Journal of Retailing and Consumer Services 88 (2026) 104478

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Implications of retailer-owned digital twins services: The trade-offs between customer experience, misfit returns reduction, and investment costs

Qin Yang [a], Lin Sun [b,*], Xu Wu [a,b], Youwei Li [c]

[a] College of Management Science, Chengdu University of Technology, Chengdu, 610059, China
[b] The Business School, Chengdu University of Technology, Chengdu 610059, China
[c] Hull University Business School, University of Hull, Hull, UK

ARTICLE INFO

Keywords:
Retail technology
Digital twin
Customer experience
Pricing strategy
Supply chain

ABSTRACT

Many prominent retailers, including Walmart, Kroger, IKEA, and Amazon, utilize Digital Twins (DTs) to enhance customer experience and reduce misfit returns by creating virtual replicas of products, service systems, shopping environments, and customer interactions. However, prior studies on DTs have mainly centered on applications within the manufacturing sectors, thereby overlooking the development of DT services owned or operated by retailers. To fill this gap, our models analyze how retailer-owned DT service is shaped by the trade-off between customer experience, misfit returns reduction and investment expenditures, as well as investigate its impact on the manufacturer's equilibrium decisions and profits. Our analysis indicates that higher levels of product misfit and consumer return losses incentivize retailers to adopt DTs. Furthermore, although retailer-owned DT may benefit manufacturers and lead to Pareto improvements, manufacturers should be cautious, as higher DT adoption costs for 'inefficient' retailers can result in a win-lose situation. This occurs because retailer-owned DTs, while potentially enhancing the manufacturer's equilibrium quality and wholesale prices, can also incentivize 'inefficient' retailers to raise retail prices further, which reduces the optimal sales volume and negatively impacts the manufacturer's overall profits. In addition to confirming the robustness of our main findings, our two extensions further reveal that, (i) there is an inverted U-shaped relationship between retailers' incentives for DT adoption and consumers' privacy concerns, and (ii) previous-period misfit returns diminish retailers' incentives for DT adoption.

1. Introduction

The emergence of technologies such as AI, big data, and VR enables the Digital Twin (DT) system to integrate a physical product with its virtual counterpart, which holds comprehensive information about the physical product (Grieves, 2015; Wang et al., 2024). Traditionally, DT technology is viewed as highly promising for manufacturing companies, as it allows them to monitor operational data in real time, predict potential failures proactively, and optimize products quality accordingly (Lim et al., 2024).

However, in fact, DTs can also provide virtual replicas within the retail sector—encompassing products, service systems, shopping environments, and customer interactions—which allow consumers to experience products in real-time, thereby reducing products misfit and consumer return losses (IBM, 2021; McKinsey & Company, 2024). That is, rather optimizing product design and quality decisions at manufacturing sector, the primary objectives for retailers adopting advanced technology are to fulfill customer experience and effectively reduce misfit returns (Li et al., 2025a, 2025b; Liu et al., 2025). In practice, major retailers such as Walmart, Kroger, IKEA, and Amazon are attempting to replace traditional text and image product descriptions with DT-based services (McKinsey & Company, 2024). Pelin Anlu Bedirhanoglu, Director of Product Size and Fit at Zalando, expresses confidence in their DT technology: "Despite being in the testing phase, we've seen up to a 40% reduction in return rates, instilling confidence in its ability to significantly improve customer and brand partner satisfaction once fully implemented" (Zalando, 2024).

* Corresponding author.
E-mail address: sunlin@cdut.edu.cn (L. Sun).

https://doi.org/10.1016/j.jretconser.2025.104478
Received 8 June 2025; Received in revised form 27 July 2025; Accepted 12 August 2025

Available online 22 August 2025

Although DTs offer significant benefits, they also generate side effects. For instance, the complexity and advancement of a DT services are positively correlated with investment costs, including hardware, sensor configuration, software platforms, and operations (Ankitha, 2025). Estimates suggest that creating a DT system typically requires an investment of $50,000 to $500,000 in these specific assets (Ankitha, 2025; RisingMax, 2024). The substantial creation costs can deter some retailers from adopting DTs, thus questioning the potential benefits. On the other hand, from a supply chain perspective, implementing an advanced technology not only generates potential value for the investor but also enables other partners to benefit without cost, which may create potential conflicts among supply chain partners (Adivar et al., 2019; Li et al., 2025a, 2025b). Consequently, a comprehensive cost-benefit analysis for all partners remains essential when implementing advanced technologies like Digital Twins (DTs) (Culot et al., 2019).

