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Bytes & Bodies: Balancing Product Quality, System Efficiency, and Personal Privacy in a Digital Customer Twin-Based Demand Management Approach

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Abstract

This study investigates the trade-offs customers make between product quality, system efficiency, and personal privacy in adopting a digital customer twin-based demand management approach. By using a conjoint analysis methodology, embedded in a laboratory experiment, participants are exposed to a smartphone-based measurement system for apparel sizing. Findings indicate that product quality is the most critical determinant for customer decision-making. Privacy concerns are particularly pronounced among customers preferring traditional shopping methods over digital ones. The study not only provides new insights into customer priorities in digital commerce but also advocates for a shift towards more effectiveness-driven supply chains. Furthermore, a new theoretical framework is proposed that matches customer demands and supply chain characteristics with customer integration through digital twins.

Keywords: Digital twin; Customer data; e-Commerce; Supply chain effectiveness; Conjoint

1. Introduction

The future of commerce is not written in the stars but in bytes and code. Annually, the global sales volume of e-commerce has been growing by roughly 20 per cent for more than five years and is predicted to further grow from USD 5,784 billion in 2023 to over USD eight trillion by 2027 (eMarketer, 2023). Key drivers for this development are unrestricted accessibility of online stores, wider selections, and expedited delivery options to the doorsteps (Jiang et al., 2013). Hence, e-commerce success builds on both products and distribution systems that satisfy individual customer demands (Lanzolla et al., 2020; Nguyen et al., 2019).

Apparel supply chains, stand as an ideal example for witnessing the impact of the shift from traditional towards e-commerce due to the intricate interplay between customer preferences, supply chain logistics, and the tactile nature of product selection (Romano & Vinelli, 2001; Simatupang & Sridharan, 2002; Su, 2009). From 2017 to 2022, the total volume of apparel sold online in the EU grew by over 90% from USD 78 to USD 150 bn (Eurostat, 2022). Moreover, in many EU countries the fraction of clothing items ordered online surpassed the share bought in physical stores (Eurostat, 2022). Then again, apparel also represents the major challenges related to e-commerce as roughly half of all clothes bought online are returned (Ivanova, 2020). Generally, clothing articles bought online are three times more likely to be returned than clothes bought in-stores (Buhler, 2018). While other types of goods are typically returned due to them being defect (Buhler, 2018), wrong size selection is the major cause for apparel returns in e-commerce (Narvar, 2021).

Aggravating, demand management issues are not only perceptible in distribution systems but also affect products, for which fit is often inconsistent across manufacturers and brands (Faust et al., 2006; Howarton & Lee, 2010; Shin & Istook, 2007; Zwane et al., 2010). This is particularly problematic when fit is a crucial qualitative factor for the product's functional capability, as for high-involvement apparel (e.g. workwear) (Oehlschläger et al., 2022). Updating size charts is resource-intense and often takes years (Faust et al., 2006). With increasing demand for individual customer solutions, a growing number of customers are becoming dissatisfied with products that do not adequately meet their specific needs (Howarton & Lee, 2010).

Having said that, technological progress promises corrective measures. In fact, recent developments in hard- and software suggest that smartphones could become a convenient and powerful solution to create digital customer representations (Ziegler et al., 2021) in the following referred to as digital customer twins. By leveraging smartphone cameras, a customer's body dimensions could be digitised (Foysal et al., 2021). Thereby obtained data encapsulate digital twins of customer's individual demands which could be consulted to improve both: process efficiency and product quality (Oehlschläger et al., 2022). However, for the implementation of this app-based system user acceptance and particularly their willingness to share

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sensitive body data is indispensable (Oehlschläger et al., 2024).

