as to better align supply with realized demand (Waller et al. 2000; Chiou et al. 2002). In parallel, more agile supply chain practices (e.g., just-in-time replenishment or quick response systems) both help align supply with current trends and reduce the risk of overstocking (Cachon and Swinney 2011). When these preventive measures fail, retailers often use reactive mechanisms such as markdowns, quantity discounts, factory outlets, and other clearance channels to liquidate excess stock (Khouja 1999; Dubey 2018).

In summary, the established literature largely treats obsolescence as a supply-side execution problem and a process outcome, with the focus on inventory control, forecasting accuracy, postponement, and end-of-season markdowns for mitigation. While Gustafsson et al. (2019) identify reduced obsolescence risk as a potential outcome of DPF adoption in a maturity framework, this emerging literature stream lacks theoretical and empirical examination of obsolescence as an item-specific process and of how DPF can influence it and through which mechanisms.

2.1.3 | Product Returns

Product returns are goods that customers send back to retailers after their purchase due to defects, dissatisfaction, incorrect size or color, or buyer's remorse. In supply chain management, product returns are defined as "a reverse flow in the traditional supply chain" and are categorized as "the activity of returning goods back through the supply chain with a focus on retailers" (Ambilkar et al. 2022, 3920). Return rates vary significantly across sectors, ranging from approximately 5%–9% for hard goods to as high as 35% in high-fashion apparel and e-commerce, where customers often purchase multiple items with the intention of returning some of them (Guide et al. 2006; Stock and Mulki 2009). Handling returns is both costly and operationally complex, as it requires reverse logistics processes such as shipping, inspecting, sorting, restocking, and/or disposing of returned items (Stock et al. 2006). Beyond the associated operational complexity and potential customer dissatisfaction, product returns also impose substantial financial burdens (Ambilkar et al. 2022; Stock and Mulki 2009) and environmental burdens (Frei et al. 2020). Lenient return policies can encourage higher return volumes, creating a tradeoff between customer service benefits and the direct costs of processing returns (Altug and Aydinliyim 2016).

The existing body of knowledge examines product returns either from the perspective of customer behavior (e.g., Wang et al. 2021; Abdulla et al. 2019) or through the process-oriented lens of reverse logistics (e.g., Han and Cueto 2016). First, the former focuses on identifying the causes of returns and reducing return rates; for instance, Shaharudin et al. (2015) link return reasons to different stages of the product lifecycle, including manufacturing, distribution, and customer-related causes. Examining returns through the lens of consumer postpurchase decision-making, Yan and Cao (2017) highlight issues such as poor product fit, incorrect sizing, or color mismatches in apparel. Abdulla et al. (2019) provide insight into consumer behavior and offer guidance for managerial decision-making and return policy design. Drawing on advice-taking theory, Wang et al. (2021) demonstrate how customers' opinions and reviews regarding product fit on online platforms can reduce return rates. Second, the more dominant stream on this topic focuses on managing product returns, as effective returns management can even improve customer loyalty, turning a positive return experience into a competitive advantage (Mollenkopf et al. 2007). This body of work typically characterizes returns as end-of-use or end-of-life processes and discusses managing them through approaches such as remanufacturing, reverse logistics, and closed-loop supply chains (Fleischmann et al. 2001; Guide and van Wassenhove 2001; Guide and Van Wassenhove 2003).

More recently, studies have highlighted the potential of emerging technologies to improve product return management, particularly by enhancing efficiency and decision-making in the reverse logistics context (e.g., Fang et al. 2016; Ambilkar et al. 2022). In line with this technological turn, Gustafsson et al. (2021) introduced DPF as a means of reducing return rates. However, while DPF presents a promising avenue for mitigating returns, existing work lacks theoretical investigation of the underlying return problem and fails to explicate the mechanisms through which DPF may contribute to returns reduction. As a result, theoretical understanding of the return problem, particularly as an item-specific process that DPF could address, remains underdeveloped.

2.1.4 | Lost Demand

Lost demand is a retail operations problem that takes the form of a persistent measurement blind spot: it is customer demand that is not observable as (lost) sales because the retailer does not offer the product that adequately meets the customer's needs. Unlike lost sales, which arise from stockouts, lost demand stems from gaps in assortment, sizing, configuration, or functional attributes on offer; therefore, it leaves no trace in transactional data. As a result, lost demand remains largely overlooked in retail operations literature, where demand is typically defined only in relation to the existing assortment.

The concept of lost demand is well-established in marketing and product innovation research, where it refers to latent customer needs that would generate demand if an appropriate offering were available (Christensen et al. 2005; Von Hippel 2005; Ulwick 2005). In physical retail, such demand remains invisible because no purchase attempt occurs; in contrast, in online retail environments, lost demand may partially appear through probing purchasing behaviors, wherein customers order products to assess suitability and subsequently return them. From this perspective, returns can be interpreted not only as reverse logistics outcomes but also as indications of lost demand under conditions of limited prepurchase information.

The measurement blind spot of lost demand is linked to the other persistent retail problems. The assortment misalignment that generates lost demand may also increase return rates, and attempts to compensate through broader assortments or higher inventory levels raise the risk of obsolescence. However, existing operational models largely treat lost sales, returns, and obsolescence as separate phenomena, without accounting for the effects of demand that remain unobserved.

DPF-related technologies have the potential to partially reduce this blind spot by making customer–product mismatches visible even when they do not result in successful sales (Gustafsson et al. 2021). This visibility introduces new theoretical questions for retail operations concerning how latent demand can be measured, how it should inform assortment and inventory decisions, and how improved demand visibility affects trade-offs among availability, variety, and inventory risk.

2.2 | Retail Supply Chain Design and Operations for Experience Products

In line with Sternberg et al. (2024) engaged research framework, this section elaborates the area of knowledge: the body of literature on retail supply chain design and operations that addresses but does not fully explain the persistent problems identified in Section 2.1.

Mass customization has long been a central paradigm in supply chain design for addressing heterogeneous customer needs while maintaining efficiency (Gilmore and Pine 1997; Salvador et al. 2020). In retail supply chains, mass customization is primarily reflected in such design choices as modular product architectures, configurable offerings, assortment breadth, postponement points, and the allocation of inventory across supply chain nodes. These design decisions are aimed at accommodating variety while preserving economies of scale, and they shape the fundamental trade-offs between responsiveness and cost.

For experience products, however, the effectiveness of mass customization as a supply chain design principle is constrained. Since product fit emerges through customer–product interactions rather than specification, customer requirements cannot be fully articulated at the time of design or assortment planning. As a result, even well-designed mass customization systems remain exposed to item-level mismatches that only become visible during customer–product interactions. Therefore, we argue that lost sales, inventory obsolescence, and product returns are consequences of supply chain designs that rely on ex ante specifications and configurations under uncertainty.

These mismatches become more pronounced in omnichannel retail environments. Omnichannel strategies decouple customer interaction from specific physical locations, allowing customers to search, evaluate, and purchase products across channels and fulfillment options (Kembro et al. 2022; Ishfaq et al. 2024). From a supply chain design perspective, this increases structural complexity by distributing inventory, fulfillment capabilities, and customer access points across multiple nodes (Gao and Su 2017). While an omnichannel design enhances availability and convenience, it also challenges traditional mass customization logic, which typically assumes predefined fulfillment paths and relatively stable order penetration points.

An important supply chain management principle is "swift and even flow", which posits that high performance comes through designing supply chains that reduce variability and keep products moving quickly and smoothly through planned processes (Schmenner and Swink 1998). In retail supply chains, this principle informs decisions about, e.g., mass customization and omnichannel operations: examples include regular replenishment cycles, stable fulfillment systems, and buffers to handle uncertain demand. From this perspective, the persistent problems are seen as disruptions in the flow that can be reduced through better forecasting, inventory placement, and process control. While this approach works well for improving productivity and efficiency, it does not explain how to deal with the variability that comes from customer–product interactions; for experience products, this kind of mismatch cannot be fully removed because it happens during the interaction, especially in omnichannel settings where fulfillment paths and customer journeys are unpredictable.

Therefore, there is a need for more adaptive systems that can respond to realized demand and interaction outcomes, rather than relying solely on fixed ex ante designs. Adaptive supply chain designs are characterized by the ability to reconfigure fulfillment paths, reallocate inventory, and shift operational roles across nodes as new information becomes available (Kauffman et al. 2018). Such adaptability requires both physical flexibility and informational insight into customer–product interactions at a level of granularity that conventional transactional data cannot provide.

DPF enables a shift toward adaptive supply chain designs by digitalizing customer–product interactions at the item level. Rather than positioning customization solely as an upstream design choice, DPF facilitates the dynamic introduction of customer specificity through matching, search, and learning across the supply chain. This capability blurs traditional design trade-offs between speculation and postponement by enabling customer-specific order penetration points and contingent fulfillment paths. In this sense, DPF extends beyond mass customization's configuration-based logic toward interaction-driven supply chain design.

2.3 | Summary: Limits of Existing Knowledge

Taken together, the four problems persist not merely due to forecasting errors or deficient inventory management, but because retail operations are conventionally managed as fulfillment processes rather than as customer–product interactions that lead to sales. In the conventional view, lost sales, obsolescence, returns, and lost demand are treated as process outcomes to be optimized, rather than interactive processes that can be improved. By embedding the digital customer–product interaction into supply chain design, DPF enables reframing the four persistent retail problems to be treated as interactive processes that can be actively managed.

Additionally, demand is indirectly inferred from sales and returns, potentially leaving significant portions of customer needs unobserved; this limits retailers' ability to learn from mismatches between offerings and customer requirements, cementing a need for trade-offs among availability, variety, and inventory risk. In contrast, technology such as DPF makes customer–product interactions visible, allowing for the four persistent retail problems to be reframed as interactive process improvement and learning challenges, rather than forecasting and inventory control problems. This perspective opens new theoretical avenues for retail operations research integrating customer experience, product characteristics, and operational decision-making. Finally, this perspective provides the conceptual grounding for the object-interactive transvections conceptualization developed in Section 4.

3 | Research Process and Methodology

Engaged research moves beyond conventional descriptive case studies to develop novel solution designs and interventions (Sternberg et al. 2024) and to link research findings back to the practical problems observed (Van De Ven 2007). In this study, we engaged with real-world challenges faced by retailers and technology developers, facilitating a move beyond gap-spotting to address novel and theoretically interesting questions in retail supply chain management. The research reported here is the last in a series of three engagements, with the third engagement shown in Figure 1. In Appendix A, we provide an overview of how the research was conducted in the three engagements in line with the structure and logic of engaged research.

In our data collection, discussing our solution proposals (as researchers) with knowledgeable practitioners was a key

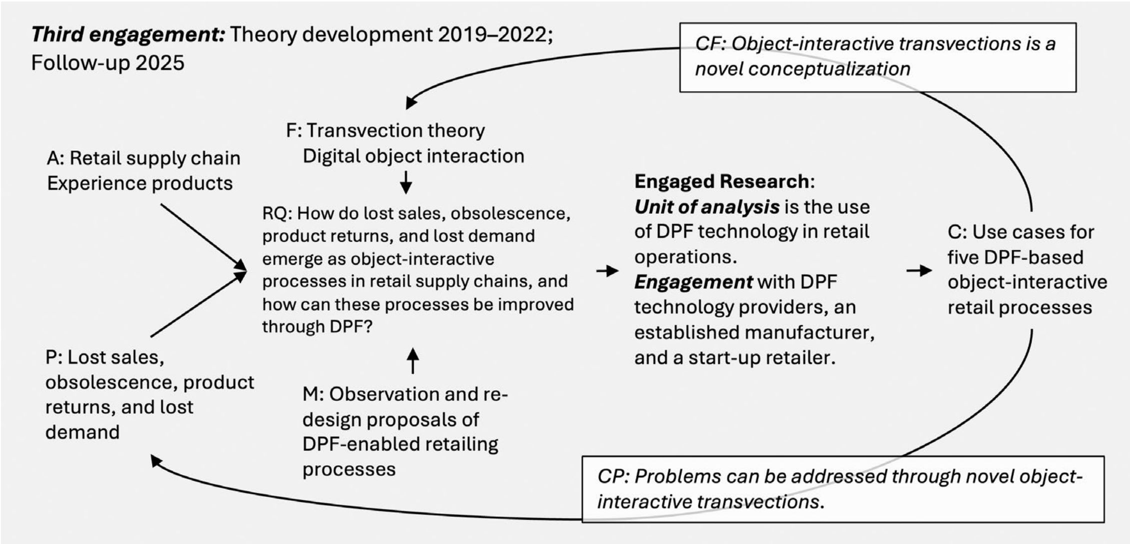

FIGURE 1 | Overview of the third engagement.

element of the engagement; Appendix B presents these solution proposals and how their presentation changed over time. The need for multiple iterations of practice to collect data when presenting knowledge at the pragmatic boundary is consistent with Van De Ven's (2007, 280) view that "an evaluation researcher has no unilateral right to impose their answers to these questions without informed consent of the people affected." In other words, when engaging with practitioners, we proposed ways to use DPF technology, and practitioners responded, creating a dialogue; by presenting solution proposals, we obtained practitioner evaluations and, importantly, encountered use cases we had not previously considered, as well as new problem framings. These engagements were followed by researchers and practitioners returning to their respective 'drawing boards': researchers refined the conceptualized design proposals with practice-informed insights, and practitioners resumed implementation with a theory-informed view of how to further develop the DPF use cases. The mutually beneficial nature of the engagement was clearly recognized by practitioners, as the following quotation illustrates:

> What you have done is actually based on data from a year back, and development happens rapidly here. So, in that case, it is a nice confirmation, a bit more theoretical from your side, that we have talked about the same development progression that we have already gone through and maybe even taking it one step further on certain things. [...] I think it's a very nice confirmation that we have thought similarly and in the same way. For us, it has always been a dialogue about development—cause and effect. [...] Afterwards comes the analysis of what worked, what didn't.
>
> –Marketing Manager, Skates Stocker

The dialogue between research and practitioners in our study went beyond "identifying and negotiating the different interests, biases, and motivations" (Van de Ven and Johnson 2006, 831) to encompass the creation of a mutually constructed understanding of the phenomena of interest. Hence, dialogue was also crucial in the analysis of the unfolding design, with interpretation by researchers inputted to practices and vice versa.

While dialogue is a central foundation in engaged research (Van de Ven and Johnson 2006) as a collaborative approach (Sternberg et al. 2024), it stands in contrast to the principle of objectivity in positivism (Jones and Bartunek 2021); this obliges the engaged scientist to provide insight into the intellectual dialogue between scientist and practitioner (Appendix A), offering the reader the possibility to "retrace the cognitive path" taken (Avenier and Cajaiba 2012, 209). We illustrate this with a proposal/practitioner response from the third engagement cycle: We proposed a design in which both customers and products were digitized and stored in digital object inventories, to be used for matching during the sales process. When we engaged with a representative from Ski Boots Networker, we learned that the company was indeed building digital object inventories, but these were not integrated to enable more effective matching in the sales process; instead, on the customer side, the company sold foot morphology data to manufacturers, to be used in product design, and on the product side, the company scanned new products as a service for manufacturers, enabling them to provide the retailer with the resulting digital product objects.[1]

3.1 | Engaged Companies and Operational Settings

In this section, we present the three companies with whom we engaged closely in the third cycle,[2] whose use cases appear in our findings.