Prior research has explored the implications of DT adoption in the manufacturing sectors (e.g., Zhang et al. (2025) and references therein), but has largely ignored the retailer-owned DT and the trade-off between retailers' investment expenditures and consumers' experience, misfit returns reduction. More importantly, it provided a poor understanding on how retailer-owned DT influences the equilibrium decisions of manufacturers. To address this, we construct a model featuring a manufacturer selling to a retailer, who sets selling prices and decides on DT adoption. When retailer-owned DTs are used, complete product information is provided, ensuring a better consumer fit and effectively eradicating returns due to misfits. Using these models, we intend to fill the gap by addressing the following research questions:

- What are the conditions for retailers to adopt DTs?
- How does the retailer-owned DTs affect the manufacturer's profitability?
- What are the implications of retailer-owned DTs on the equilibrium decisions of both the retailer and manufacturer?
- How do the potential privacy concerns and previous-period misfit returns affect the equilibrium decisions and profits?

We first confirm that there exists a cost threshold below which the retailer is willing to adopt DTs. This threshold increases with the misfit rates and/or the return losses. Surprisingly, our findings indicate that although retailers' adoption of DTs helps manufacturers improve equilibrium quality and wholesale prices, manufacturers may not necessarily benefit from it. Specifically, when the inefficient retailer incurs high costs from implementing DTs, the manufacturer's quality improvements will lead to an increase in wholesale prices. This, in turn, incentivizes retailers to raise the retail price even further, leading to a decrease in optimal sales volume and the manufacturer's overall profits.

Thus, when implementing DT technology, we recommend that retail managers should pay particular attention to considering misfit returns: Retail-level managers should understand that for products characterized by high return rates and/or significant misfit losses, adopting retailer-owned DTs would be profitable by improving customer experience and lowering return volumes. While, when dealing with products that have negligible misfit problems and low return losses, these managers should be aware that implementing DTs might not be cost-effective, and thus, adoption is not recommended. On the other hand, regarding managers in the manufacturing sector, our analysis suggests that they should preassess the efficiency of retailers implementing DTs: although retailers with high efficiency using low-cost DT technology may present a potential win-win scenario, however, they should proceed with caution regarding the retailer-owned DTs launched by inefficient retailers.

We then extend our models to consider two specific contexts: first, situations with low customer acceptance stemming from privacy concerns; and second, dynamic scenarios where past misfit returns affect the retailer's current DT adoption choice. In addition to confirming the robustness of our main findings, our analysis then uncovers two additional insights: (i) an inverted U-shaped relationship arises between retailers' incentives for adopting DT and consumer privacy concerns; and (ii) prior-period misfit returns weaken retailers' motivation to adopt DT. As such, we suggest that both the retailer and the manufacturer should take appropriate measures to avoid the negative consequences that arise from consumer privacy concerns and from previous-period product returns.

The paper is structured as follows. Section 2 provides a literature review. Sections 3 and 4 detail our model formulation and equilibrium solutions. Section 5 presents our findings, and section 6 extends our models to cover low customer acceptance and dynamic scenarios featuring misfit returns from prior sales. Section 7 concludes with a discussion and future research directions.

2. Relevant literature

To achieve our research objectives, we focus on related papers discussing customer experience, misfit returns, the implementation of DT in manufacturing and price and quality decisions.

Customer experience has attracted considerable and sustained interest, as it reflects the consumer's direct or indirect reaction resulting from their interactions with the company (Meyer and Schwager, 2007). For example, Howard and Sheth (1969) emphasizes that emotional states not only influence consumers' purchase intentions and decision-making processes but also determine brand loyalty and the overall consumption experience. Recently, Van Doorn et al. (2010) argued that customer experience involves various engagement behaviors beyond buying. However, Siqueira et al. (2020) found that customer experience is shaped by both internal and external touchpoints. More recently, Kumar et al. (2023) identify key drivers of customer experience in grocery apps through online review analysis, informing strategies to boost satisfaction among users. Serval studies, including Wang et al. (2024), Pantano et al. (2024), Li et al. (2025a, 2025b), and Xie et al. (2024) have explored the relationship and influence between customer experience and the advancement of technologies such as AI, AR and chatbots. Collectively, these studies devote scant attention to the interplay between retailer-owned DT services and customer experience. Moreover, they all ignore how the adoption of retailer-owned DT services affects the manufacturer's quality decisions and profits, which is also a key focus of our paper.