Evidently, there is a plethora of research on the prerequisites of technology acceptance (King & He, 2006) in terms of e-commerce (e.g. Gefen & Straub, 2000), smartphone (e.g. S. C. Kim et al., 2016) and mobile-commerce adoption (e.g. Groß, 2015). These contemplations share the basic assumption that customers or users are subject to cost-benefit considerations in which they will use a digital system when the perceived benefits (e.g. its usefulness) exceed the perceived costs (King & He, 2006; Legris et al., 2003). Costs tend to be described either monetarily (Revels et al., 2010; Zolkepli et al., 2021) or in terms of the perceived effort (i.e. the transaction costs) required to use the system (Devaraj et al., 2002). As an increasing number of digital systems leverages user data to operate (Brenner et al., 2014), the literature often takes this fact into account by measuring whether customers would perceive a service provider to be trustworthy with their data (Gefen et al., 2003; Khoa, 2021). However, this overlooks the transactional nature of data with data being directly shared in exchange for a specific service, like a currency (Gates & Matthews, 2014). Interestingly, Weydert et al. (2020) as well as Ackermann et al. (2022) not only found that data sensitivity significantly decreases customer willingness to share data but also that this is not affected by monetary incentivisation. Moreover, Weydert et al. (2020) observed an inverse relationship, meaning that increasing the amount of money offered could even decrease data sharing willingness. Hence, and in line with Ackermann et al. (2022), sensitive information sharing is highly purpose-driven and thus, customer data sharing motivation has to be intrinsically stimulated by a digital system's capabilities rather than by external factors.

In this light, there remains a gap in juxtaposing personal data sharing, as proxy for perceived costs of a digital customer twin-based demand management approach, with the system's perceived benefits in terms of the enhanced efficiency and quality it might cause, leading to the following research question:

RQ: *How do customers assess the trade-offs between process efficiency, product quality, and personal privacy when adopting a digital customer twin-based demand management approach?*

To address this, an experiment grounded in a case study setting explores the logic that enhanced supply chain performance – both in terms of efficiency and product quality – is enabled by accurate and individualised customer data. However, this relationship is not unidirectional; rather, customers' willingness to share data is contingent upon their perception of these supply chain improvements. By systematically contrasting these factors, the study assesses, how varying efficiency and quality levels influence customer data-sharing behaviour, thereby linking supply chain configuration directly to technology acceptance and customer satisfaction.

2. Conceptual background

2.1 Digital customer twin-based demand management

Effective demand management is crucial for aligning customer needs with supply chain operations (Christopher & Ryals, 2014). The challenge lies in configuring supply chain activities (efficient vs. responsive) to match both product nature and customer demand variability (Christopher & Towill, 2000; Fisher, 1997). When customer demand becomes increasingly heterogenous, the ability to predict this demand and respond accordingly increases in significance (Simatupang & Sridharan, 2002). Thus, to ensure that the right products are available when and where they are needed, also determining customer satisfaction, a nuanced understanding of demand patterns and adequate supply chain processes are required (Christopher & Ryals, 2014). To create this understanding, digital customer integration became a new and important component (Aslam et al., 2023). Digital customer twins promise to elevate this integration to the next level, as they can identify, recommend, and even enable to create products that perfectly fit customer demands (Bolton et al., 2018)

This work defines digital customer twins as realistic representations of human attributes that interact with customers through various interfaces, replicating human appearance, behaviour, and communication (Far & Rad, 2022; Miao et al., 2022). While application areas are as diverse as entertainment or healthcare, the focus of this research will be laid on e-commerce. Thereby, emphasis will be put on precise digital demand representation rather than lifelike interactions of avatars in the metaverse.

Digital customer twins differentiate themselves from other types of digital customer interactions, such as digital assistants (AI-powered entities that assist customers in navigating digital platforms (Vimalkumar et al., 2021)) or digital models (generic and static digital representations of human figures (Bolton et al., 2018)), in terms of interaction modes, data sources, and functionalities. Specifically, digital customer twins are detailed, qualitative, and dynamic digital replicas of real-world demands (Oehlschläger et al., 2024). Through timely user input via smartphones, sensors, or wearables, they capture unique attributes in detail, thus realistically representing individual demands (Miao et al., 2022).

2.2 Product quality

Customers only give credit to the delivery of products of excellent quality (Simatupang & Sridharan, 2002). With respect to Park et al.'s (1986) types of customer needs (functional, social, and experiential), product quality is defined as the intrinsic ability of a product's functional attributes to completely satisfy a customer's functional demands (J.-O. Kim et al., 2002). Consequently, previous research significantly tested the positive influence of functional demand satisfaction on purchasing behaviour (J.-O. Kim et al., 2002).