We engaged with Dress Shoe Customizer in the first cycle, who was already using DPF and introduced us to the technology: when we presented our idea of digitizing customers and products to improve the competitiveness of physical retail, the company representative explained that this capability to

TABLE 1 | Operational settings for DPF use cases at the three engaged companies.

	Dress Shoe Customizer	Skates Stocker	Ski Boots Networker
Product type	Dress shoes	Ice-hockey skates	Ski boots
Brands retailed	Own brand	Own brand	Multiple brands
Supply chain role	OEM and retailer	OEM	Platform provider
Number of retailers	Single shop	1000+ brand-dependent retailers	500+ brand-independent retailers
Type of product recommendation	Matching-to-production design	Matching-to-stock	Matching-to-stock
Supply strategy	Make-to-order	Make-to-stock	Make-to-stock
Product variety	Five shoe families, with multiple design features	Three skate families, with multiple design features	Vast, yet no variations within a boot model
Problems	Limited supply Long delivery lead times	Convincing end-customers as to the best buy Tacit knowledge as basis for inventory decisions	End-customers are unsure about the fit Bottlenecks at rental stores

digitalize both products and customers already existed. Dress Shoe Customizer was engaged in the first cycle (pre-study), then in the case survey of the second cycle, and finally in the third cycle of engagement. We identified two additional companies—Skates Stocker and Ski Boots Networker—during the second cycle. As with any emerging phenomenon, the number of DPF use cases was limited. Of all the companies and use cases identified in the second cycle, we selected these two for the third cycle because they used DPF for purposes beyond mass customization.

The operational settings for DPF use at the three companies—Dress Shoe Customizer, Skates Stocker, and Ski Boots Networker—are presented in Table 1. The table summarizes retail operations characteristics: product type and variety, supply chain type, product recommendation type, supply strategy, and motivation to implement DPF. All three engaged companies use DPF as a product recommendation system consisting of a scanner paired with accompanying product recommendation software.

Dress Shoe Customizer is a startup that sells make-to-order dress shoes online and operates a physical retail shop. It matches scans of customers' feet to scanned shoe-last designs used in manufacturing. Dress Shoe Customizer maintains a small in-store inventory that allows ordinary off-the-shelf sales, but it does not actively promote them. Off-the-shelf sales involve no delivery lead time, but the available assortment is narrow: the shelf-stocked shoes are all produced from the same last and therefore fit only a subset of shop visitors.

Skates Stocker is an original equipment manufacturer (OEM) of ice hockey skates, with approximately 1000 retailers worldwide. Skates Stocker's product variety is limited to three professional skate families, and the fitting solution is a closed system operating solely within Skates Stocker's supply chain that recommends only skates from those three families. Prior to implementing DPF, Skates Stocker pursued traditional retail sales, where customers tried products off the shelf and (if necessary) received help from knowledgeable sales assistants. After implementing DPF, it operates a more customer-centric retail supply chain, dynamically aligning upstream operations with downstream customer requirements.

Ski Boots Networker provides a DPF platform for a network of ski-boot retailers selling off the shelf. The network comprises approximately 500 retailers equipped with scanners, and ski-boot brands are incentivized to appear on the fitting platform so as to maintain visibility to retailers and customers across the network and thus to remain competitive. Retailers that sell or lease ski boots without any digital fitting tools rely on store assistants' tacit knowledge and manual measurement tools to find ski boots that fit; store assistants record customer feedback on boot size, fit preferences, and outcomes after each fitting trial. Implementing DPF reduces the need for store assistants to make repeated trips between the stockroom and the fitting area. In addition, with DPF, information on customer fit and preferences can be collected and shared with ski-boot brands.

3.2 | Data Collection and Analysis

Table 2 presents the data collected on DPF use cases in the third engagement cycle. The primary data comprise semi-structured interviews (face-to-face and video calls), participant observation of the engaged companies' operations, follow-up correspondence, and secondary materials. Data collection was designed to align with the iterative, problem- and solution-focused nature of engaged research. As Van De Ven (2007, 255) notes, "managing knowledge at the pragmatic boundary requires multiple iterations. Addressing the consequences cannot be resolved with one try but requires an iterative process of sharing and assessing knowledge, creating new agreements, and making changes where needed."

TABLE 2 | Data collection on use cases in the engaged companies.

Company	Interviews	Site visits	Supporting data	Longitudinal follow-up	Engagement focus
Dress Shoe Customizer	Retailer interview, CEO (1 h, 09/2017) Retailer interview, CEO and CFO (1 h, 04/2018) Retailer interview, CEO and CFO (2 h, 10/2018) Retailer interview (evaluation), CEO and COO (2 h, 11/2019) Retailer interview (evaluation), CEO and CFO (1 h, 03/2020)	Participant observation at the retailer (1 h, 09/2017)	Bi-weekly to monthly follow-up calls, 2018–2020 Company websites and marketing materials	Retailer follow-up interview, CEO (1 h, 05/2025)	Evolution of business model; rationale for DPF use; integration of matching-to-stock with customization; operational challenges and trade-offs
Skates Stocker	Technology provider A interview, VP product (1 h, 09/2017) Manufacturer interview, Marketing manager (2 h, 10/2018) Manufacturer interview, Demand planning manager (1 h, 11/2018) Retailer interview, store manager (1 h, 12/2018) Manufacturer interview (evaluation), Marketing manager (2 h, 02/2020)	Participant observation at Technology provider A (1 h, 09/2017) Participant observation at a retailer (1 h, 12/2018)	Follow-up emails after each interview with additional questions and clarifications Company websites and marketing materials	Technology provider A follow-up email, VP product (05/2025)	Retailer onboarding process; use of customer data for supply planning; internal evaluation of DPF impact on sales processes
Ski Boots Networker	Technology provider B interview, CEO (1 h, 06/2018) Technology provider B interview, CEO (6 h, 04/2019) Retailer interview, store assistant (2 h, 04/2019) Technology provider B interview (evaluation), CEO (1 h, 03/2020)	Participant observation at a retailer (1 h, 04/2019)	Follow-up emails to Technology provider B with additional questions and clarifications Company websites and marketing materials	Technology provider B follow-up interview, CEO (1.5 h, 05/2025)	Platform development strategy; incentive structures; end-user adoption challenges; data flows between network actors

We used interview protocols tailored to each respondent's role and to the evolving stage of the engagement (see Appendix C for example protocols). Early interviews focused on understanding why and how DPF technology was implemented and on exploring business rationales, technological enablers, and anticipated outcomes. As the research progressed, follow-up interviews focused on evaluating existing use cases, identifying challenges in practice, and generating ideas for new applications and further development. This iterative approach enabled us to "design through dialogue"—that is, to jointly explore how problems are framed and what potential solutions look like in context.

Both early and follow-up interviews pursued insights into the use case designers' rationales, while on-site observations provided firsthand exposure to the emerging use cases. To "harness temporality in the service of theory construction" (Timmermans and Tavory 2012), we digitally recorded most encounters and semi-structured interviews. We took field and follow-up notes to facilitate revisits of the moment of data creation. We conducted follow-up interviews as dialogues focused on preliminary findings throughout the study (see Appendix B), which describes interactions conceptualizing the use cases. We also collected secondary data on the use cases from company websites and presentation materials. The first two rounds of engagement (see Figure A1), conducted before our detailed use case analysis, provided indirect data and contextual understanding of the use cases.

The rightmost column of Table 2 summarizes the focus areas for each engaged company. Specifically, at Dress Shoe Customizer, interviews explored the integration of matching-to-inventory in a mass-customization strategy, the evolution of the company's business model, and operational trade-offs in digital fitting practices. At Skates Stocker, the interview protocols addressed supply chain planning and forecasting, scanner-driven replenishment, and evaluation of DPF's impact on downstream sales processes. At Ski Boots Networker, discussions focused on the platform strategy, how DPF enables cross-brand retailing, and how digital object databases were constructed and monetized.

The flexible yet purpose-driven interviews bridged the gap between solution proposals and theoretical abstraction—in line with the engaged research approach, in which use cases are co-explored with practitioners and iteratively assessed for feasibility and theoretical contributions (Van De Ven 2007). To ensure methodological rigor, we systematically documented each empirical touchpoint across the four use cases. Table B1 in Appendix B consolidates all interviews, observations, and follow-up sessions to provide transparency on how insights were generated, validated, and iteratively refined over time; the table makes visible the chain of evidence connecting empirical engagement to conceptual development. Table B1 provides full traceability of evidence, while Table B2 complements Table B1 by summarizing the engagements and analytical contributions across the four use cases.

4 | Problematization and Reframing Toward Object-Interactive Transvections

In this section, we problematize and scrutinize the assumptions and argumentation in the established field of knowledge. As elaborated in Section 2, the field of retail logistics and supply chain management conceptualizes the coordination of material flows and resources as a set of processes, with lost sales, obsolescence, product returns, and lost demand treated as outcomes of those processes (e.g., Fisher 1997; Oh et al. 2012). Commonly conceptualized approaches to mitigating these undesirable outcomes are speculation and postponement (Pagh and Cooper 1998). However, we challenge the established position that these problems are merely outcomes, and we ask whether they might instead be approached as processes—specifically, incomplete object-interactive processes—that can be completed through object interactions.

To address our novel problematization, we develop a theoretical conceptualization that takes classic transvection theory (cf. Alderson and Martin 1965) as one starting point and the concept of digital object interaction (Wegner 1997) as the other. First, classic transvection theory conceptualizes how supply chain strategies and activity structures create value by placing the right product in customers' hands (Hulthén and Gadde 2007). Second, digital object interaction provides a reconfigurable and adaptable way to program and control operations, and it has been successfully used to enable on-demand direct digital manufacturing and materials management (e.g., Stark et al. 2023).

We begin by presenting classic transvection theory and its relevance to the effective design of retail supply chains, whereafter we introduce our novel conceptualization: object-interactive transvections. We operationalize this conceptualization with DPF (Gustafsson et al. 2019) as an enabler of digital object interaction to improve retail supply chain performance, offering opportunities to increase sales while reducing lost sales, product returns, and inventory obsolescence.

4.1 | Completing the Sale: Classic Transvection Theory

A *transvection* is a completed sale and includes all actions and processes in the retail supply chain required to transform the original inputs into the end product placed in the hands of the ultimate consumer (Alderson 1965). Transvection theory allows us to conceptualize how the retail supply chain delivers the right product to the right customer through a series of sortings and transformations (Priem et al. 1997), with a successful sale process specified as the product reaching an individual customer's hands. Concepts from classic transvection theory provide key building blocks for our conceptualization and design of retail supply chains for experience products. As an entity, the retail supply chain transforms materials in form, place, and time as well as sorts and directs material items through supply chain echelons, with speculation and postponement enabled as supply strategies to deal with the problems of supply meeting demand (Dubois et al. 2004; Engelseth and Felzensztein 2012). Transvection theory has developed over time to incorporate subsequent retail-logistics innovations, such as mass customization and online retailing (Hulthén and Gadde 2007; Kembro et al. 2022).

Transformation is "a change in the physical form of a product or in its location in time and space" (Alderson and Martin 1965, 123). Different types of resources in the retail supply chain perform activities that transform materials and product items (Hulthén and Gadde 2007; Priem et al. 1997). To produce a transvection—that is, delivering an individual product item into an individual customer's hands—each transformation along the way increases the product's value by changing its features in at least one of the dimensions of form, time, or place (Hulthén and Gadde 2007). Form transformations are activities that change a product's physical features, such as manufacturing, assembly, and packaging. Place transformations include warehouse handling, transportation, loading and unloading, and other activities that physically move products. Time transformations comprise activities in which product items wait for a subsequent sorting, such as warehouse storage or retail shelf display. Each additional transformation of a product item is directed by a sorting[3]; as a result, the individual transvection becomes a stop-and-go sequence of activities, with intervening sortings between each pair of transformations (Alderson and Martin 1965).

Sorting is the decision-making activity in product handling through which supply components (e.g., goods and materials) are assigned to their respective transformation resources (Hulthén and Gadde 2007). Sorting is performed using both physical resources (e.g., human planners) and digital resources (e.g., databases and information systems). Sorting is conceptually distinct from supplier-side assignment and buyer-side selection (Alderson 1965; Alderson and Martin 1965; Hulthén and Gadde 2007). For the former, the supplier performs an assignment to direct a product to a resource used for the subsequent transformation (e.g., choosing a trailer for transportation or a warehouse for storage). For experience products, customers need to experience the product before selection.

Improving supply chain performance has often been pursued through designs that avoid reversing a completed sorting within a transvection. In speculation-based designs, the individual product and the end customer are not paired until the final purchase is made (Hulthén and Gadde 2007), while transvections based on postponement enable a build-to-order production approach (Hulthén and Gadde 2007) wherein the end customer's selection and confirmed order initiate the transvection. Preponement, in contrast, shifts certain sorting activities earlier to simplify transformations later in time (Kembro et al. 2022).

4.2 | Addressing the Sale-Completion Problem: Object-Interactive Transvections

Building on our engaged research (Section 3) and the DPF use cases (Section 5), we address how DPF and other digital technologies can offer new ways to complete a sale. We conceptualize sales, lost sales, inventory obsolescence, and product returns as object-interactive transvections (Table 3); in this conceptualization, object interaction is the generative mechanism underlying both complete and incomplete transvections. This open-ended, object-interactive conceptualization of transvections extends the notion of transvection beyond successfully completed sales (where the customer accepts the product in hand) to include incomplete sales (where the customer fails to find a product, the customer rejects the product in hand, or the product remains unmatched with any customer).

In the established view, lost sales and inventory obsolescence are outcomes (e.g., Bijvank and Vis 2011; Fisher et al. 2001); to mitigate these undesirable outcomes, companies adopt different supply chain designs to improve performance (Fisher 1997). With the rise of online retailing, product returns have become an increasingly important reverse flow that reduces sales and increases costs (Ishfaq et al. 2024). In classic transvection theory, only a successfully completed sale is considered a transvection

TABLE 3 | Object-interactive transvection extends the item-specific process view of transvection theory to product returns, obsolescence, lost sales, and lost demand.

		Theoretical conceptualization		
	Problem	**Conventional retail supply chain literature**	**Classic transvection theory**	**Object-interactive transvection**
Framing of problem	Completing a sale	Process outcome, not a process	Item-specific sorting and transformation process	Completed object-interactive and item-specific process
	Product return	Reverse process, not an outcome	Not specified	Incomplete object-interactive and item-specific process
	Inventory obsolescence	Process outcome, not a process	Not specified	Incomplete object-interactive and item-specific process
	Lost sale (product not in stock)	Process outcome, not a process	Not specified	Incomplete object-interactive and item-specific process
	Lost demand (product not in assortment)	Not specified	Not specified	Incomplete (potential) object-interactive and item-specific process

(Alderson 1965; Alderson and Martin 1965), whereas a lost sale falls outside the theory's bounds. Moreover, while storage is classified as a time transformation when it leads to a sale, its status is unspecified when it results in inventory obsolescence; likewise, while home delivery is a place transformation when it completes a sale, the theory does not specify how to classify it when the product is returned. Accordingly, neither conventional supply chain management nor classic transvection theory conceptualize the possibility of incomplete sales, rendering both largely blind to possible ways of completing sales through the digitalization of product–customer interactions.

The problems of lost sales, obsolescence, product returns, and lost demand are especially pronounced for products for which customers cannot assess whether its attributes match their preferences without physically trying it on. Fit-dependent products are heterogeneous and entail many parallel processes, which require a variety of sorting activities across the retail supply chain (Hulthén and Gadde 2007): distributors assort product types and sizes for inclusion in distribution inventory; retailers decide what to offer to customers at the point of sale; and before purchase, customers visit the store to sort out and select products that fit. In retail supply chains for fit-dependent products, items may be manufactured and stocked in multiple sizes (make-to-stock) or be customized (make-to-order) (e.g., Holmström et al. 2001).