There are numerous literatures has studied misfit returns. For example, Wan et al. (2020) investigated a monopolistic retailer's returns policy under a money-back guarantee or no-refund. Then, Rokonuzzaman et al. (2021) investigated the important role of a retailer's return policy in consumers' decision making. Liu et al. (2023) discovered that offering return-freight insurance or opening a physical showroom does not help consumers reduce product mismatch, nor does it necessarily expand market demand. Particularly, Lin et al. (2024), Cao et al. (2025), Pei et al. (2025) and Kanyal and Patra (2025) proposed that merchants can utilize tools like extended warranties, virtual showroom experiences, free sample trials, and hassle time to reduce misfit returns. These papers do not consider the possibility of adopting DT to reduce misfit returns. Nevertheless, they served as the inspiration for our exploration of this theme.

Recent studies have studied implications of DTs in manufacturing. Grieves (2015) explored how the DT can evolve from a conceptual tool to a critical component of an enterprise-wide closed-loop product lifecycle, reducing costs and fostering innovation. Huang et al. (2022) proposed a framework for rapid product development based on digital twins, replacing costly and inefficient physical validation with digital validation. However, Kokkonen et al. (2023) and Jia et al. (2023) constructed a digital twin shop floor using the complex digital twin modeling method on quality management at different manufacturing scales. Zhang et al. (2025) presented a digital twin-based design method for shop-floor reconfiguration, utilizing dynamic fidelity models to address the challenges of uncertainty and complexity. Sun et al. (2025) provide a thorough review of digital twin modeling technology and its use in manufacturing. The above literature, collectively validating that

DT technologies positively influence equilibrium decisions of quality. In contrast, rather than focusing on the implications of DTs in production, we provide an alternative, complementary approach that considers the influence of the retailer's DT adoption on the optimal decisions of manufacturing firms.

Many researchers highlight price and quality decisions under the assumption of static market demand dynamics. For instance, Chai et al. (2020) address the quality differentiation in the presence of differentiated channel policies. Yang et al. (2023) study a supply chain where the manufacturer distributes a classic product via a retailer while deciding endogenously whether to launch a new, network-externalities product through a direct channel. Recently, Chang et al. (2025) analyzed how providing vertically differentiated products affects the effectiveness of easing channel competition in improving the manufacturer's profit. Another body of research focuses on price and quality decisions related to multi-generation products. Agrawal et al. (2016) offered a demand-side rationale for a high-durability product design strategy: the exclusivity-seeking consumer behavior associated with conspicuous consumption. Then, Hu et al. (2023) established that the manufacturer can always increase profit by improving the quality of new products and reducing the quality depreciation rate. Meanwhile, Liu (2023) considered a two-period game with differentiated durable products, where an entrant releases an improved version in period 2. Recently, Das et al. (2025) explored manufacturers' responses to frequently updated products by examining the price and quality of multi-generation products. Following this stream of research, this paper treats product quality as a decision variable for the manufacturer, but it takes a distinct approach by primarily examining how retailer-owned DTs impact the manufacturer's quality decisions.

3. Modeling framework

We develop two models based on the retailer's choice to adopt DT or not: The first is a benchmark model, Model B, where the retailer sells products without DT, and consumers may return products due to misfit. The second is Model D, where the retailer equipped with DT and provides complete product quality information to fulfill customer experience and effectively eliminates the loss from misfit-related returns. In both of our models, the manufacturer (M) acts first, determining the quality improvement of g and wholesale price of w. Subsequently, the retailer, the second player R, decides the selling price of p.

We first determine the demand based on customer experience, which is determined by the utility function. That is, all consumers purchase a product based on their utility of U, which is derived from the product's basic value, v. It should be noted that the value, v, uniformly distributed over $[0, \bar{v}]$ represents the market size, which normalize to one, i.e., $\bar{v} = 1$, for ease of exposition (Khouja and Hammami, 2023). To capture the positive impact of quality improvement on the customer experience, we assume that a consumer is willing to pay an "extra" value of g, for the additional quality improvement (Rahman et al., 2025; Zhao et al., 2024). Suppose that the investment cost function associated with quality improvement is given by kg^2 (Biswas et al., 2023; Yin et al., 2010).