Liang et al.'s (2022) analysis of value factors for clothing products found that customers consistently listed material quality and product fit together, merging them into a single intertwined concept that shapes their perception of the respective product. Unlike most material factors (e.g. tear and seam strength), fit can be evaluated without expert knowledge and before the purchase (Klerk & Tselepis, 2007; Rayman et al., 2011). Logically, empirical evidence suggests that, regardless of age group, sex, or cultural region, fit is the major determinant for apparel purchasing decisions (Ghaani Farashahi et al., 2018; Howarton & Lee, 2010; Hsu & Burns, 2002; Klerk & Tselepis, 2007). Therefore, this research leverages fit as proxy for customer perception of product quality.

Contrary to the significance of fit, authors such as Howarton and Lee (2010), Seram and Kumarasiri (2020), or Shin and Istook (2007) report massive difficulties for customers to categorise themselves into a standard size due to the lack of sizes that accommodate the full range of body shapes. Faust et al. (2006) conservatively calculated that it would take more than 70 different size combination to satisfy the demands of the entire female population of the US. Thus, many apparel manufacturers do not cater to the heterogenous functional demands of individual customers (Howarton & Lee, 2010).

As previously mentioned, digital customer twins represent the collection, transmission, and analysis of individual customer demand data which might be leveraged to solve incumbent quality issues with product fit (Oehlschläger et al., 2022).

2.3 System efficiency

By eliminating geographic and time constraints (i.e. removing the need to travel to physical stores during opening hours), buying goods online provides tremendous convenience compared to in store purchases (Jiang et al., 2013). This, however, presupposes that customers are aware of their respective demands and articulate how product attributes would satisfy these demands. Technically, clothing products should be easy to vend online, as basic attributes of a particular article can be researched prior to purchase (Nelson, 1970). Then, e-commerce transforms clothing from a search good to an experience good (Nelson, 1970; Ofek et al., 2011), or at least adds an experiential element to the purchasing process (Balaram et al., 2022). In an e-commerce setting, customers are unable to physically interact with products before purchasing and thus, rely on product descriptions, images, and charts to make purchasing decisions (Balakrishnan et al., 2014; Balaram et al., 2022; Su, 2009). This can introduce a level of uncertainty and therefore, customers may not be able to accurately assess attributes like fit before buying (Balakrishnan et al., 2014; Su, 2009). Hence, the inability to try clothes can lead to high return rates, as customers often find that the purchased items do not fit as expected (Ivanova, 2020). This inefficiency not only increases costs for retailers (Asdecker, 2022) but also adversely affects customers as they need to engage in inconvenient return activities while they also have to wait longer for their demands to be fulfilled (Diggins et al., 2016; Walsh & Brylla, 2017).

By enabling customers to create accurate digital representations of their body measures, smartphone-based digital customer twins can facilitate highly personalised shopping experiences. Hence, this approach could enhance the efficiency of clothing distribution by reducing return rates and increasing customer satisfaction, thereby potentially outperforming both traditional and e-commerce models that lack digital body data integration (Foysal et al., 2021; Hernández et al., 2019).

2.4 Personal privacy

Personal privacy is a fundamental concern in the digital age (Bélanger & Crossler, 2011). To maintain trust between costumers and service providers, sensitive data must be handled with care and integrity (Flavián & Guinalíu, 2006; Gefen et al., 2003).

Body data represents intimate and unique characteristics of an individual's physical form and can thus be used to infer various personal attributes, from health status to identity verification. This makes it particularly sensitive and subject to privacy concerns (Bansal et al., 2010). Research found that customers are often reluctant to share such sensitive information due to fears of misuse or unauthorised access (Acquisti et al., 2015; Solove, 2004; Weydert et al., 2020).

Here, body data can be conceptualised as the 'currency' with which customers 'pay' for the digital system (Gates & Matthews, 2014). This analogy underscores the exchange nature of the transaction: customers provide their sensitive body data in return for benefits such as improved product fit, convenience, faster delivery, and reduced likelihood of returns. This exchange is akin to the broader concept of data as a currency in the digital economy, where personal information is traded for access to services and products (Tene & Polonetsky, 2012).