Focusing on product–customer interactions, we conceptualize five object-interactive transvections in the retail supply chain. Our conceptualization includes successfully completed transvections of either inventory-based or customization-based fulfillment, both of which are well-established in the retail operations literature (cf. Gilmore and Pine 1997; Rajagopalan and Kumar 1994; Sorescu et al. 2011). In addition to completed transvections, our novel object-interactive conceptualization recognizes four incomplete/potential (open-ended) transvections; except for product returns (treated as reverse flows), these incomplete transvections have not previously been conceptualized as processes in the supply chain literature (cf. Bijvank and Vis 2011; Fisher 1997). In other words, of the five proposed object-interactive transvections between customers and products, one completes the sale and four involve a sales process that remains incomplete (i.e., open-ended). In online retailing, when a stocked product does not fit the customer, it is returned, reversing the flow and extending the lead time to complete a sale—the first incomplete transvection (Hjort et al. 2019). When a size is stocked but no matching customers are found, inventory obsolescence builds up—the second incomplete transvection. When a customer cannot find a size that fits, the sale is lost—the third incomplete transvection. Finally, regarding lost demand, the supply chain does not provide what the customer is seeking, and the supplier remains unaware—the fourth incomplete (potential) transvection. From the demand perspective, lost sales reflect an unsuccessful search, and returns reflect sales not kept by the customer (Lemon and Verhoef 2016). Successfully matching customer and product converts these incomplete transvections into completed ones, thereby object-interactively managing retail logistics to reduce product returns, lost sales, and inventory obsolescence.

In the retail supply chain, completed transvections (sales) are characterized by two types of interactions: (1) a customer–production interaction, when the customer interacts with the supply chain by placing an order (in transvection terms, making a selection), and (2) a physical customer–product interaction, when the customer puts the product into use and demand is fulfilled. The customer's interaction with the supply chain[4] is where a product becomes connected to a customer through the customer's choice (Holmström et al. 2001); the customer's interaction with the product is where the customer validates that choice and the product is put into use or returned (Gustafsson et al. 2019). In retail, products are usually produced before customers select them—representing sales-from-stock—although some retail products with customized elements are made to order (Piller et al. 2012)—resulting in coupled flows in manufacturing. In sales-from-stock, product design and assortment planning are key upstream activities, with each affecting the fulfillment or nonfulfillment of demand (Galipoglu et al. 2018; Pagh and Cooper 1998).

4.3 | DPF as an Enabler of Object-Interactive Transvections

The operational basis of DPF is the interaction between digital counterparts representing physical customers and products (Gustafsson et al. 2019). A digital counterpart is a unique digital object linked to an individual physical object, with the digital counterpart owning and controlling information about the corresponding physical object (Främling et al. 2007). Adding a digital counterpart to each physical object fundamentally changes the supply chain structure by enabling the digital interaction of individual objects (Wegner 1997), making objects active participants in the initiation and control of supply chain activities (Holmström et al. 2019) and granting products a degree of autonomy and control over their own transvections (i.e., product–production interaction).

With regard to placing an individual product in the hands of the ultimate customer, fitting—an object interaction between customer and product—holds high practical relevance. In conventional retail, customers assess fit by trying on the product after searching and selecting but before the purchase decision (Ketzenberg et al. 2000); in online retail, customers assess fit physically only after purchase and delivery, returning the product if it does not fit (Gustafsson et al. 2021). In both contexts, physical fitting is required to finalize the sale, which entails bringing the customer and the product together physically in one location. Thus, physical fitting completes the transvection by placing the end product in the hands of the ultimate consumer, whether in a retail outlet or in the customer's home.

The digitalization of fitting can shift manufacturing from make-to-stock to customization and mass customization. Scanning technology used in current DPF implementations was originally developed for mass customization (Piller and Berger 2003; Piller et al. 2012), where DPF in combination with product modularity supports postponement strategies (e.g., assemble-to-order, add-ons) so as to better match demand. However, DPF can also reduce demand mismatches in mass-produced goods by enabling more customer-oriented designs in product development, more customer-oriented offerings in marketing (Gustafsson et al. 2019), and order-and-wait sales (Rajagopalan and Kumar 1994) when customers lack physical access to the product. Reducing demand mismatches prevents disruptions to the successful completion of retail sales caused by the absence of either the product or the customer.

Once digital counterparts are available, the fitting activity can be redistributed and carried out in parallel by many actors for different purposes. Fitting is no longer limited to one customer and one product at a time or to the 'front office' of the supply chain (i.e., physically being in a specific retail store): any supply chain actor can fit one customer to many different products, one product to many different customers, or many different customers to many different products. From the perspective of transvection theory (Hulthén and Gadde 2007), DPF combined with sorting expands the scope of sorting activities and changes the set of available transformations in the retail supply chain. Conventionally, different product types and forms are physically sorted in the retail supply chain to facilitate operational efficiency and product flow (Kembro et al. 2022), but with DPF, new types of digitalized sorting based on interactions between digital product and customer counterparts become available, including *sorting out* fitting products, *assorting* fitting products for a selected set of customers, and *arranging* customer–product sets by fit. Digitalized sorting differs from physical sorting in that it is object-interactive and can be easily reversed, repeated, and conducted in many locations simultaneously. The range of sorting and transformation opportunities enabled by DPF stands in stark contrast to physical product fitting, which can constrain retail sales. We explored these opportunities in our engaged research with pioneering practitioners, which led us to identify four use cases that we hereafter describe as operational practices.

5 | DPF Use Cases in the Engaged Companies

In this section, we present the four DPF use cases identified through our research engagements: (1) DPF-based fulfillment switchover, (2) DPF-based assortment planning, (3) DPF-based product design, and (4) DPF-based networked switchover. For each use case, we describe the technology-enabled interaction and the operational practice(s) it supports. We conclude each use case description with a theoretical interpretation (drawing on Section 3) and performance implications identified with the engaged companies. In Section 5.5, we revisit the three companies to examine how the use cases have evolved.

5.1 | DPF-Based Fulfillment Switchover

In two of the three companies, DPF dynamically reconfigured customer-specific fulfillment based on actual products' availability across the supply chain. As a result, any possible product location identified through vertical and/or horizontal search could serve as the potential order penetration point (OPP) (Figure 2). The purpose of this switchover is to increase sales while simultaneously reducing the risk of obsolescence. DPF-based fulfillment switchover is a dual-directional shift between inventory-based and customization-based fulfillment—namely, between time and form transformations. For order-and-wait sales (as at Dress Shoe Customizer), the switchover is visible to customers only as reduced delivery time; in Skates Stocker's retail logistics, the switchover is directly visible to customers because it involves a change from a standard product to a customized made-to-order product.

Fulfillment switchover rests on DPF-enabled object interaction (digital customer–product interaction), which can not only drive customization—modifying the product to the customer's specifications (i.e., a form transformation)—but also support matching to stock—comparing customer specifications with available products (i.e., a time transformation). Switching from customization to matching enables opportunistic use of in-transit inventory, rather than relying solely on make-to-order manufacturing. Conversely, switching from matching to customization reduces the need for inventory and variant proliferation by fulfilling part of demand through

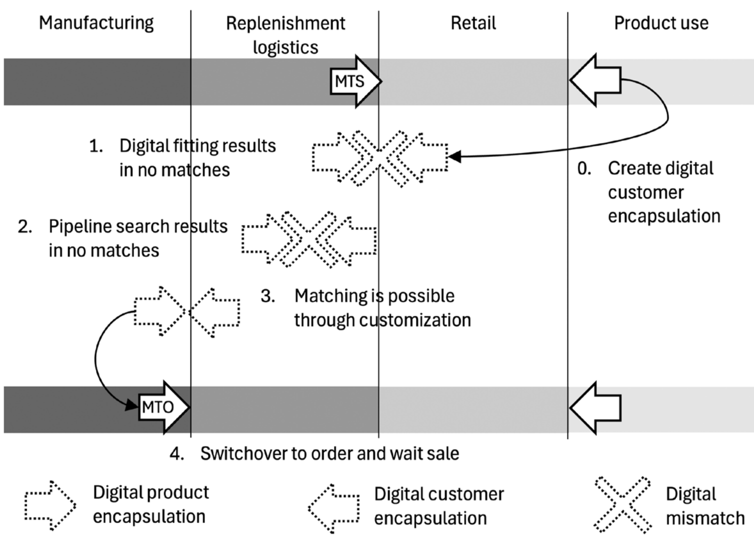

FIGURE 2 | DPF-based fulfillment switchover between time (match-to-stock) and form (customization) transformations (and vice versa) to increase sales and reduce inventory obsolescence.

manufacturing, thereby lowering the risk of lost sales and inventory obsolescence.

The business model of Dress Shoe Customizer entails holding little or no inventory and relying on form transformations (make-to-order) rather than time transformations (make-to-stock). Unlike traditional off-the-shelf retailers, which hold large inventories in order to deliver products immediately to customers (Mou et al. 2018), Dress Shoe Customizer offers a delivery lead time of six to eight weeks for make-to-order dress shoes. Using DPF for customization reduces the risk of inventory obsolescence at the cost of longer fulfillment lead times, while traditional retail prioritizes immediate delivery and thus incurs a higher risk of both inventory obsolescence and lost sales when customers cannot find a good fit.

Dress Shoe Customizer aims to produce only shoes that fit a known customer:

> Every pair of shoes produced should have feet to fit.
>
> –CEO, Dress Shoe Customizer

However, to scale up, Dress Shoe Customizer also uses DPF to dynamically switch some customer orders from matching to shoe lasts (a form transformation) to matching to stock (a time transformation). When the sales volume rises, Dress Shoe Customizer places batch orders for specific variants with its contract manufacturer and then uses DPF to match customers to products already in production or in transit. This fulfillment switchover enables opportunistic fulfillment of a portion of customer orders from inventory, thereby facilitating swifter order fulfillment and reducing unit prices negotiated with the contract manufacturer.

Conversely, in Skates Stocker's DPF implementation, the switchover runs from matching to stock (a time transformation) to customization (a form transformation), which is offered to customers with more exact requirements who are willing to pay a higher retail price and wait for delivery. Additionally, when a size is out of stock, Skates Stocker can offer on-demand customized manufacturing to avoid losing the sale. This practice involves 3D printing to modify the lasts, enabling the direct manufacturing of digitally customized skate designs. Thus, while most demand is fulfilled by matching customers to conventionally manufactured skates in the inventory, a portion of sales consists of custom skates produced on demand in Skates Stocker's highly digitalized factory.

> When producing custom skates, you take the scan data and 3D print a last on which you build the skate. [...] We do not use unique lasts for each pair of skates; that would be a waste of resources. We have standard lasts for 9.75 D, 10 D, etc. One for each quarter size width. Using CAD software, the standard last is compared with the scan and everything that sticks out is 3D printed.
>
> –Marketing Manager, Skates Stocker

Ski Boots Networker does not employ a switchover between matching to stock and full-boot customization; rather than customizing and manufacturing complete ski boots to order, it uses DPF to offer customized add-ons for standard ski boots (a form transformation). Specifically, retailers use DPF to upsell fit-improving add-ons through Ski Boots Networker's solution; for example, the scanner captures stance pressure and flags foot issues. Insole upselling is currently an important source of sales for retailers on Ski Boots Networker's platform. During a site visit, a retailer demonstrated how the scanner's output serves as a persuasive sales tool, effectively prompting customers to buy additional insoles.

> Some people come with friends or a partner. We often see that the accompanying person wants insoles for their ski boots as well, so we get a lot of additional insole sales.
>
> –Store Assistant, Ski Boots Networker

As participating brands broaden their product offerings, DPF-based upselling can extend beyond insoles to customization of the full ski boot.

In theory (Hulthén and Gadde 2007), a DPF-based fulfillment switchover completes the transvection through individual digital customer–product interactions. In the case of Dress Shoe Customizer, this interaction, as part of the operational practice, blurs the boundary between speculation and postponement, since customer selection can occur at any point between manufacturing and the retail shelf. In the case of Skates Stocker, the operational practice extends customer selection from choosing among appropriate products to choosing the appropriate form transformation. In the case of Ski Boots Networker, the operational practice enables adding an additional (form) transformation to improve fit and thereby increase customer value. From the perspectives of conventional (flow-based) supply chain literature and classic transvection theory, a dynamic OPP creates ambiguity because it is incommensurate with a static conception of supply chain structure. Object-interactive transvections entail open-endedness, where the exact structure of a transvection (including both sorting and transformation) is determined on a customer-by-customer basis, based on digital customer–product interactions.

From a retail supply chain performance perspective, improving performance has traditionally involved trade-offs between upstream manufacturing and distribution on the one hand, and downstream retail operations on the other (Fisher 1997; Mou et al. 2018). Implementing a DPF-based fulfillment switchover does not eliminate this trade-off, but it enables situational choice: by switching between fulfillment from physical inventory anywhere in the supply chain and make-to-order production, DPF enables new operational practices that improve profitability by simultaneously increasing sales and reducing obsolescence. What was a static, structural choice (match-to-stock *or* customization) becomes an object-interactive, operational decision (match-to-stock *and* customization).

5.2 | DPF-Based Assortment Planning

DPF-based assortment planning emerged as a use case in Skates Stocker's implementation and is illustrated conceptually

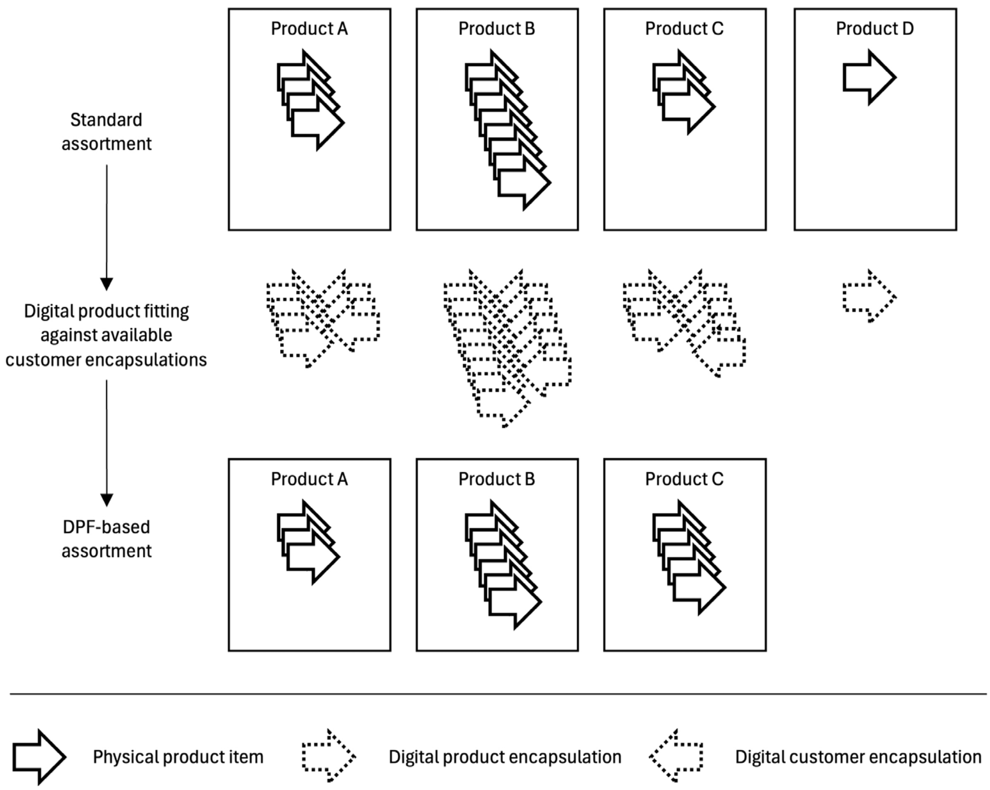

FIGURE 3 | DPF-based assortment planning.

in Figure 3. Traditionally, upstream decision-making in retail supply chains is distant from customers (Kaipia et al. 2017; Narayanan et al. 2019) and relies on expert assessments and aggregated data (Fisher 1997). With DPF, upstream supply chain planning can access digital customer counterparts at each retail location, which enables assortment planning based on identified potential customers. Furthermore, assortments can be adjusted using information about where sales are lost or captured in the retail stores.