In the benchmark model, the retailer's lack of DT technology may lead to consumer uncertainty about products, potentially resulting in misfit returns. Accordingly, when a consumer buys a product that doesn't align with their needs or expectations, they incur a utility loss of $-rp$ because of the costs associated with returning it, where r represents the loss rates for misfit (Khouja and Hammami, 2023; Thomas and Dillenbeck, 2004). It is should be noted that, such utility loss encompasses the hassle costs associated with product returns, including the time consumers must dedicate, travel expenses they incur, and any restocking fees they may have to pay (Shulman et al., 2009). Then, like Olsder et al. (2022), Zhao et al. (2022), and Tao et al. (2025), a consumer's different utility on purchasing decision under risk can be write as follows.

Table 1
Variables and definitions.

Variable	Definition
$\bar{v}$	The market size
w_i	The wholesale price in Model i, $i \in (B, D)$
g	The levels of quality improvement in Model i
p_i	The retail price in Model i
q_i	The sales volumes in Model i
c	The unit cost for adopting DT technology
k	The scaling parameter for the quality investment
e	The probability of a product misfit
r	The loss rate from misfit
π_i^j	Player j's profit in Model i, $j \in (\mathrm{M}, R)$

$$U = \begin{cases} v + g - p & \text{if the product meets the needs} \\ -rp & \text{if the product misfits the needs} \end{cases} \tag{1}$$

Where U is the utility of that gain or loss. Considering consumers' potential uncertainty about product quality, we assume the probability of a product misfit is, e, which associates with product returns. Then, based on the payment schemes in (1), we can derive the expected utility of a consumer purchasing a product under Model B is $U_B = (1-e)(v + g - p) + e(-rp)$. As such, the consumer will purchase the product if $U_B \geq 0$, which is equivalent to saying they will purchase the product when $v \geq \frac{(g-p)(e-1)+erp}{1-e}$. Recall that, $v \in U\,[0, \bar{v} = 1]$, we thus can derive the demand functions of the product as follows.

$$q_B = \begin{cases} 1 + g - p - \frac{erp}{1-e} & \text{if } p < \frac{(1+g)(1-e)}{1+er-e} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

In Model D, the retailer sells products with DT that provides complete product quality information, effectively eliminating the loss of misfit-related returns. In other words, $U_D = (1-e)(v+g-p)+e(0)$ represents the consumer's utility with DT services, $e(0)$ represents the possible utility loss for misfit, meaning that, through allowing consumers to experience products in the DTs, the consumer's ability to effectively avoid misfit products that allows us to assume a zero loss for misfit. Following a similar approach to that used for Model B, Model D's product demand functions can be derived as follows.

$$q_D = \begin{cases} 1 + g - p & \text{if } p < 1 + g \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

In accordance with established practice, we only focus on the scenario of $q > 0$ in equilibrium. Furthermore, to align with the evidence that DT technology generally involves costs for hardware, sensor configuration, software platforms, and operations (Ankitha, 2025), we assume a unit cost of c for the retailer's adoption of the DT technology. Such an additional unit cost for new technology adoption is quite common in the marketing literature (see, e.g., Arya et al. (2007), Biswas et al. (2023) and Sarkar et al. (2024)), and is consistent with the fact that creating a DT system typically requires an investment of \$50,000 to \$500,000 in specific assets (Ankitha, 2025; Risingmax, 2024).

All relevant variables are defined in Table 1.

4. Equilibria

4.1. Adopting traditional systems (Model B)

Recalled that, in the benchmark model, Model B, the retailer sells products without DT, and consumers may return products due to misfit. Then, given the demand function in (2), the manufacturer's and retailers' objective functions in Model B are given by:

$$\begin{aligned} &\max_{w_B, g_B} \pi_B^M = w_B q_B - kg^2 \\ &\max_{p_B} \pi_B^R = (p_B - w_B) q_B \end{aligned} \tag{4}$$

Table 2
Equilibrium decisions and profits in both models.