3. Methodology

3.1 Case description

This work is embedded in a case related to the workwear supply chain for a specific emergency service organisation (ESO) in Germany. ESOs include police, fire authorities, first responders, and the defence sector (Carter, 2008). ESO members require specific, tailored clothing to engage in critical and challenging situations (Traumann et al., 2019). The case thus exemplifies a high-involvement product requiring a precise understanding of individual needs and active user engagement to ensure effective demand management (Martin, 1998; Oehlschläger et al., 2024). In contrast to that, the present ESO reports not only poorly fitting apparel (inhibiting performance and increasing material wear) but also laborious, time-consuming, and costly outfitting processes. Often, personnel travels long distances to physical warehouses to try on ill-fitting products. This frustrating process can take up to eight hours.

Naturally, embedding the method in such an idiosyncratic case could jeopardise the findings' generalisability. The large number of interrelated application areas as well as the case's distinct challenges, however, make it highly relevant to explore. Furthermore, the case study approach allows for an in-depth investigation of a signature scenario and thus aligns with the study's experimental design.

3.2 Technical implementation

A minimum viable product (MVP) was created and thoroughly tested for its technical abilities in a two-week experiment. The MVP's responsibility was to capture probands' body measurements, interpret these, and transform them into size recommendations. This interactivity of adjusting recommendations based on individual data input is why the MVP is referred to as a digital customer twin approach.

To obtain body dimensions, participants performed a 360-degree spin in front of the camera of an *iPhone 11 Pro*. The program recorded a ten second video, which was directly transferred to a cloud server. Participants' faces were pixelated and the video was automatically deleted after the algorithm extracted body measurements. Participants wore tight clothing and used a neutral background. Thereafter, algorithms computed 30 body measurements (from ankle to neck) based on ISO standards 7250-1 and 8559-1. These body measures were then matched to product dimensions and size recommendations by a pretrained algorithm on a digital platform linked to a mock-up SAP system. There was no transfer of personal images between the smartphone scan and the digital platform; only the 30 computed body dimensions were transmitted and stored in the system. Here, participants were asked to 'order' ten selected articles in the recommended sizes. Subsequently, these very articles were given to the participants for physical try on and fit evaluation (subjectively as well as objectively performed by three observing clothing technicians).

3.3 Design, sampling, and data analysis

The research question was addressed through a conjoint analysis, that was deliberately kept simple and easy to comprehend for participants. The simplicity in the research design aligns with the experimental setting of the study. Conjoint allows to evaluate customer prioritisation of the aspects of digital customer twin-based demand management collectively rather than in isolation. It provides participants with information about a specific choice situation termed stimulus (Backhaus et al., 2023; Hair et al., 2019). Thereby, the conjoint analysis aligns with real-world decision-making, where customers also weight decisive criteria simultaneously (Backhaus et al., 2023). Hence, by creating stimuli that incorporate the three determinants (process efficiency, product quality, and personal privacy) in concert, a realistic assessment of customer preferences can be captured.

Each criterion was designed with two levels: high and low (e.g. high efficiency vs. low efficiency). This binary approach facilitates clear comparisons while reducing the response complexity and minimising task fatigue (Aguinis & Bradley, 2014). Consequently, the study used a total of eight stimuli, each representing a unique combination of the criteria in their high or low forms. Appendix A1 provides an overview of the eight stimuli. Participants were asked to rank the stimuli from most to least attractive. This ranking-based approach ensures that each stimulus is directly compared against all others, providing a complete assessment of all stimuli and criteria (Backhaus et al., 2023). To refine the questionnaire and stimuli plausibility, a pre-test was conducted among selected members of the ESO (n=10) (Hair et al., 2019).

Sampling was conducted among affiliates of the ESO (n=104) after being exposed to the technical part of the experiment. This ensured that participants could make informed judgments about the trade-offs between the different criteria. It should be noted that according to Rose and Bliemer (2013), there is no general threshold for an appropriate sample size for a conjoint analysis. Roughly 80% were male, the average age was 35 (median = 32) years, and the average tenure with the ESO was 12 (median = 9) years. Moreover, when being asked about their general preference, 79 (~76%) appreciated a switch to the new digital customer twin-based distribution system while the remaining 25 (~24%) would rather keep the incumbent physical system.

With respect to the conjoint analysis' basic principle, a customer's decision to adopt the new distribution system is based on the assessment of its utility (U) which is equal to the sum of the utility factors for quality (Q), efficiency (E), privacy (P), and a constant (C). Each of these factors are weighted in accordance to their respective relevancy to the decision-making process, resulting in three coefficients. This leads to the following utility function: $U = C + \alpha Q + \beta E + \gamma P$. The corresponding values were calculated with the CONJOINT function of SPSS, following Backhaus et al. (2023).