Skates Stocker's supply chain comprises geographically distributed actors and centralized functions. Its upstream planning function uses DPF-based assortment planning to incorporate customer fit into decisions about which skate types to manufacture and which size ranges to offer at each location. With digital customer counterparts shared across the supply chain, DPF is implemented in both product development (elaborated on in the next section) and assortment planning. As the demand planning manager explained, DPF helps match inventory size distributions to local customers across different locations:

> A goal with the scanner and the technology we have is to reduce inventory levels. I currently use the [scanner] data to derive what percentages [of customers] fall within each size and how many have scanned for that model.
>
> –Demand Planning Manager, Skates Stocker

Before the fitting solution was implemented, Skates Stocker's supply chain management (SCM) function relied on transaction data together with distributor and retailer orders for decision support. Now, customer scans provide valuable input for SCM decisions about assortments and location-specific inventory levels, as the SCM function knows the numbers of hockey players in each region and their foot-size distributions. Using this information, upstream decision-makers can reduce lost sales while simultaneously lowering inventory-holding costs without increasing obsolescence risk.

> ...the process of deciding on the right assortment is both quicker and more accurate. For example, a long-tail size like size 12. Everybody [the retailers] buys at least one pair of size 12 each year just to have it in stock, but it never sells. So if you look at the whole supply chain, let's say a Finnish store chain, if they have 12 stores and each retailer stocks one pair of size 12 skates, they end up having 12 pairs of those skates, but there are only two Finnish players who have size 12. And then they have size 12 in the other brands too, so they end up having 200 pairs of size 12, and then you wonder, 'what happened?!' Now, we do this more efficiently, so we place two pairs in size 12 in the stores where we deem it most probable that the purchase will happen. We have the data, since we have scanned the players' feet.
>
> –Marketing Manager, Skates Stocker

Implementing DPF-based assortment planning introduces aggregated digital customer–product interactions upstream to better meet downstream customer needs. In conventional supply chain literature, this would be understood as improved accuracy in upstream planning, while in classic transvection theory it corresponds to improved sorting and alignment of objects across stages of the transvection. In both cases, these improvements are enabled by digital object interaction. As the digital customer–product interaction is brought upstream (albeit in aggregate), what would conventionally be a speculation strategy becomes less speculative. Object-interactive transvections allow for real-time sorting decisions based on identified (existing) potential customers, adding an aggregate dimension to selection and further blurring the boundary of speculation.

Traditionally, retailers reduce lost sales by expanding product variety—and, with it, inventory levels—to ensure that more models and sizes are available (Mou et al. 2018); this raises inventory-holding costs and obsolescence risk, especially for seasonal or time-sensitive products. DPF-based assortment planning aligns assortments with the measured aggregate potential customer base, thereby expanding sales opportunities without proportionate increases in inventory or the carrying costs thereof. In effect, DPF shifts the operational performance frontier by decoupling part of the classic variety–obsolescence trade-off.

5.3 | DPF-Based Product Design

In the DPF-based product design use case, digital customer counterparts can be aggregated to shape a product variety that best serves the customer base. With DPF, manufacturers can observe where sales are lost or captured in stores and feed that information into the design process. On this point, Skates Stocker initially offered three professional skate families and one leisure line. After a year of DPF-enabled logistics—and after building up an extensive digital inventory of customer counterparts—Skates Stocker began to explore redesign opportunities for its professional skate families. By then, it had scanned more than 300,000 customer feet; using those scans to design the next collection, the company determined it could meet variety and functional needs with two, rather than three, professional skate families. Similarly, Ski Boots Networker is expanding its solution to support product design, enabling competing brands to compare fit, as explained by its CEO:

> … the brand is interested in foot scans to improve its products. We can charge brands for information on the platform. They are also interested in competitors' shoes—how does my shoe look, and why is this shoe selling so well? This shoe from brand X, for example, fits very well, so everyone else is interested in why it fits so well, and so on.
>
> –CEO, Ski Boots Networker

In the physical shop, Skates Stocker's DPF implementation enables store assistants to switch among skate families and demonstrate fit to customers. In addition to helping customers find the right skate, this interaction generates valuable insight into customer preferences by revealing which foot types (as captured by scans) purchase the recommended model and which select an alternative. Advanced features in new skate collections can lead customers to purchase skates that are suboptimal in fit or to opt for more expensive customization; this information feeds product development—for example, by identifying needs for new, advanced skate designs for smaller-size junior and female hockey players. Additionally, when a customer scans for a specific skate model that is out of stock, the DPF solution records model-level lost sales. Data on how store assistants switch among skate families and sizes inform upstream decisions on product-family design to mitigate future lost sales.

From the perspective of transvection theory, DPF can be used to define the form transformation in production by arranging customers into fit-based cohorts to satisfy fit and other functional needs (Figure 4). Unlike classic customization, where the form transformation is defined for an individual customer (Hulthén and Gadde 2007), DPF's object interaction enables product designers to configure products for a specific set of customers, improving downstream customer–product and customer–production interactions. Although this practice can be accommodated in conventional supply chain literature and classic transvection theory in terms of the structural conceptualization of the supply chain, it introduces ambiguity for the OPP and the point of customer selection because upstream activities are now shaped by digital customer interactions. In the object-interactive transvection perspective—and in contrast to DPF-based assortment planning, which primarily affects sorting decisions—DPF-based product design determines the form transformation based on identified potential customers, thereby extending aggregate selection to the design stage and further blurring the concept of customization (Gustafsson et al. 2019).

In fit-dependent product design, the key trade-off is between providing broad functional coverage through multiple product lines and limiting production inefficiency and distribution complexity (Sharman 1984). By grounding design decisions in aggregated fit data, DPF-based product design enables companies to tailor product lines to actual customer needs while holding or even reducing variety, as depicted in Figure 4. Consequently, DPF-based product design can shift the operational performance frontier by partially decoupling the traditional trade-off between variety-driven costs (e.g., inventory and distribution complexity) and lost sales.

5.4 | DPF-Based Networked Switchover

The DPF-based networked switchover use case (Figure 5) was observed at Ski Boots Networker. Unlike the other two companies, which retail only their own brands, Ski Boots Networker sells multiple brands, and so its digital inventory contains far more digital counterparts of products and customers. The company continues to add brands and retailers to the DPF solution, with the aim of establishing a platform (Hagiu 2014; Hagiu and Wright 2015); as a result, participating brands can be included in retailers' digital matching processes across the network. In principle, this solution enables any retailer to sell any participating brand via DPF in an order-and-wait sales process (Rajagopalan and Kumar 1994) without holding in-store stock of every brand. As the brand network grows, customers are exposed to greater product variety, which increases the likelihood of finding the

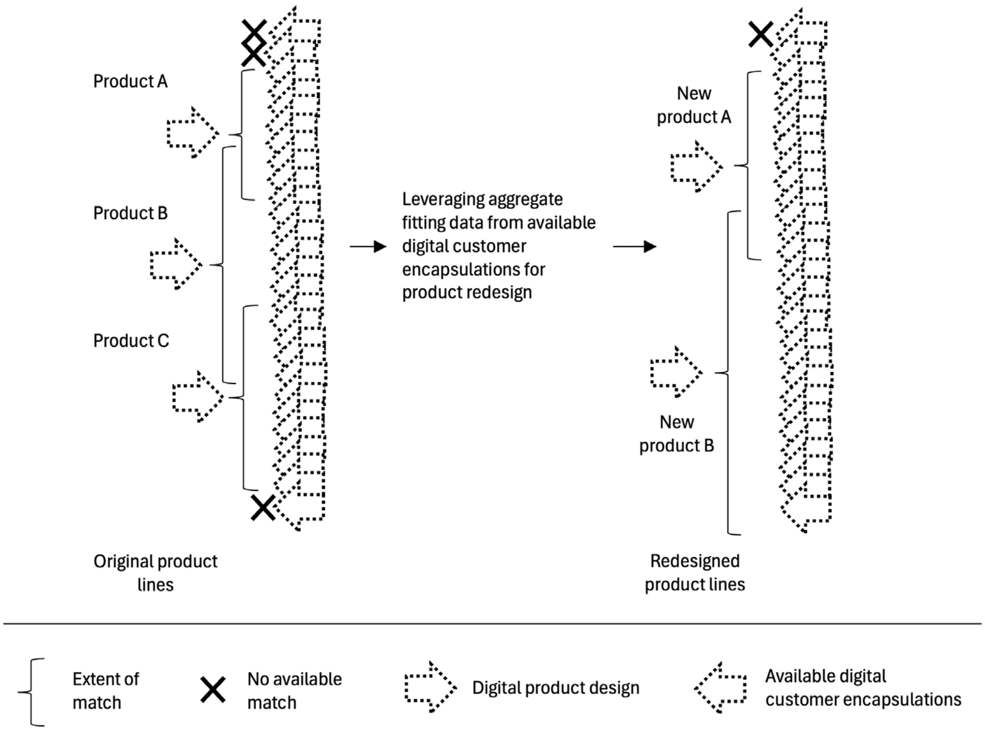

FIGURE 4 | DPF-based product design.

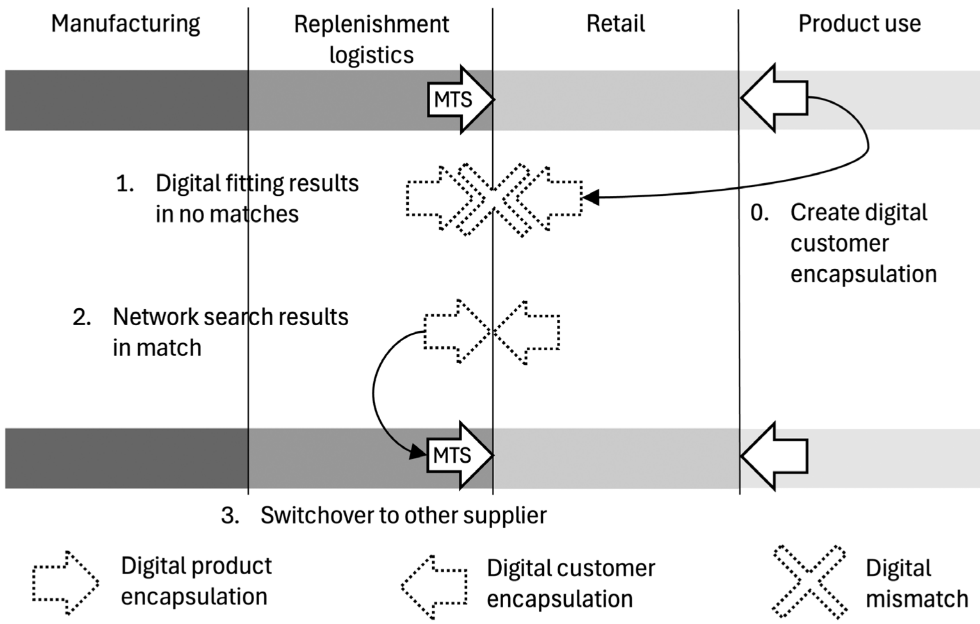

FIGURE 5 | DPF-based networked switchover.

best-fitting ski boots. Customers can also reuse their scans when ordering online; in this way, DPF facilitates omnichannel efficiency, with online and physical stores serving specialized roles (Oh et al. 2012).

Because Ski Boots Networker's platform serves many brands, it offers an exceptionally broad product variety. According to the CEO, matching customers to available make-to-stock products via DPF can yield a fit comparable to full customization.

> We came originally, many years ago, from the customization side [...], but, in my opinion, it's the dream that this will take over many industries, and it hasn't really happened in reality...it's still very much in niche markets. Big brands that tried to do that [go into customization]—Nike, Adidas, all those—they stopped it, more or less. The standard production and the variety of brands are so huge that it tends to be

> like a customized product in the end if you find the right selection.
>
> –CEO, Ski Boots Networker

The DPF network of retailers and supply brands functions as a platform (Hagiu and Wright 2015) that improves retail logistics by enabling the sharing and reuse of digital product and customer counterparts. Conventionally, retailers of experience products require wide assortments—including many long-tail items—to boost sales (Mou et al. 2018), which reduces retail efficiency: customers struggle to find a good fit, and sales assistants spend considerable time on fitting support (Gustafsson et al. 2019). As retailer participation in the platform grows, brands' incentives to join increase (cross-side network effects). Importantly, brand owners pay a single scanning fee per model; subsequent reuses of the product counterpart by any retailer incur no additional charge.

DPF-based networked switchover resembles DPF-based fulfillment switchover, but with a key difference: the latter performs vertical matching within supply chains, whereas the former performs horizontal matching across supply chains. From the perspectives of conventional supply chain literature and classic transvection theory, such cross-echelon flows could be read as a failure of planning and inventory pre-positioning. However, in the object-interactive transvection perspective, networked switchover leverages the open-endedness of the transvection: sorting a product to a specific retail location does not fix the sale at that location but enables ship-from-store-to-store strategies (Li 2020). Networked switchover can also increase customers' involvement by allowing them to collect the product from another retailer if they prefer.

Introducing DPF into a network of physical retailers that share digital counterparts of products and customers expands the product variety available at each retailer without a corresponding increase in local inventory (Gao and Su 2017). With order-and-wait sales, retailers in the DPF network are no longer constrained by local availability, because sales can be booked against network inventory. Through networked switchover, DPF alters the relationship between sales and the inventory footprint required to achieve them. Moreover, beyond sharing customer counterparts across the network, the practice extends store-based operations into online retail for returning customers with the reuse of existing customer and product counterparts. For pure-play online retailers, access to a DPF network offers a way to increase sales and reduce inventory while mitigating fit-related problems (e.g., customers ordering multiple sizes and the subsequent returns) (Gustafsson et al. 2021).

5.5 | Longitudinal Follow-Up of the Engaged Companies

After the third engagement cycle, we revisited the engaged companies to assess how their DPF use cases had evolved. Outcomes varied: Ski Boots Networker and Skates Stocker reported business growth attributable to their DPF use cases, whereas Dress Shoe Customizer discontinued operations after the COVID-19 pandemic disrupted its DPF use case.

As a start-up, *Dress Shoe Customizer* operated a physical retail store in a prime location in Stockholm and used DPF to provide custom-made shoes. Its business model was based on producing only what customers ordered to reduce overproduction and returns. Using DPF for fulfillment switchover was intended to support growth. However, the COVID-19 pandemic severely disrupted the business, and the anticipated growth did not materialize: customer visits to the shopping center ceased under pandemic restrictions, while full rent obligations remained. Because the business depended on in-person scanning to create customers' digital foot scans, operations became impossible during the pandemic, and the company ultimately closed.