Adopting traditional systems (Model B)
Optimal decisions:
$g_B = \frac{1-e}{e+8k-8ek+8ekr-1}$, $w_B = \frac{4k(1-e)}{e+8k-8ek+8ekr-1}$,
$p_B = \frac{6k(1-e)}{e+8k-8ek+8ekr-1}$, $q_B = \frac{2k(1-e+er)}{e+8k-8ek+8ekr-1}$,
Optimal profits:
$\pi_B^M = \frac{k(1-e)}{e+8k-8ek+8ekr-1}$, $\pi_B^R = \frac{4k^2(1-e)(1-e+er)}{(e+8k-8ek+8ekr-1)^2}$.
Adopting DT systems (Model D)
Optimal decisions:
$g_D = \frac{1-c}{8k-1}$, $w_D = \frac{4k(1-c)}{8k-1}$, $p_D = \frac{6k-c+2ck}{8k-1}$, $q_D = \frac{2k(1-c)}{8k-1}$
Optimal profits:
$\pi_D^M = \frac{k(1-c)^2}{8k-1}$, $\pi_D^R = \frac{4k^2(1-c)^2}{(8k-1)^2}$

$q_B = 1 + g - p - \frac{erp}{1-e}$ denotes the sales volumes in Eq. (2). This indicates that without retailer-owned DTs, consumers face uncertainty regarding product, potentially increasing the likelihood of returns. That is, on the one hand, $\partial q_B/\partial e = \frac{-rp}{(e-1)^2} < 0$, meaning that, the higher probability of product misfit, e, the fewer the quantities sold in the market. On the other hand, $\partial q_B/\partial r = -\frac{ep}{1-e} < 0$, the higher the loss rate caused by misfit, r, the fewer the quantities sold in the market.

In both of our models, the manufacturer (M) acts first, determining the product's quality of g and wholesale prices of w. The retailer, the second player R, decides the selling prices of p. Table 2 presents the equilibrium decisions and profits for the benchmark model, derived using backward induction.[1]

4.2. Adopting DT services (Model D)

In Model D, the retailer sells products with DT that provides complete product quality information to fulfill the customer experience and effectively eliminates the loss from misfit-related returns. Then, given the demand function in (3), the manufacturer's and retailer's objective functions in Model D are given by:

$$\max_{w_D, g_D} \pi_D^M = w_D q_D - kg^2$$
$$\max_{p_D} \pi_D^R = (p_D - w_D - c) q_D \tag{5}$$

Where $q_D = 1 + g - p$ is the sales volumes in (3), cq_D is the cost of adopting DTs. Then, Eq. (5) indicates the fact that, although the DT technology can effectively prevent misfit, thereby avoiding losses for consumers, retailers face a marginal cost of c for its adoption. Using backward induction again, we derive the equilibrium decisions and profits for Model D, shown in Table 2.

5. Analysis and insights

In this section, we intend to make a comparison on the outcomes of both models and provide insights addressing the questions raised earlier in this paper.

5.1. The conditions for retailers' DT adoption

In this paper, since the retailer has the flexibility to adopt DTs technology, we first examine the conditions for retailers to adopt DTs. That is, comparing the retailer's profitability in Models B and D yields the following proposition.

Proposition 1. *There exists a cost threshold of $\bar{c}$, below which the retailer prefers to adopt DTs; moreover, $\partial \bar{c}/\partial e > 0$, $\partial \bar{c}/\partial r > 0$*

[1] For clarity, all the technical analysis for the paper is provided in the appendix.

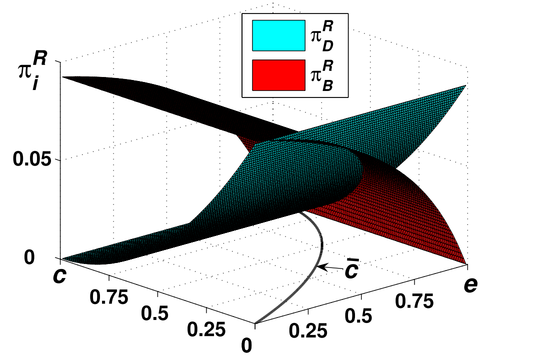


Fig. 1. Comparing retailer's profits under both models (with $k = 0.7$, $r = 0.2$).