To gain deeper insights, the utility and relevance assessments were also further contrasted between two market segments: supporters of a shift to the new digital system ('app') and supporters of the traditional one ('store'). An a priori segmentation approach was applied to identify these subgroups by using a variable that directly enquired the participants' preferences, following Desarbo et al. (1995).

Validity measures were computed with SPSS to ensure the statistical robustness and reliability of the findings. These are presented in Table 2. Pearson-r (the correlation between the predicted preferences based on the conjoint model and the actual preferences expressed by the participants) as well as Kendall-τ (ordinal association between the preference ranking predicted by the model and the actual one provided by participants) were very close if not equal to 1 for all segments. According to Backhaus et al. (2023), these values imply high predictive accuracy, consistent rankings, and high model validity.

Table 2. Scenario validity measures.

	Value			**Significance**		
Segment	Total	App	Store	Total	App	Store
Pearson- r	0.998	0.999	0.996	<0.001	<0.001	<0.001
Kendall-τ	0.929	0.929	1.000	<0.001	<0.001	<0.001

4. Findings

For the overall sample, Table 3 provides insights on the criteria's' utility values whereas Table 4 displays insights on the criteria's relevance values. Please note that the inversion of utility values results from the usage of a binary system for the criteria.

Table 3. Utility assessment (overall sample).

Criteria	**Level**	**Utility factors**	**Standard deviation**
Quality	Low	– 1.733	0.057
	High	1.733	0.057
Efficiency	Low	– 0.752	0.057
	High	0.752	0.057
Privacy	Low	– 0.127	0.057
	High	0.127	0.057
Constant		4.5	0.057

Table 4. Relevance coefficients (overall sample).

Criteria	**Relevance coefficients**
Quality	54.880
Efficiency	23.272
Privacy	21.848

By far, product quality ranks highest with a utility value of 1.733. This indicates, that quality is the most critical factor for customers, also reflected by the fact that it accounting for more than half of the decision-making process. Efficiency is the second most important criterion (utility value = 0.752). While still important, efficiency has less impact on customer preference compared to quality. Nevertheless, a system perceived as efficient still considerably enhances its attractiveness. The utility for privacy is far smaller than for the other criteria. Vice versa, among study participants the sharing of sensitive body data only reduced the utility of the overall digital customer twin-based system by –0.127. Relatively, however, system efficiency (~23.3%) and personal privacy (~22.8%) possess similar relevance factors, suggesting that privacy and efficiency are equally important to the customers' overall decision-making.

Table 5. Utility assessment (segments).

Criteria	**Level**	**Utility factors**		**Standard deviation**	
		App	Store	App	Store
Quality	Low	– 1.744	– 1.700	0.049	0.090
	High	1.744	1.700	0.049	0.090
Efficiency	Low	– 0.753	– 0.750	0.049	0.090
	High	0.753	0.750	0.049	0.090
Privacy	Low	– 0.035	– 0.420	0.049	0.090
	High	0.035	0.420	0.049	0.090
Constant		4,5	4,5	0.057	0.090

Table 6. Relevance coefficients (segments).

Criteria	**App**	**Store**
Quality	55.513	52.882
Efficiency	22.058	23.948
Privacy	21.430	23.169

Table 5 and Table 6 report the respective utility and relevance values for each of the two previously introduced segments ‘app’ and ‘store’.

Still and for both segments, high product quality is paramount, with very similar utility values and relative importance of more than 50 per cent. This reinforces the notion that product quality is the most critical factor across the board. Furthermore, utility values for efficiency are nearly identical between the two segments. Relatively, efficiency is slightly more important for the ‘store’ group (23.9%) than the ‘app’ group (22.1%). Although this could suggest that customers who favour traditional stores place slightly more emphasis on efficiency in their decision-making process, the difference is effectively marginal. The most notable difference is visible for the privacy criterion. Albeit being relatively equally important to both segment with privacy being only 1.7 percentage points more important to the ‘store’ segment than the ‘app’ segment, the utility values differ a lot. The ‘app’ segment perceives the utility for privacy relatively neutral (0.035), indicating that privacy concerns only marginally impact their overall utility. In contrast, the ‘store’ segment shows a much stronger reaction to privacy, with a deduction of 0.420 to their utility for sensitive data sharing. This highlights, that privacy is particularly meaningful to those who are generally more critical of the digital twin-based approach.