Other than the pandemic, the use of DPF for fulfillment switchover faced manufacturing-related constraints. Ordering individual, custom-made shoes from the factory raised both material and manufacturing costs: for each pair sold, the start-up had to procure specific materials, pay for skilled labor, and invest in machinery capable of producing small, non-repetitive batches. Even at higher volumes, matching customers to shoes already in production or in transit primarily shortened delivery times, but it did not materially reduce per-unit costs.

At *Ski Boots Networker*, the business has grown in both the range of DPF solutions and the number of participating physical retailers. However, the DPF-based networked switchover has not taken hold in its broadest form—that is, retailers referring customers across organizational boundaries; instead, participating physical retailers primarily match customers to inventory under their control, across their own stores and distribution centers.

Since the third engagement cycle, Ski Boots Networker has developed and introduced two new scanners and has identified professional athletes as a new customer segment. Because the original high-end 3D scanner captures detailed foot geometry but requires operator training and experience, the company now offers a tiered portfolio of scanning technologies designed to streamline the in-store experience and suit generalist retail settings: (i) the original high-end 3D scanner, used for professional sports and custom footwear; (ii) a simplified 2D scanner for generalist retail stores that uses a top-down camera to capture foot length and width, which is faster, easier to use, and requires less staff training; and (iii) a smartphone-compatible plastic measuring device that is a low-cost, digitized version of a traditional foot gauge, in which customers or staff capture measurements via a smartphone app and printed markers. The third solution targets retailers with limited budgets who cannot invest in more advanced equipment. This tiered approach enables retailers to select a scanning solution that matches their operational needs and customer expectations, thereby balancing precision, usability, and cost.

Skates Stocker has maintained its two core professional skate families while adding a new lifestyle/recreational line. A key enabler of this evolution has been the continued development and use of advanced scanning technologies. Accordingly, DPF use for product redesign and assortment planning remains integral to improving retail operations.

Skates Stocker has extended its use of DPF to new product categories. Since the third engagement cycle, it has introduced a new in-store DPF solution that captures head scans and records the athlete in action while shooting; this system supports the fitting of helmets and sticks in addition to skates, marking a shift from product-specific customization to a more holistic, athlete-centered approach. In addition, a full-body scan captures detailed anatomical data, facilitating more precise gear recommendations across multiple equipment types. These new DPF applications are deliberately preserved as in-store experiences rather than offered for remote use, to emphasize accuracy and service quality.

6 | Discussion

Our main theoretical contribution—object-interactive transvections—took shape through the engaged, interactive research process, to ultimately serve as the theoretical lens for understanding the observed use cases (CF in Figure 1). Accordingly, we already presented it in Section 4, together with its conceptual foundations and motivation, in order to trace the theoretical iterations that led to this contribution. Therefore, in this section, we briefly reflect on that foundation (Section 4) and its applications (Section 5), then elaborate on this theoretical base to develop a well-informed proposal for future research. As part of the latter, we discuss the performance effects of the DPF use cases, illustrating how solving the four persistent problems in retail through DPF also leads to eliminating persistent trade-offs, which results in a performance frontier shift in retail logistics (CP in Figure 1). We then broaden the concept of fit by discussing recent technological developments that are likely to enable DPF-based practices in other retail contexts. Finally, we outline practical implications and conclude with key limitations and directions for future research.

6.1 | A Novel Theoretical Conceptualization: Object-Interactive Transvections for Understanding the Effect of DPF

As a technology, DPF emerged to enable effective customization by allowing products to be tailored based on digitally-captured fit information (Sievanen and Peltonen 2006). However, our findings show that the digital object interactions enabled by DPF hold implications that extend well beyond customization. Specifically, DPF enables the completion of transvections without requiring product customization by improving customer–product matching within existing inventories and across supply chain networks. In this way, DPF addresses the same fundamental problem that mass customization was designed to solve—namely, poor fit between heterogeneous customer needs and standardized product offerings—but through a fundamentally different operational logic.

Rather than increasing variety through downstream transformation, object-interactive transvections shift the emphasis toward digitally-enabled matching, sorting, and selective arrangement throughout the upstream retail supply chain across different locations. Conceptually, object-interactive transvections expand the scope of logistics and supply chain management from managing predefined supply chain processes that result in sales to actively managing the completion of open-ended transvections, including those that would otherwise result in lost sales, obsolescence, returns, and lost demand. From this perspective, outcomes traditionally treated as failures in mass customization and supply chain research become intentional features of an open-ended supply chain structure.

Conceptualizing retail in terms of object-interactive transvections facilitates a new understanding of the operational mechanisms underlying improvements in retail performance; consequently, we can frame our theoretical accounts to explain both productivity and profitability, which have been a persistent theoretical challenge (e.g., Schmenner 2004). While mass customization research has emphasized postponement, modularity, and flexible manufacturing as the means to achieve both efficiency and responsiveness (Gilmore and Pine 1997; Salvador et al. 2020), our conceptualization shows that digital customer–product interactions can achieve similar or superior outcomes without necessarily invoking customization. As we describe, successful fulfillment (make-to-order, match-to-stock) and incomplete fulfillment (lost sales, obsolescence, returns, and lost demand) are all object-interactive transvections. Introducing incomplete fulfillment builds on the open-endedness of transvections, extending theoretical scrutiny from structural analyses of complete transvections to dynamic analyses of how a transvection can be completed. Beyond traditional customer–production and physical customer–product interactions, DPF introduces digital customer–product interaction at both the individual and aggregate levels, which are pivotal in coping with the open-endedness of transvections. Operationally, these interactions address demand uncertainty (Fisher 1997) and realign supply chain actor interests (Lee 2004; Mak and Shen 2021). On this foundation, we can begin to develop a logistics and supply chain management theory that addresses both the productivity and the profitability of retail operations.

A DPF-based fulfillment switchover begins with a customer–product interaction mismatch and replaces it with the closest-matching open-ended transvection, whether matching to a product already in transit or matching to one that will be custom manufactured. A DPF-based networked switchover works similarly, but it widens the search for a matching product beyond a single retailer's supply chain to a network of retailers. In terms of existing transvection concepts, these switchovers are akin to selective arrangement, since not all products and customers are sorted. Through DPF-based switchovers, the digitalization of fitting reduces the need for customization, which is remarkable given that DPF technology was initially developed for customization (Sievanen and Peltonen 2006). Nevertheless, for this effect to materialize, suppliers must openly share digital counterparts of their products to enable switchovers via order-and-wait sales. In DPF-based networked switchovers, fit can be improved by matching to stock as effectively as in customization but with shorter delivery lead times and improved performance across manufacturing, distribution, and retail.

In addition, DPF-based assortment planning and DPF-based product design affect sorting and transformation activities that also occur in transvections without DPF. Using aggregated customer representations improves decision-making in these activities, making both assortment planning (a sorting activity) and product design (the definition of a transformation activity) more efficient and accurate. Furthermore, DPF-based product design blurs the boundary between standard and customized products by enabling assortments to be designed for known and existing customers. This makes speculation strategies (make-to-stock) less speculative and postponement strategies (make-to-order) less dependent on physical transformation (cf. Pagh and Cooper 1998).

Hence, our contribution to the mass customization literature is its demonstration that digital object interaction can substitute for customization by enabling high-quality customer–product matches within standardized product assortments. Rather than extending mass customization, object-interactive transvections reframe the problem it seeks to solve, namely the coordination of heterogeneous customer needs with efficient supply chain operations. This reframing has direct implications for supply chain design, as it shifts attention from configuring flexible production systems to configuring digital interaction capabilities that increase match and search potential across supply chain nodes.

Transvection theory is inherently customer-focused, as its principal unit of analysis is the transvection—the sequence of transformations and sortings needed to place the end product in the hands of the ultimate customer (cf. Alderson and Martin 1965, 123). As discussed in the literature (see Section 4), transvection theory supports analysis of both the traditional product-flow supply chain and the customer-specific supply chain. Our study highlights the impact of digitally representing the customer in the retail supply chain: through digital object interaction, digital counterparts of products and customers influence how a product moves through the supply chain, culminating in a transvection. In other words, the open-endedness of the transvection is managed via digital object interaction, enabling supply chain decisions that are contingent on the specific customer–product match.

The DPF-based switchovers blur the distinction between speculation and postponement, as they imply a variable, customer-specific OPP. Furthermore, the predefined sequential structure of retail operations becomes no longer necessary, because digital object interactions can introduce new transformations and sortings where needed. Postponement and speculation strategies can thus be viewed as archetypical descriptions that emerged in non-digital contexts, while digitalization, combined with operational practices such as those described in our use cases, allows transvection-specific configurations of interactions. Non-digital interactions typically require a process definition, whereas digital interactions can be inserted where needed and therefore do not necessarily require such a definition.

In explaining the effect of DPF, we distinguish between individual and aggregate digital customer–product interactions occurring in object-interactive transvections. This distinction provides a starting point for structuring the conceptual landscape of our theoretical extension. To translate this distinction from technical to operational interactions, we differentiate between search interactions and match interactions: a *search interaction* seeks to match one customer to an available product (fulfillment and networked switchovers), whereas a *match interaction* seeks to match a product or product type to available customers (assortment planning and product design). The former aims to complete a transvection; the latter aims to increase the likelihood of a successful transvection.

Relating this differentiation to a structural view of the supply chain, we propose two concepts for managing open-ended transvections. We introduce the concepts of match potential and search potential as supply chain design variables. First, the *match potential* of a supply chain node denotes the extent to which the node is managed based on knowledge of actual (known) customers and their needs. Similar to the speculation–postponement dichotomy, high upstream match potential can compensate for low downstream match potential, and vice versa. With DPF in a digitally integrated supply chain, both high upstream and high downstream match potential can be achieved simultaneously, to yield more accurate upstream transformations and sortings coupled with downstream activities that tie together the loose ends, enabling a shift from product-centric to customer-centric supply chain design. Second, the *search potential* within and across supply chains denotes the vertical and horizontal extent to which the (digitally represented) customer can search for a matching product. In this way, the problems that motivated mass customization become manageable detours in object-interactive transvections, rather than structural constraints on supply chain performance.

6.2 | A Novel Solution to Persistent Problems: Pushing the Retail Performance Frontier and Redefining Trade-Offs Through DPF

In our study, we shed light on how DPF constitutes a new solution to the four persistent retail problems (discussed in Section 2) by enabling management thereof through object-interactive processes rather than treating them as outcomes to be minimized through forecasting and inventory decisions. Through our engaged research, we demonstrate that DPF-based operational practices intervene directly in the mechanisms that generate these problems and enable digital customer–product interaction across supply chain nodes. An underlying cause across the four problems is limited supply chain visibility into customer–product fit with uncertainty. In conventional retail operations, mismatches are inferred indirectly from sales, returns, and inventory levels, leaving not only lost demand but also many mismatch mechanisms unobservable. Mass customization partially addresses these mismatches by allowing customers to tailor products (Salvador et al. 2020), but it still relies on customer commitment prior to production and does not eliminate uncertainty about aggregate demand and fit distributions. In contrast, DPF addresses this root cause by digitalizing customer–product interaction, which enables retailers to detect, evaluate, and manage mismatches as they occur. In doing so, DPF shifts retail operations toward an adaptive system logic (cf. Kauffman et al. 2018) in which supply chain decisions are continually revised based on real-time interaction data, rather than periodically recalibrated through forecasts.

Lost sales are addressed through DPF-based fulfillment and networked switchovers, which expand the effective search space for a fitting product beyond the store or local inventory. To this end, DPF operationalizes key ideas from omnichannel research by enabling customer-specific, real-time integration of inventory and fulfillment options across channels at the level of the individual transvection, rather than treating channels as parallel but loosely coupled systems (cf. Kembro et al. 2022). To wit, when a local match fails, the transvection can be extended upstream (through customization or in-transit inventory) or laterally (through networked inventory), enabling the completion of sales that would otherwise be lost. Operationally, DPF transforms lost sales from terminal failures into contingent, open-ended processes, reducing the need to increase local inventory levels in order to achieve high service levels.

Inventory obsolescence is addressed both ex ante and ex post. With DPF-based assortment planning and product design, upstream decisions are grounded in aggregated digital customer counterparts rather than inferred demand, which reduces the likelihood that products are produced or stocked without a corresponding customer base. Additionally, fulfillment switchovers enable opportunistic matching of products already in production or transit, reducing the accumulation of unmatched inventory. In contrast to mass customization, which mitigates obsolescence by postponing commitment to specific product variants (Salvador et al. 2020), DPF reduces obsolescence by increasing the likelihood that existing products will find a matching customer; obsolescence is thus reframed from a purely inventory-control failure to an incomplete transvection that may still be completed through additional matching.

Product returns are addressed through intervening before the physical customer–product interaction occurs. By enabling digital fitting prior to purchase, DPF reduces the incidence of poor initial matches, particularly in order-and-wait and online contexts. Moreover, the interaction data generated during unsuccessful matches can be retained and reused, improving subsequent matching decisions by enabling learning from mismatches instead of merely processing their consequences. More fundamentally, returns are reframed as incomplete object-interactive transvections, rather than exogenous reverse flows.

Lost demand is addressed by reducing the measurement blind spot inherent in conventional retail data. DPF makes unsuccessful matching attempts visible even when no transaction occurs, thereby generating information about unmet needs that would otherwise remain invisible. Aggregating such interaction data enables upstream learning about assortment gaps, size distributions, and design features by expanding the informational basis of demand beyond realized sales and returns, weakening the coupling between assortment expansion and inventory risk.

Collectively, these problem-specific interventions alter the structure of key retail trade-offs. Rather than optimizing among availability, inventory, and returns within fixed constraints, DPF-based practices relax these constraints by enabling targeted matching, adaptive fulfillment paths, and reuse of interaction data. From a performance perspective, this constitutes a shift in the retail operational performance frontier (Schmenner and Swink 1998): higher sales and service levels can be achieved alongside lower inventory exposure and return-related costs through direct engagement with the mechanisms that generate the four persistent retail problems.

Nevertheless, DPF-based practices are also constrained by new asset frontiers (Vastag 2000). Specifically, DPF-based switchovers—both fulfillment and network—rely on the retail supply chain's capability to match available products to an individual customer and then create a customer-specific fulfillment process (i.e., a transvection). For their part, DPF-based assortment planning and product design can be operationally implemented in conventional retail supply chains, but they require digital inventories of both digital products and digital customers. Moreover, because actual performance is bounded by the performance frontier, digitalization alone does not improve performance without appropriate operational practices; at the same time, the performance frontier is constrained by the asset frontier. Thus, new operational practices will not yield performance improvements without sufficiently comprehensive digitalization (Vastag 2000), which we theorized as search and match capabilities in Section 6.1. In addition, our longitudinal follow-up indicates that the asset frontier is highly contingent on the type of customer a firm seeks to serve.

6.3 | Recent Technological Developments and DPF

Technological developments including augmented reality (AR), machine learning (ML), and artificial intelligence (AI) introduce new ways of conducting DPF (Pereira et al. 2022). In online apparel shopping, AR enhances the shopping experience by recreating dressing-room elements in virtual fitting rooms, allowing customers to visualize garments on digital avatars reflecting diverse body shapes or on their own scans (where available) (Batool and Mou 2024). AI- and ML-based systems process 3D body scans to generate personalized size recommendations and visualizations, further enhancing the digital fitting experience. These DPF applications in online apparel retail can extend the practices of DPF-based fulfillment switchover to online sales; reported outcomes include reductions in return rates of up to 20% (Mehrotra 2025) and decreases of up to 40% in consumer tactics to mitigate fit uncertainty (e.g., ordering multiple sizes of the same item) (McDowell 2024).