We provide a numerical study to reanalyze Proposition 1. As Khouja and Hammami (2023) mentioned, secondary gift markets for those refunds offered in store credit or gift cards, can be used to estimate the consumer loss of misfit-related returns. Observing secondary marketers, e.g., Raise.com, pay between 75% to 90% of gift card face value, like Denning et al. (2016) and Khouja and Hammami (2023), we then use the consumer loss of misfit-related returns of $r = 0.2$. Consistent with Zhang et al. (2021), Biswas et al. (2023) and Das et al. (2025), we assume the cost of quality improvement is quadratic and chose the scaling parameter of $k = 0.7$. Fig. 1 illustrates that, when $c < \bar{c}$, the retailer's profits for adopting DT technology is higher than that in adopting traditional systems, i.e., $\pi_D^R > \pi_B^R$. Put differently, the retailer would prefer to adopt the DT technology if and only if the marginal cost of adopting the DT technology is not pronounced, i.e., $c < \bar{c}$. However, as the marginal cost for adopting the DT technology is significant, i.e., $c > \bar{c}$, although DT technology can effectively eliminate the loss of misfit-related returns, adopting DT systems may not be cost-effective for retailers, and thus, their adoption is not advised, i.e., $\pi_D^R < \pi_B^R$.

The studies by Ankitha (2025) and RisingMax, (2024) offer empirical evidence that corroborates our findings, highlighting the challenges of implementing DT technology, namely a high technological barrier and the requirement for significant financial resources for enterprises. High implementation costs remain a major obstacle to the adoption of this technology, particularly for small and medium-sized enterprises. In practice, many small business owners and their employees lack the necessary skills to effectively utilize new technologies, making it difficult to fully realize the potential benefits of digital transformation. To advance DT technology for small and medium-sized enterprises, the U.S. Department of Commerce has finalized $285 million in funding aimed at enabling these enterprises to iterate on design changes faster, test them in a DT system, and harness artificial intelligence to optimize manufacturing components (Meritalk, 2024).

Proposition 1, however, further reveals that the thresholds of $\bar{c}$ increases with the product return rates, i.e., $\partial \bar{c}/\partial e > 0$. Meaning that, higher product misfit rates encourage the retailer to adopt DTs technology. This aligns with our expectation that greater consumer uncertainty about product would create stronger incentives for retailers to adopt DTs technology as preventive measures to mitigate the negative effects. On the other hand, the thresholds of $\bar{c}$ also increases with the loss rates of r, i.e., $\partial \bar{c}/\partial r > 0$. Meaning that, higher the return losses encourage the retailer to adopt DTs technology. This suggests that higher return losses induce in a consumer would also lead to stronger incentives for retailers to adopt DTs technology.

To facilitate the discovery of implications associated with DT technology, our subsequent analysis focuses solely on the region where retailers have the flexibility to adopt the DT system, i.e., where $c < \bar{c}$.

5.2. Impacts on the manufacturer's profitability

Having explored the first issue, we now focus on the second: How does the retailer-owned DTs influence the manufacturer's profitability?

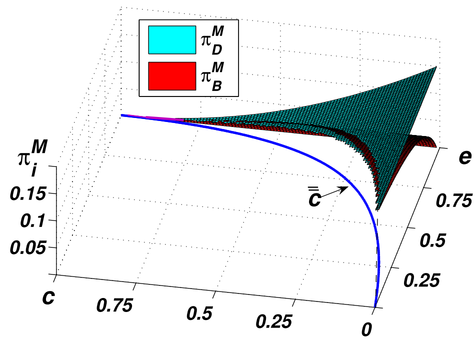


Fig. 2. Comparing manufacturer's profits under both models (with $k = 0.7$, $r = 0.2$).

The equilibrium outcomes in Table 2 yield the following proposition regarding the manufacturer's profit differential across the two scenarios.