5. Discussion

The fact that product quality was identified as preeminent criterion for customer decision-making is not only consistent across segments, regardless of distribution channel preference, but also in line with previous research’s assessment on quality as major determinant for purchasing decisions (Ghaani Farashahi et al., 2018; Howarton & Lee, 2010; Hsu & Burns, 2002; Klerk & Tselepis, 2007).

Despite customer online sharing behaviour often being depicted as careless in public media (Acquisti et al., 2020), with Sahota (2020) recently even declaring privacy dead, privacy still remained a notable concern in the findings, particularly among customers who favour traditional stores over digital systems. This corresponds to studies on the relationship between nascent technologies and privacy such as Bawack et al. (2021), Y. Kim and Peterson (2017), or Liu et al. (2020) and highlights that trust and privacy concerns are still to be taken serious in digital adoption. Furthermore, this finding adds to Ackermann et al.’s (2022) and Weydert et al.’s (2020) observation, that the willingness to share data depends on intrinsic perceptions of the particular application case. This would also be in line with the often cited *privacy paradox* (i.e. the contrast between willingness to share information and actual sharing (Acquisti et al., 2020)) as the finding indicates that customers would de facto share their data if properly motivated by the digital system for instance by the prospect of receiving high-quality products.

Interestingly, system efficiency, while enhancing customer utility by ensuring timely and convenient product delivery, is far less influential for customers to share personal data. Shifting the primary focus from the customer to the supply chain, which embodies the system enhanced by digital customer twins, it becomes apparent that this finding contrasts with the predominant emphasis of this research stream. In the supply chain literature, attention is put on efficiency gains through customer data, particularly in optimising logistics and reducing inventory inefficiencies such as the bullwhip effect (Lee et al., 1997). Additionally, this stream often treats customer data quantitatively, focusing on volumes, frequencies, and transactions (Agarwal & Dhar, 2014). This perspective, while beneficial for supply chain operations, may overstate customers' willingness to share data purely for efficiency purposes and overlook other critical aspects (Weydert et al., 2020). Arguably, efficiently managed distribution systems have become a baseline expectation for customers nowadays rather than a differentiation factor (Hofmann & Rüsch, 2017). In summary it is reasoned that customers would be willing to share data for an integrated benefit (Ackermann et al., 2022), but merely assuring operational efficiency might be insufficient to justify it from the customer's perspective. Thus, the integrated benefit also requires qualitative components (Martinelli & Tunisini, 2019).

Longstanding, research explores various approaches for demand management to accommodate multifarious efficiency and effectiveness related aspects. The most prominent approach matches product characteristics – including the product’s respective demand heterogeneity with the overall system’s propensity for efficiency (efficient / lean vs. agile / responsive) (Christopher et al., 2004; Christopher & Towill, 2000; Fisher, 1997). In this light, Fisher (1997) famously asked: ‘*What is the right supply chain for your product?*’ Stopping at the product level might, however, be deficient, as previous research suggested that the individuality and heterogeneity of customer demands particularly necessitate close collaboration and information sharing in supply chains (Romano & Vinelli, 2001; Simatupang & Sridharan, 2002). Therefore, some approaches aim to prioritise the customer even further. These alter Fisher’s (1997) question to: *‘What is the right supply chain for your customer?’* and propose differentiating supply chains according to the intensity of integrating customer- and distribution side (Collin et al., 2009).

With that in mind, the research in this work propagates that the streams on digital customer integration and supply chain configuration should be further connected, thereby also directly responding to Martinelli and Tunisini's (2019) call for more theoretical explorations on new digital technologies that integrate customers in supply chain. As a digital customer twin-based approach facilitates the holistic integration of customer demands, it could lead to more responsive supply chains (Williams et al., 2013). Vice versa, effective supply chains may engender customer willingness to share data. These contemplations affect supply chain configuration characteristics on a strategic level (Christopher & Towill, 2000).