Apart from explicit customer scanning, some DPF solutions infer a customer's digital counterpart from the dimensions of products the customer already owns. For example, Virtusize reports a 30% reduction in size-related returns (Virtusize 2024). Other AI-enabled platforms that recommend items based on similarity to previous successful fits include True Fit, Fit Analytics, and Amazon; True Fit draws on datasets of millions of consumers and thousands of brands to deliver personalized size predictions, while Fit Analytics combines brief user input with algorithmic learning. Access to such databases can enable DPF-based assortment planning and product design at a larger scale and improve the efficiency of DPF-based fulfillment and networked switchovers.

Other emerging technologies—such as AR/VR avatars, dynamic digital shadows, and digital twins (which can evolve through real-time sensor data, usage monitoring, or repeated interaction)—could enable more adaptive, continuously updating representations of fit (Batool and Mou 2024). For example, smart textiles, embedded IoT sensors, and wearables can generate detailed fit data during actual use, creating opportunities for more precise matching, sorting, and re-matching over time. Accordingly, these technologies may improve accuracy and expand DPF applications.

With new technological DPF solutions, the scope of practical relevance expands. The footwear use cases can extend to apparel and other product categories, both online and in physical retail. In apparel, digital prototyping—using 3D design software and avatars representing diverse body types and sizes—has enabled brands to adopt the DPF-based product design use case (Steinke 2025). Designing garment fit across diverse body types before physical production reduces the need for trial batches prior to volume production; this direct digital product creation shortens the product-development cycle and reduces material waste and sample-production costs.

Beyond apparel and footwear, accessories such as eyewear, hats, jewelry, and watches can also benefit from DPF; AR and real-time body tracking mimic mirror-based fitting on customers' devices (Konarzewski and Reiner 2023; Wu et al. 2024). For example, AR-powered virtual try-on features enable users to visualize rings, bracelets, and watches on their hands or wrists with high realism (Konarzewski and Reiner 2023; Wu et al. 2024). For eyewear specifically, integrating AR with ML has improved personalization (Thapa et al. 2025).

Furthermore, product fit is one of the most significant barriers to online second-hand shopping (Frahm et al. 2025), because buyers typically cannot return purchased items that do not fit. Thus, DPF offers an opportunity to significantly facilitate the online resale of used items. Platforms such as Fit: match leverage LiDAR-enabled smartphones to create digital body avatars (Barrett 2022). By collecting and retaining both customer-specific and item-specific data, DPF could recommend second-hand garments with a higher likelihood of fit.

6.4 | Practical Implications

DPF holds significant implications for the design and management of retail supply chains, as it helps address persistent, long-standing challenges such as lost sales, inventory obsolescence, and costly returns. By embedding digital customer–product interaction directly into supply chain activities, DPF enables companies to shift from rigid processes to adaptive practices that more effectively match supply and demand.

For retail supply chain managers, realizing the benefits of DPF requires more than adopting new digital tools: it demands rethinking how supply chain nodes are coordinated, the role of inventory, and how match and search capabilities are built and leveraged across the retail supply chain. Firms need to invest not only in the technologies that enable digital customer–product interaction but also in the operational capabilities to use digital representations of customers and products in day-to-day decision-making. This involves developing the ability to leverage aggregated customer representations upstream (e.g., assortment planning and product design) as well as enabling flexible, customer-specific fulfillment downstream.

While the use cases described in this study were developed in specific retail contexts where product fit is tightly coupled with functionality, the underlying mechanism—that is, managing open-ended transvections through digital customer–product interaction—is relevant beyond the contexts studied here. In Section 6.3, we highlight cases in which the notion of fit and DPF extend to products for which social, emotional, and aesthetic aspects shape customer choice. In such retail contexts, managers facing high return rates, excess inventory, and demand uncertainty should consider how to adapt DPF practices and principles to their product categories and supply chain structures. Additionally, the emergence of elite and professional sports as a new application domain illustrates how DPF can create value in contexts where fit precision has direct performance and financial implications. For professional teams, improved equipment fit is linked not only to athlete comfort but also to reduced injury risk and avoidance of costly downtime—what one CEO referred to as protecting "million-dollar athletes." These developments expand the scope of DPF beyond retail logistics and product assortment into performance-critical environments, highlighting how new use cases can surface when DPF is embedded in highly specialized operational settings.

Our follow-up with the companies illustrates that the success of DPF-based practices depends not only on product type but also on the alignment of technology and operational capabilities with distinct customer needs. For example, while some customers may require high-end scanners and custom fitting, others can be served with simpler mobile or in-store solutions for matching. The evolving scale and scope of scanning at Ski Boots Networker and Skates Stocker indicate that retail managers need to critically assess their technology choices, customer-engagement practices, and operational flexibility to capitalize on DPF. As digitalization becomes more integrated in physical retail environments, the capacity to deploy object-interactive transvections will increasingly shape firms' ability to balance cost efficiency and customer satisfaction, as well as potentially support sustainability ambitions.

6.5 | Limitations and Directions for Future Research

While our study demonstrates how DPF can reshape retail supply chain practices by managing open-ended transvections via digital customer–product interaction, its findings should be interpreted in light of its contextual and methodological limitations.

The four use cases formulated in this study were developed in the context of footwear retail, where physical fit is closely connected to product functionality. We assume that new supply chain practices emerge first where conventional processes struggle most, so footwear is an appropriate starting point, as poor physical fit directly drives high return rates, obsolescence, and lost sales. Nevertheless, questions remain about how these use cases generalize to other product categories in which fit is more linked to aesthetic, emotional, or social aspects. Therefore, future research should examine how the underlying mechanism—managing open-ended transvections through digital customer–product interaction—extends to these other forms of fit. In addition, as discussed in Section 5.3, AR and VR solutions are likely to play an important role in creating digital customer counterparts, which enable customers to explore and experience products digitally. These technologies can enable rich digital representations of customers' aesthetic and experiential preferences, addressing more subjective aspects of fit that are harder to capture through physical measurements and static data alone.

From a supply chain design perspective, this reconceptualization of fit as an open-ended, digitally managed transvection points to a shift similar to that observed in digitally enabled production systems, such as additive manufacturing. Prior research on additive manufacturing has shown how digitalization enables dynamic switchovers between alternative production and fulfillment structures when conventional supply chains struggle with problematic demand (Holmström and Gutowski 2017; Akmal et al. 2022). Our findings suggest that DPF plays a comparable role in retail supply chains by facilitating switchovers among inventory-based fulfillment, networked inventory use, and customer-specific matching as the customer–product interaction unfolds. Therefore, future research should examine how DPF affects classical supply chain design decisions, such as the placement of customer OPPs, the configuration of omnichannel fulfillment networks, and the conditions under which adaptive, interaction-driven designs outperform fixed, ex ante supply chain structures.

A technological limitation in our use cases was that the digital counterparts underpinning DPF were relatively static, in that they relied on single scans of products and customers. However, emerging technologies such as AR and VR avatars and dynamic digital shadows can provide more adaptive, continuously updated representations of fit (Batool and Mou 2024). Future research could explore the theoretical and operational implications of such dynamic digital counterparts, building on prior research on product–production interactions wherein dynamic digital counterparts of products and production resources enable object-interactive production control (Stark et al. 2023).

While our study traces the evolution, underlying rationales, and observed outcomes of DPF in the companies studied, our engaged research approach has important limitations. To start, we did not quantitatively benchmark the use cases against pre-DPF operations, nor did we systematically investigate contextual or firm-specific factors (such as supply chain integration maturity, customer-segment characteristics, or partner-network structures) that might facilitate or constrain adoption. Furthermore, while we touch on upstream planning and product design, we did not empirically examine the potential benefits of DPF for manufacturers actively digitalizing product design and production engineering for fit-dependent products (cf. Stark et al. 2023). Addressing these gaps in comparative studies, longitudinal data, and multilevel analyses would deepen understanding of when and how object-interactive transvections deliver the greatest operational and strategic benefits.

We expect additional DPF use cases to emerge, and they likely already exist. Accordingly, a promising opportunity for further engaged research lies in developing and exploring use cases in which the open-endedness of transvections extends beyond the first-customer use phase. For example, fit may have important implications after the initial sale, as it could reshape the economics of second-hand markets. Treating end-of-use situations as incomplete transvections would allow future research to examine how digital customer–product interactions can facilitate precise re-matching of products to new users and feed back into upstream processes. This perspective positions DPF not only as a tool for improving first-use fulfillment but also as an enabler of more circular, sustainable supply chain designs that maximize value across multiple product life cycles.

Finally, while our focus is on retail, the same theoretical logic may extend to other sectors where individual-level fit is critical yet difficult to operationalize through static processes. For example, healthcare relies on matching patients to care pathways based on diagnostic information—a problem that can be framed in terms of fit (Johnson et al. 2020). However, such applications raise questions about ethical use, data security, and regulatory compliance. Future work could examine how principles of digital object interaction can inform these contexts while respecting privacy and governance constraints (cf. Choi et al. 2021).

Taken together, these research directions highlight how our study offers an initial conceptualization of how DPF can reshape supply chain practices by managing open-ended transvections; establishing the broader potential and limitations requires further research.

7 | Conclusion

Our study contributes to retail supply chain research by showing how DPF can be theorized and operationalized through the lens of *object-interactive transvections*. Traditional retail supply chains—especially for fit-dependent products—are constrained by the need for physical product fitting and the operational limitations this imposes. Our object-interactive conceptualization of DPF-based retail logistics posits that actors with access to digital counterparts of products and customers can match them digitally, which opens opportunities to complete otherwise incomplete transvections and improve supply chain performance. By conceptualizing supply chain activities as open-ended sequences that are dynamically shaped by digital customer–product interactions, we move beyond a static view of supply chain design and highlight how firms can address persistent challenges, such as lost sales, inventory obsolescence, and costly returns.

Through four use cases—fulfillment switchover, assortment planning, product design, and networked switchover—we show how DPF enables supply chains to adapt more flexibly to actual customer needs in which fit is critical. This reframing helps illustrate how companies can overcome trade-offs traditionally treated as fixed, thereby shifting the operational performance frontier. Our study also emphasizes that the performance benefits of DPF rely not only on digital infrastructure but also on the capability to organize search and matching across supply chain nodes in ways that were previously impractical.

By incorporating one completed and four incomplete fulfillment processes (the latter corresponding to lost sales, inventory obsolescence, lost demand, and product returns) into the conceptualization of object-interactive transvections, our work extends existing theory on digitalization in retail supply chains and offers new directions for managing supply chain performance. As technologies like VR, AR, and digital twins continue to evolve, the potential for object-interactive transvections to enable more precise and responsive supply chains will continue to expand.

As discussed above, future research should continue exploring how this mechanism can be refined and extended across other forms of fit, product categories, and sectors where individual-level matching is critical yet complex. Future work should also examine emerging technologies that could augment DPF practices. Moreover, our findings lay the groundwork for investigating how digital customer–product interaction can not only close gaps in first-use fulfillment but also support more sustainable, circular supply chain strategies across multiple product life cycles.

Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

[1] We also found that many physical retailers only use the digital product inventory in the sales processes. After customers are scanned, the scans are discarded and not retained for further systematic use and accumulation in a digital customer object inventory, representing an available but unused possibility for retailers.

[2] We do not list or describe all the companies from the first and second engagement cycles here. These engaged companies and descriptions can be found in the corresponding publications for those previous cycles (<REFS to be added after review>).

[3] Assignments and selections entail different types. Allocation is an assignment of products to a forthcoming transformation (e.g., from a homogeneous original set, a supplier allocates a homogeneous subset to transportation or storage). Sorting-out is an assignment from a heterogeneous original set to multiple homogeneous subsets (e.g., an online retailer sorts out returned products so that they can be reallocated to inventory). Assortment is a selection from multiple homogeneous subsets to create a heterogeneous set (e.g., a retailer selects products to present on the shelf to the customer). Accumulation/assembly are selections that create a homogeneous set (e.g., customers selecting fitting products for purchase in a shopping basket).

[4] In procedural conceptualizations of the supply chain, this type of interaction is described as the order penetration point, or the decoupling point.

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Appendix A

How the Engaged Research Unfolded Across Cycles, How Problematization Evolved, and How the Theoretical Framework Emerged

This appendix describes how solution development and data collection progressed hand in hand, gradually reshaping our understanding of both the persistent problems and the proposed solution designs.

The first two cycles of the engaged research are shown in Figure A1. The initial engagement aimed to reduce the competitive disadvantage of physical retail relative to online retailers. Working with four physical footwear retailers—one of which was implementing DPF—we explored how these companies could digitalize to improve their competitiveness. In this first engagement, we learned how DPF could be used for fitting and began to discuss alternative applications with the companies.

The second engagement focused on the problem of finding a well-fitting experience product. The research questions concerned how implementing companies use DPF and what complementary solution elements are needed. To address these questions, a case survey was used (Larsson 1993). In addition to contributing a DPF maturity model, this engagement identified further DPF practices and contributions beyond fitting in retail supply chains. A range of potential DPF use cases was discussed.

The third cycle—which is the focus of this paper and is reported here—conceptualizes distinct DPF use cases. These use cases constituted our unit of analysis. In analyzing them, we explored how DPF technology addresses the real-world problems (P) of lost sales, inventory obsolescence, product returns, and lost demand. Through engagement with practice, we developed object-interactive transvection theory as the theoretical framework (T) and formulated the research question of how use of DPF can address these recognized real-world problems (P) by treating them as processes amenable to improvement.

When the research began in 2016, practitioners increasingly recognized that physical retail in many product categories was at a disadvantage relative to online retailers. The national retail association that provided the research grant sought to explore how digitalization could help physical retailers compete more effectively with online rivals. Alongside digitalization, mass customization served as an initial theoretical lens. One of the retailers engaged in the first cycle sought to leverage DPF as the basis for a novel mass-customization business model.

In the second engagement cycle, we focused on customers' difficulty in finding a well-fitting experience product. The research question concerned the purposes for which DPF was used and the complementary solution elements needed to fulfill those purposes. The theoretical frameworks guiding this cycle were supply chain maturity and DPF.

In engaged research, the role of problematization is to scrutinize key assumptions and argumentation within a research field and, by challenging prevailing theoretical positions, to formulate novel research questions. In the first two engagements, this problematization function was not yet central. Scrutiny of theoretical assumptions came to the forefront in the third engagement cycle, which focused on the problems of lost sales, inventory obsolescence, product returns, and lost demand.

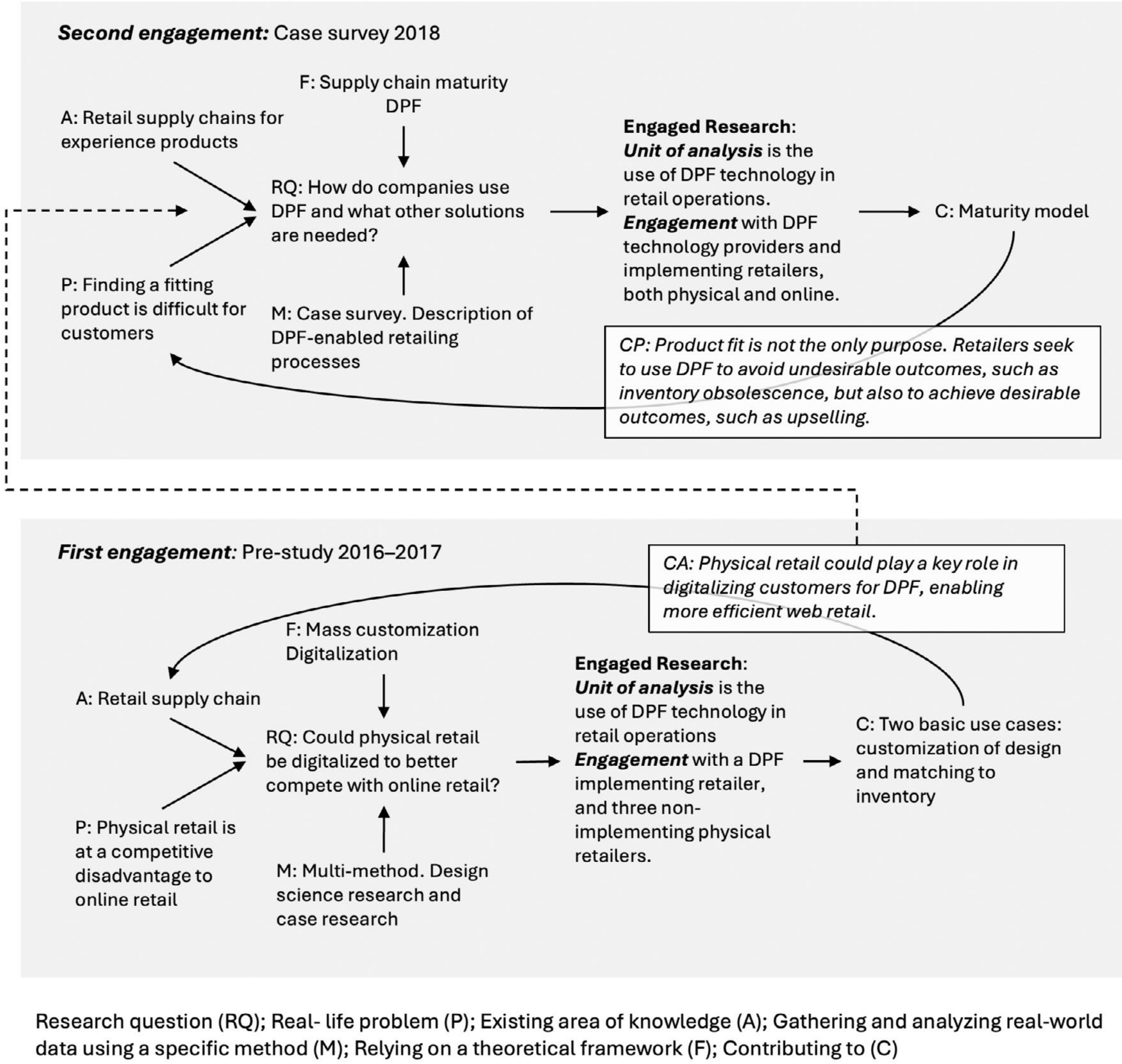

FIGURE A1 | The first and second engagement cycles.

We initially approached these problems from the established theoretical perspective of swift and even flow, viewing DPF as a means to facilitate such flow. However, the theory of swift and even flow—an established framework for enabling efficient and responsive supply chains—seeks improvement primarily by reducing variation (Schmenner 2004; Schmenner and Swink 1998). This emphasis limits the framework's usefulness for addressing the focal practical problems in this study. To better align theory and problem, we first considered modifying the framework to emphasize swift flow that responds to variation, enabled not by reducing variation but by DPF-enabled product–customer matching.

Even after this modification, we found that the problematization constrained rather than expanded the solution space. For example, switching from customization to mass production would, under a swift-and-even-flow framing, be considered an improvement, whereas reducing lost sales by switching from make-to-stock to mass customization would be interpreted as a performance decline. Using DPF, a footwear retailer can serve niche needs through customization; yet under a swift-and-even-flow framing, such a move would signal strategic mismatch and reduced performance rather than a valuable partial solution to a practical problem.

We therefore searched for an alternative theoretical framework and turned to transvection theory, which has been used to examine supply chain structure (Kembro et al. 2022) and customization in supply chains (Hulthén and Gadde 2007). Modifying the transvection framework to treat practical problems as incomplete transvections offered a new perspective. Under this modified framework, the scope of DPF use cases becomes wide-ranging, encompassing both the avoidance of these problems and their remediation by enabling incomplete transvections to be completed.

Throughout the research engagements, our focus has been on the technological dimension of practice—specifically, how DPF enables new or modified supply chain practices. Consequently, the unit of analysis is not individual companies, but the DPF use cases developed by technology providers and implemented by retailers in varied ways. This unit of analysis was defined in the initial engagement and progressively elaborated in each subsequent research cycle as new insights emerged.

The first cycle of engagement revealed that although DPF was originally developed to enable mass customization, it also has another potentially practical use case: matching customers to products already in inventory. Our contribution to retail supply chain management is to identify and theorize this inventory-matching use case of DPF. From this perspective, deploying DPF in physical retail offers a potential solution to a problem commonly faced in online retail. Accordingly, digitalization in the form of DPF does not inherently give physical retailers an advantage over online channels; instead, it highlights a complementary and enabling role for physical stores.

The second engagement cycle revealed that product fit is not the sole purpose of introducing DPF. Retailers use DPF to avoid undesirable outcomes such as inventory obsolescence and to achieve desirable outcomes such as upselling. We also found indications that manufacturers, when combining DPF with complementary digitalized operations, can reduce both lost sales and inventory obsolescence. This cycle therefore contributes to addressing practical problems faced by both retailers and manufacturers of experience products.

The third engagement cycle contributed a novel framework and theoretical perspective for understanding how to address the problems of lost sales, inventory obsolescence, and product returns. When we attempted to apply existing frameworks to DPF-enabled operations in retail supply chains—specifically speculation and postponement and swift and even flow—we found them insufficient. This led us to develop the object-interactive transvections framework. The DPF use cases presented within this framework demonstrate how the studied practical problems can be addressed through object-interactive transvections.

Appendix B

Emergence and Development of DPF Use Cases

This appendix illustrates how the four DPF use cases emerged through iterative engagement with practice and complements Figure A1. Each use case is anchored in specific observations made during these engagements (see Table B1) and subsequently abstracted into a generalized solution concept. The schematic Figures B1–B4 visualize how company-specific practices evolved into broader conceptualizations. Each use case was co-constructed through interactions with company representatives. Interviews, site visits, and evaluation discussions provided the empirical grounding for the schematics presented in this appendix. Importantly, presenting and discussing these schematics with practitioners was itself a central part of the engaged research method, as it yielded confirmations, refinements, and new ideas that extended beyond our initial framing. Together, these use cases provide the empirical grounding for the conceptualization of object-interactive transvections developed in the main body of the paper. Table B2 provides an overview of data sources and engagements across the four use cases.

Fulfillment switchover emerged from early engagements with Dress Shoe Customizer. We initially set out to explore matching practices in retail but predominantly encountered customization practices. One particularly mature practice was found at Dress Shoe Customizer. In our first round of engagement, we conducted three interviews with the CEO and CFO (Table 2, 2017–2018), collecting data on how their DPF practice functioned. Subsequent analysis abstracted these practices to a more conceptual level, which led us to the postponement and speculation framework.

Applying the postponement and speculation lens revealed that DPF use was inherently dynamic. Rather than representing a choice between customization and matching, DPF enabled a dynamic switchover between the two. During a site visit to Dress Shoe Customizer's store (Table 2, 09/2017), we observed that the DPF technology was used in practice to redirect customers to existing stock when they were unwilling to wait for customization.

In searching for additional DPF practices, we encountered Technology provider A. An interview and site visit (Table 2, 09/2017) contributed to our understanding of their technology and its use, and this engagement led us to one of their customers, Skates Stocker. During our first interview with Skates Stocker's Marketing Manager (Table 2, 10/2018), conducted at their headquarters, the DPF technology was demonstrated to us. Skates Stocker employed a DPF practice similar to that of Dress Shoe Customizer but with a stronger emphasis on matching rather than customization. This contrast further supported our emerging understanding of DPF as enabling dynamic switching between matching and customization.

During the same interview, we discussed our emerging generalized DPF solution concept, which had been developed based on engagements with Dress Shoe Customizer and Technology provider A (Table 2, 09/2017). The Marketing Manager confirmed the validity of this generalized conceptualization. Across these engagements, we observed that DPF served a dual role: enabling matching-to-stock when feasible, while also enabling make-to-order customization when stock was unavailable.

These insights led us to conceptualize the use case of DPF-based fulfillment switchover, defined as the capacity to dynamically shift between stock-based fulfillment and customization depending on product availability and customer preferences. At this stage, the generalized solution concept was visualized as shown in Figure B1.

Following further engagements with Dress Shoe Customizer—aimed at delineating how their DPF practice could evolve (Table 2, interviews and follow-up calls up until 2019)—we presented the schematic shown in Figure B1 during an evaluation with the CEO and COO (Table 2, 11/2019). In this evaluation, we also presented early versions (then referred to as “pathways”) of additional use cases enabled by generalized DPF. Based on feedback from this evaluation, we refined our generalized DPF concept.

In particular, Dress Shoe Customizer emphasized the value of feeding back “ill-fits” (i.e., cases where no suitable fit exists in the current assortment) to inform the design and production of better-fitting products. This insight later became an embryo for the product design use case. After this evaluation round, we returned to our conceptual development and produced the refined schematic shown in Figure B2.

Assortment planning emerged from recognizing the strategic value of fitting data during engagements with Skates Stocker. The company revealed that the customer model databases generated by DPF were not only useful for in-store fitting but also held significant strategic value for assortment planning decisions. An interview with the Demand Planning Manager (Table 2, 11/2018) showed that aggregated fitting data informed decisions regarding which sizes and product variants to stock, as well as production planning across global markets. Based on these insights, we updated our generalized DPF concept to incorporate assortment planning.

In a later evaluation discussion (Table 2, 02/2020), we presented the refined schematic (Figure B3), which explicitly included the assortment planning dimension. This refinement repositioned DPF from a downstream sales-support tool—consistent with our observations of DPF in operation at multiple retailers (Table 2, 09/2017, 12/2018, 04/2019)—to an upstream decision-support tool. We thus conceptualized the use case of DPF-based assortment planning, highlighting how fitting data can be leveraged across the supply chain to shape what products are produced, stocked, and offered.

The use case of DPF-based *product design* emerged from further exploration of how customer scan data flowed upstream to manufacturers. This was identified through interviews with Skates Stocker's technology provider (Table 2, 09/2017) and Ski Boots Networker's technology provider (Table 2, 06/2018; 04/2019). Both explained how aggregated scan data were sold to manufacturers to inform shoe-last design and size grading. Retailer interviews and on-site participant observations (Table 2, 12/2018; 04/2019) confirmed that product offerings increasingly reflected customer morphology, contributing to reduced returns and obsolescence. These engagements informed the product design use case, in which customer data flows from retail operations back into R&D and manufacturing, creating a feedback loop that improves product–customer fit. Figure B3 illustrates both the assortment planning and product design use cases.

Networked switchover emerged from observations of a platform-based retail ecosystem. Engagements with Ski Boots Networker revealed a fundamentally different organizational model: a multi-brand, multi-retailer platform. This insight emerged from interviews with the CEO (Table 2, 2018–2020) and participant observation at a retailer (Table 2, 04/2019). We observed and discussed the company's ambition to build a platform in which multiple brands could be included in retailers' digital matching processes.

When we presented the idea of a joint network involving multiple brands and retailers to Skates Stocker (Table 2, 02/2020), the response

TABLE B1 | Empirical engagements and their contributions to the four DPF use cases.

Data source	Engagement description	Use case 1: fulfillment switchover	Use case 2: assortment planning	Use case 3: product design	Use case 4: networked switchover	Outcome/ emerging insight
Retailer interview, CEO (1 h, 09/2017)	DPF practice, customization emphasis	Initial conceptualization; customization-heavy practice forms one side of switching	—	—	—	Matching not present; conceptual extension toward customization; early link to postponement/speculation
Participant observation at retailer (1 h, 09/2017)	On-site observation	Observed dynamic redirection from customization to stock	—	—	—	Early conceptualization of dynamic DPF (switching between customization and matching)
Retailer interview, CEO and CFO (1 h, 04/2018)	Business progression	Confirmed stable ongoing switching practices	—	—	—	Reinforced baseline conceptualization.
Retailer interview, CEO and CFO (2 h, 10/2018)	Evolution discussion	Helped refine schematic; supported generalized switching logic	—	—	—	Supported Version 1 schematic in Figure B1
Retailer evaluation interview, CEO and COO (2 h, 11/2019)	Evaluation of Version 1	Validation of dynamic switching	—	Identified “ill-fit feedback” loop	—	Led to Version 2 schematic in Figure B2; seeded product design use case
Retailer evaluation interview, CEO and CFO (1 h, 03/2020)	Follow-up	Confirmed evolved switching	—	—	—	Additional refinement
Technology provider A interview, VP product (1 h, 09/2017)	Technology explanation	Underpinnings of switching; connection to Skates Stocker	—	Data flows upstream to manufacturers	—	Grounded technical feasibility for switchover and product design

(Continues)

TABLE B1 | (Continued)

Data source	Engagement description	Use case 1: fulfillment switchover	Use case 2: assortment planning	Use case 3: product design	Use case 4: networked switchover	Outcome/emerging insight
Participant observation at Technology provider A (1 h, 09/2017)	Technology demonstration	Understanding enabling conditions	—	Demonstrated upstream-data potential	—	Supported emergence of product design use case
Manufacturer interview, Marketing manager (2 h, 10/2018)	DPF use at HQ	Confirmed matching-heavy DPF practice	—	—	—	Strengthened matching side of dynamic switchover
Participant observation at retailer (1 h, 12/2018)	Skates Stocker store visit	Grounded use of DPF matching practice	—	—	—	Reinforced dual role of DPF
Manufacturer interview, Demand planning manager (1 h, 11/2018)	Use of aggregated fitting data	—	Fitting data guides assortment and production	—	—	Foundation for assortment planning
Retailer interview, store manager (1 h, 12/2018)	In-store execution	Tactical switching in practice	—	—	—	Confirmed everyday use of switchover
Manufacturer evaluation interview, Marketing manager (2 h, 02/2020)	Evaluation of refined concept	—	Confirmed assortment planning logic	Confirmed product design logic	—	Validated Figure B3
Technology provider B interview, CEO (1 h, 06/2018)	Early platform vision	—	—	Scan data sold upstream	Enabled multi-brand/retailer thinking	Early seeds of networked switchover
Participant observation at retailer (1 h, 04/2019)	Ski Boots Networker store	—	—	Morphology-informed offerings	Multi-brand fitting visible	Grounding for network-level logic

(Continues)

TABLE B1 | (Continued)

Data source	Engagement description	Use case 1: fulfillment switchover	Use case 2: assortment planning	Use case 3: product design	Use case 4: networked switchover	Outcome/ emerging insight
Technology provider B interview, CEO (6 h, 04/2019)	Deep dive on platform	—	—	Data to manufacturers	Multi-brand ecosystem	Identified shared digital inventory logic
Retailer interview, store assistant (2 h, 04/2019)	Operational DPF use	Demonstrated switching at store level	—	—	—	Confirmed switchover practice
Technology provider B evaluation interview, CEO (1 h, 03/2020)	Evaluation of networked model	—	—	Manufacturer data model validated	Networked switchover vision validated	Confirmed long-term platform vision
Retailer follow-up interview, CEO (1 h, 05/2025)	Longitudinal follow-up on switching	Confirmed continued relevance of dynamic switchover; updates on how practice evolved	—	—	—	Provided longitudinal validation of use case 1; confirmed to last over time
Technology provider A follow-up email, VP product (05/2025)	Longitudinal check-in on technology & data flows	—	Confirmed that customers show an increased interest in using scan data to improved inventory planning	Confirmed ongoing role of scan data in manufacturer processes; updates on data-sharing models	—	Strengthened long-term confirmation of use case 3
Technology provider B follow-up interview, CEO (1.5 h, 05/2025)	Longitudinal follow-up on platform vision	—	—	—	Confirmed continued strategy toward shared digital inventory and multi-brand matching	Validated long-term ambition of networked switchover; confirmed viability

TABLE B2 | Overview of data sources and engagement across the four use cases.