Thus, it is suggested to extend Fisher's (1997) framework by a third layer indicating the level of digital customer integration, defined as the customers' willingness to express their demands through digital means. This additional layer enables the conceptual integration of digital customer twins as both a facilitator and manifestation of digital customer integration within the broader theoretical landscape. It also allows for a comprehensive analysis of the alignment between demand heterogeneity, supply chain strategy, and customer integration from an organisational perspective. An overview is given by Table 7.

Table 7. Matching demand heterogeneity, supply chain strategies, and digital customer interaction.

	Homogenous demand		**Heterogeneous demand**	
	Efficient supply chain	**Responsive supply chain**	**Efficient supply chain**	**Responsive supply chain**
Little integration	***Match*** Cost efficiency; Operational simplicity	***Mismatch*** Inefficient use of resources; Little insights in demand	***Mismatch*** Poor demand fulfilment	***Limited match*** Aligned supply chain strategy; Inadequate data for responsive strategy
Extensive integration (digital customer twin)	***Limited match*** Enhanced forecasting ability; Potential overinvest-ment in data collection	***Limited match*** Enhanced adaptability; Potentially overcomplex	***Limited match*** Improved demand insights; Misfit of supply chain strategy and demand nature	***Match*** High adaptability; New dynamic capabilities; Optimal customer satisfaction

Moreover, a corresponding illustration is provided by Figure 1. This model outlines the respective circumstances that provoke the pursuit for either product- or customer-centric supply chains while also visualising the impact of the digital customer integration level that is most meaningful to pursue for the given circumstances. Consequently, Figure 1 provides recommendations for strategy adjustments: If the current supply chain configuration does not align with the level of demand heterogeneity or the extent of customer integration (resulting in a misfit), managers should consider increasing customer integration efforts and/or adjusting their supply chain strategy accordingly.

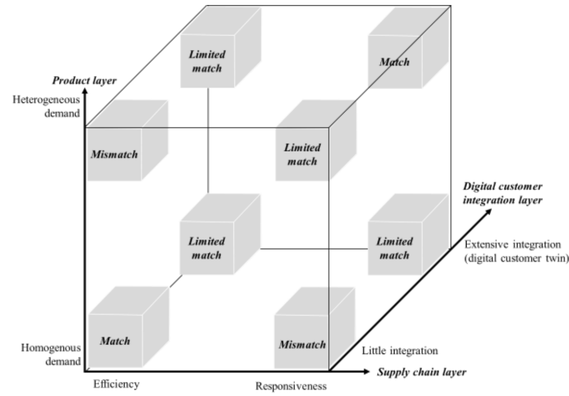

Figure 1. Matching supply chain strategies, demand, and digital customer interaction.

6. Conclusion

This study highlights the need for a more balanced approach in understanding customer data in supply chains as well as motivations for customers to share these. By showing that customers' data-sharing decisions are influenced by perceived improvements in supply chain performance, and that these decisions, in turn, enable further enhancements in efficiency and product quality, the study illustrates a feedback loop. This loop underscores the iterative nature of technology adoption, where improvements in one area reinforce advancements in the other.

While efficiency improvements are essential, they are not sufficient on their own to incentivise data sharing. Organisations must go beyond the implicit expectation that their distribution systems function smoothly and focus on delivering value that resonates with customers on an individual level. By doing so, they can create a more compelling value proposition for customers, encouraging greater willingness to share personal information, and ultimately enrich data-driven capabilities. Consequently, the use of high-fidelity customer data should not only translate into more effective products and services but also enhanced and differentiated supply chain strategies.

Naturally, this study is not free from limitations. Strictly speaking, criteria used in the conjoint analysis should not correlate with each other (Backhaus et al., 2023). However, willingness to share sensitive data is crucial for the effectiveness of digital customer twin-based demand management. Vice versa, if customers are unwilling to share data, the system cannot function. The present research tried to mitigate this by construing data sharing as 'price' customers pay for using the system – following the logic of many conjoint analyses in marketing where a monetary price has to be paid for a certain product (e.g. Olson, 2013), despite price correlating with other product attributes.

Moreover, the study was grounded in a case study approach, chosen for its relevance in understanding individual needs and user engagement critical to effective demand management. While this ESO case was well-suited for the experimental design, the specific demographics may constrain the finding's generalisability. Future research should consider replicating the study in a purely B2C environment to validate the results and ensure broader applicability.

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