Use case	Data sources	Engagement with practice	Analytical contribution
Use case 1: Fulfillment switchover	Retailer interview, CEO (1 h, 09/2017) Participant observation at retailer (1 h, 09/2017) Retailer interview, CEO and CFO (1 h, 04/2018) Retailer interview, CEO and CFO (2 h, 10/2018) Retailer evaluation interview, CEO and COO (2 h, 11/2019) Retailer evaluation interview, CEO and CFO (1 h, 03/2020) Technology provider A interview, VP product (1 h, 09/2017) Participant observation at Technology provider A (1 h, 09/2017) Manufacturer interview, Marketing manager (2 h, 10/2018) Participant observation at retailer (1 h, 12/2018) Retailer interview, store manager (1 h, 12/2018) Retailer interview, store assistant (2 h, 04/2019) Retailer follow-up interview, CEO (1 h, 05/2025)	Explored how DPF operated in day-to-day sales situations; observed customer redirection between customization and in-stock options; validated emerging schematics in evaluation meetings	Identified DPF as dynamic switching between matching and customization; established the core mechanism of "fulfillment switchover" as a foundational practice
Use case 2: Assortment planning	Manufacturer interview, Demand planning manager (1 h, 11/2018) Manufacturer evaluation interview, Marketing manager (2 h, 02/2020) Technology provider A follow-up email, VP product (05/2025)	Investigated how fitting data was aggregated and shared internally; discussed decision-making processes for stock, production, and market allocation	Identified DPF as an upstream decision-support tool: fitting data informs assortment decisions, shifting DPF role from downstream sales aid to strategic planning input
Use case 3: Product design	Retailer evaluation interview, CEO & COO (2 h, 11/2019) Technology provider A interview, VP product (1 h, 09/2017) Participant observation at Technology provider A (1 h, 09/2017) Manufacturer evaluation interview, Marketing manager (2 h, 02/2020) Technology provider B interview, CEO (1 h, 06/2018) Participant observation at retailer (1 h, 04/2019) Technology provider B interview, CEO (6 h, 04/2019) Technology provider B evaluation interview, CEO (1 h, 03/2020) Technology provider A follow-up email, VP product (05/2025)	Investigated how customer morphology data flowed from retailers to manufacturers; discussed how manufacturers interpreted and used aggregated scan data	Conceptualized the DPF-based product design loop, where customer morphology data informs last design and size grading, reducing returns and improving fit
Use case 4: Networked switchover	Technology provider B interview, CEO (1 h, 06/2018) Participant observation at retailer (1 h, 04/2019) Technology provider B interview, CEO (6 h, 04/2019) Technology provider B evaluation interview, CEO (1 h, 03/2020) Technology provider B follow-up interview, CEO (1.5 h, 05/2025)	Examined ambitions to build a multi-brand platform; observed reactions to cross-brand matching; validated networked concepts in follow-up interviews	Developed the networked switchover concept: DPF as a platform enabling cross-brand matching and shared digital inventory, showing potential to expand assortment without physical stock bloat

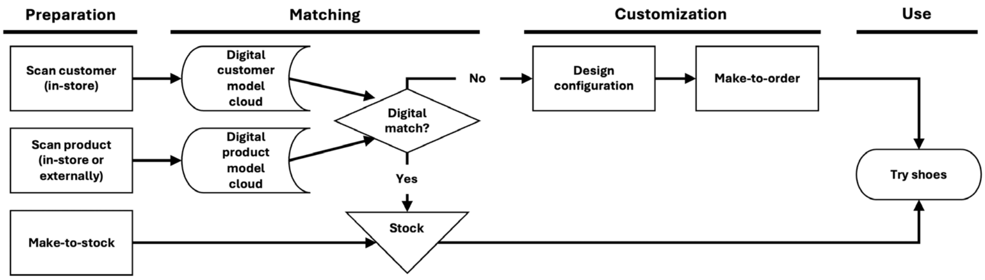

FIGURE B1 | Fulfillment switchover—version 1.

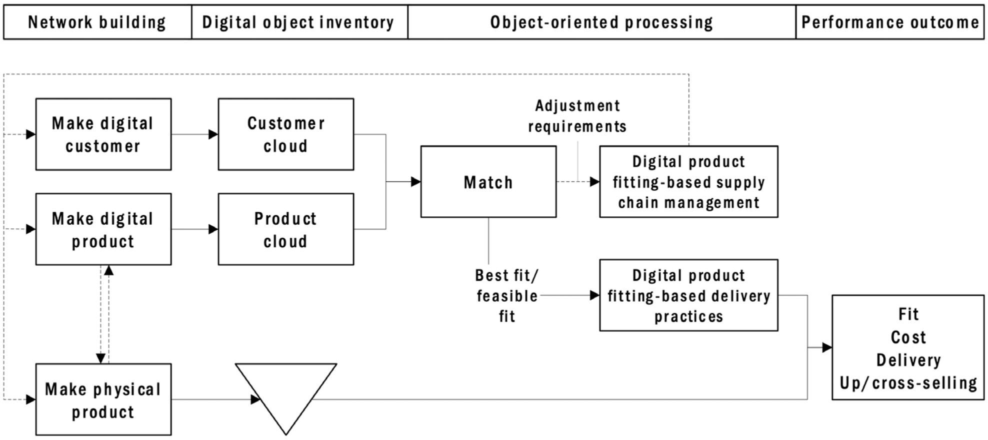

FIGURE B2 | Fulfillment switchover—version 2.

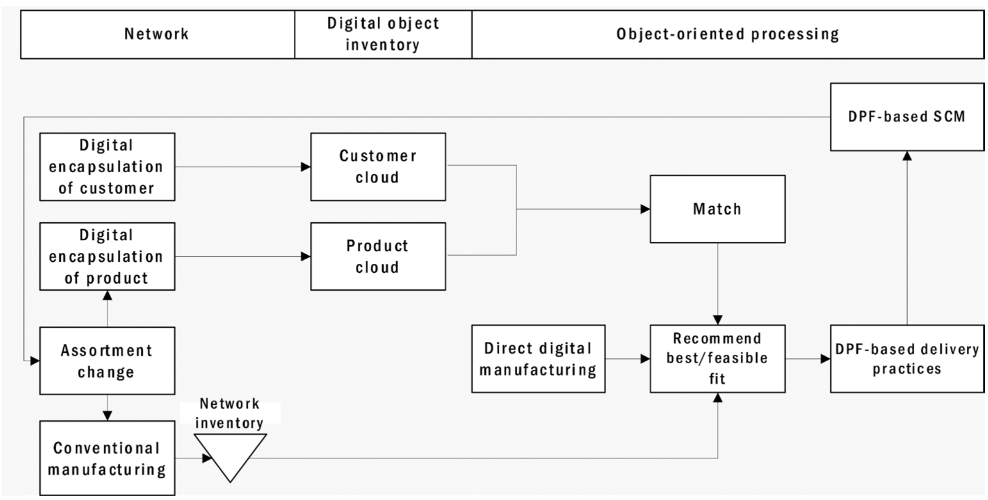

FIGURE B3 | DPF-based assortment planning and product design.

was highly negative. As one of the world's leading skate providers, Skates Stocker sought customer lock-in and viewed the presentation of competing brands to its customers as a threat, despite the potential to attract customers from other brands.

In contrast, Ski Boots Networker integrated both brands and retailers into a shared DPF system, creating a shared digital inventory. This shifted the problem from the firm level to the network level: How can multiple brands and retailers use DPF to expand assortment without increasing physical inventory? We conceptualized the value proposition as a networked switchover, in which customers can be matched to products across multiple brands, even when a given store does not physically hold the product.

In follow-up interviews (Table 2, 05/2025), we discussed how such a shared digital inventory could enable retailers to sell products they do not physically stock. The CEO confirmed that this remained the company's long-term vision. These insights culminated in the use case of DPF-based networked switchover, conceptualizing DPF as a platform solution, as visualized in Figure B4.

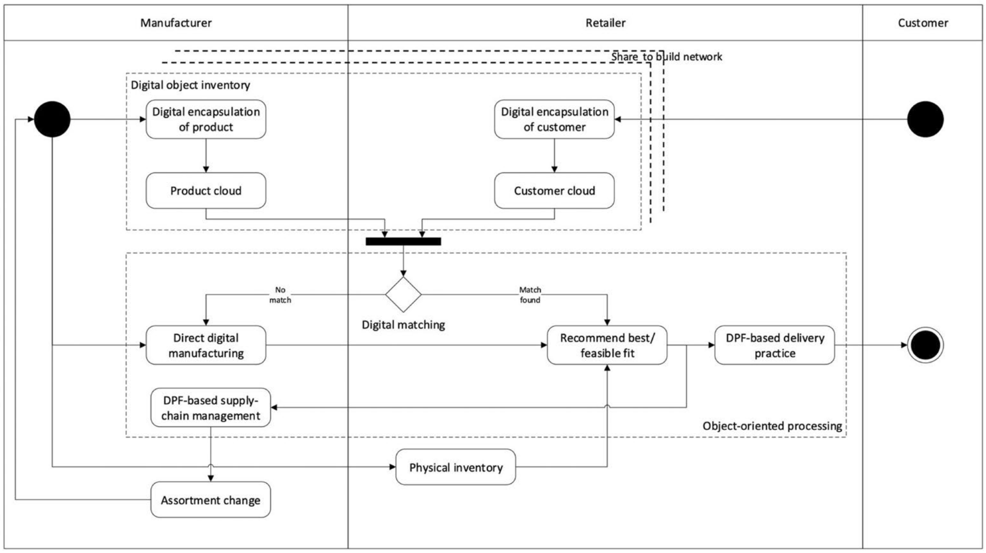

FIGURE B4 | DPF-based networked switchover.

Appendix C

Examples of Interview Protocols

This appendix includes interview protocols used during in and video-call interviews. These protocols were designed to elicit insights into the rationale behind adopting DPF, operational challenges, and outcomes.

Technology Providers of Ski Boots Networker and Dress Shoe Customizer

Business idea

1. What was the initial business idea, and what is the current idea?

Model databases

Who produces the models (e.g., technology provider, customers, suppliers)?

1. How are the models produced?
2. What is the cost of model production?
3. Who has access to the models?
4. Who uses the models (e.g., technology provider, customers, suppliers)?
5. What are the models used for?

Retail success stories

1. What are the key success stories?
2. What was done in these cases, and what performance improvements were achieved?

Use in retail

1. How many implementations are there, and for which purposes?
2. Which retailers have implemented the system and later abandoned it? What obstacles were encountered?
3. Why do retailers initially want to implement this system?
4. Why do retailers continue to use it?
5. How do you see the future of this technology in retail?

Skates Stocker's Technology Provider

Business idea

- What was the initial idea?
- Whose idea was it?
- How did you start testing the application?
- How long did it take to move from idea to a finished product?
- What initiated the product development?

Model databases

- How are products modeled?
- How are customers modeled?
- Who has access to the models?
- If customers are modeled in-store, are the models saved for use in other stores or chains, or are they sold to companies on a transactional basis, leaving subsequent use to the firm?
- Have you considered modeling customers in other ways (e.g., 2D measurements, reference models)?

Scanner operations

- How does the fitting algorithm work?
- For which types of products does the scanner work?
- What are the application areas (physical retail, online retail, or both)?
- What is included in the solution you sell?

Challenges

- Have you encountered problems when installing the scanner at customer locations?
- What problems arose during scanner development?

Actor perspective

- Who is the target group of companies?
- Have you received feedback from customers, and what did they say?

- Do you see other potential applications from which companies could benefit?

Skates Stocker

Implementation success and problems

- What difficulties arose in developing the fitting algorithm?
- What problems has the fitting solution (scanner and recommendation software) mitigated?
- What was the main reason for collaborating with the technology provider? Did the provider approach you?

Supply chain operations

- How many stores do you have?
- How are stores replenished?
- What is the estimated tied-up capital at the store level and supply chain level?
- How is forecasting conducted, and which methods are used?
- Is demand easy or difficult to forecast? Is it predictable or unpredictable?
- Is the product seasonal? What does the sales pattern look like?
- Do you have an aftermarket supply chain? If so, what does it look like?
- Can you describe how a pair of skates travels from the production facility to the final destination (the store)?
- What is the inventory management objective, and how well are you meeting it?
- What is the overall performance metric for operations?
- Can you describe the product life cycle?
- What is the production cost of a pair of skates?

Retail operations

- Do you handle reverse logistics (returns only, or repairs as well)?
- How is scanning performed?
- How do customers perceive the scanning service?
- How long does it take to serve a customer using the scanner?
- Do customers browse products before requesting assistance?
- Do you face any difficulties in performing retail operations?
- What would be the next step to improve retail operations?
- What lead time is required for make-to-order products?
- What is the average stock-out rate?
- How large is the product portfolio (number of SKUs, sizes, brands)?
- What is the retail price range of the skates?
- Do you have a daily sales target?

Dress Shoe Customizer

Scanning process

- How is scanning performed?
- How does the customer configure the selected shoes?
- What does the interface look like?
- Do you have a webshop?
- How many scans have been conducted so far?
- How many scans generate sales (approximately a 1:1 ratio)?
- How many lasts do you match to?
- Can all shoes be produced on all lasts?

Order process

- How are orders placed with the factory?
- Does production start immediately upon order, or is a batch required?
- When does the customer pay, and when and by whom is the factory paid?
- What is the lead time from order placement to delivery?

Distribution

- Which company transports the shoes?
- Are single units dispatched from the factory, or are batches required?

Production

- What is the lead time from order placement to production completion?
- Are the shoes handmade, machine-made, or a combination?

Store

- How is matching performed (to lasts or scans)?
- How many shoes are held in sellable stock?
- How many demonstration shoes are displayed (not for sale)?
- How many shoe styles are offered?
- Do you launch full collections or individual shoes over time?
- How many off-the-shelf shoes have been sold so far?
- How many made-to-order shoes have been sold?
- How are customers served when requesting off-the-shelf shoes?
- Have customers received their shoes yet, and what has been their response?

Ski Boots Networker

Business idea

- How did the network form?

Model databases

- How are customers modeled?
- How are products modeled?
- Who owns the models?
- How many product models are included in the network?

Retail operations

- How many retailers are connected to the network?
- Are the retailers part of the same chain or independent?
- How extensive is the assortment in terms of product variety?
- Does the assortment adequately cover customer needs?
- How many customers are scanned per day?
- What is the store layout?