Proposition 2. *The manufacturer benefits from the retailer-owned DTs only when $c < \bar{\bar{c}}$; moreover, $\partial\bar{\bar{c}}/\partial e > 0$, $\partial\bar{\bar{c}}/\partial r > 0$.*

Fig. 2 corroborates the results that we obtain in Proposition 2. That is, on the one hand, Proposition 2 confirms the traditional marketing wisdom that retailers' efforts to reduce product return rates can also benefit manufacturers. (Cao et al., 2025; Xu et al., 2023; Zhang et al., 2021). This may align with the results in the report of the "Digital Twin Market Size, Share, and Trends", which states that retailers' investment in DT technology not only eliminates the loss of misfit-related returns but also promotes the adoption of related technologies, thereby providing manufacturers with more efficient solutions (Marketsandmarkets, 2025). Furthermore, like Proposition 1, Proposition 2 further indicates that the thresholds of $\bar{\bar{c}}$ increases with the product return rates and the loss rates, i.e., $\partial\bar{\bar{c}}/\partial e > 0$ and $\partial\bar{\bar{c}}/\partial r > 0$. The intuition behind the result is the same as that in Proposition 1, so we will not repeat it here.

Based on the profit comparisons in Proposition 1 and 2, identifying the two thresholds of the marginal cost of $\bar{c}$ and $\bar{\bar{c}}$ leads to Corollary 1 provides the following corollary without proof.

Corollary 1. *When $c < \bar{\bar{c}}$, retailer-owned DTs create a win-win situation for both retailer and manufacturer. However, when $c > \bar{\bar{c}}$, they may lead to a losing outcome for manufacturers.*

As Fig. 3 shown, the thresholds of $\bar{c}$ is always greater than the thresholds of $\bar{\bar{c}}$. Meaning that, when the retailer adopts the DTs technology, the manufacturer becomes more concerned with the marginal cost of c. According to Proposition 1 and 2, we therefore can conclude that, if $c < \bar{\bar{c}}$, a win-win outcome (Pareto gains) can arise from promoting efficiency gains by eliminating the loss of misfit-related returns. However, when the cost of implementing DTs technology is high, i.e., $c > \bar{\bar{c}}$, we would face a dilemma regarding DTs adoption. That is, as evident from Fig. 3 and Proposition 2, Corollary 2 demonstrates that when the costs for the retailer to implement DTs are substantial—specifically, when $c > \bar{\bar{c}}$ —the costs outweigh the benefits derived from reducing product returns through DT implementation. Consequently, the retailer would require the upstream manufacturer to bear a portion of the DT implementation costs, thereby squeezing the manufacturer's profitability. Then, although adopting DTs can eliminate the loss of misfit-related returns, the substantial implementation costs ($c > \bar{\bar{c}}$) associated with it make it unprofitable for the manufacturer.

While many industry observers have primarily focused on the potential benefits of digital twin systems in applications within the manufacturing (e.g., McKinsey & Company, 2024, IBM, 2021) and/or retail sectors (e.g., Kelly, 2022; Zalando, 2024), they have largely overlooked how retailer-owned DTs affect manufacturers' profitability. In particular, Corollary 1 reveals that the higher adoption costs for the retailer-owned DTs can result in an unprofitable situation. This argument is partly supported by the perspective expressed in Forbes (2023), which points out that some manufacturers are concerned about the situation regarding the digital twin systems of some smaller retailers. The manufacturers worry that these retailers, facing substantial investments, are unable to keep up with those investments in terms of both product offerings and sales scale. This mismatch may lead to a decline in their profits, thereby reducing their willingness to participate in the DT system(s) [related to or operated by these retailers].

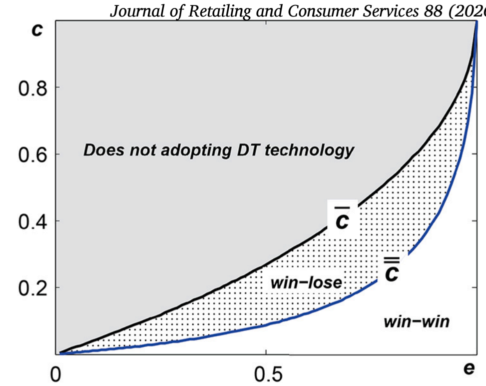


Fig. 3. Impacts of retailer-owned DT on both players' profits (with $k = 0.7$, $r = 0.2$).

To understand the reasons behind Corollary 1, we need to examine the implications of DTs adoption on the optimal decisions of both players.

5.3. Implications on the optimal decisions

We first pay our attention on how retailer-owned DTs affects the manufacturer's quality decisions. Comparing the manufacturer's quality and wholesale price in Table 2 provides the following conclusion:

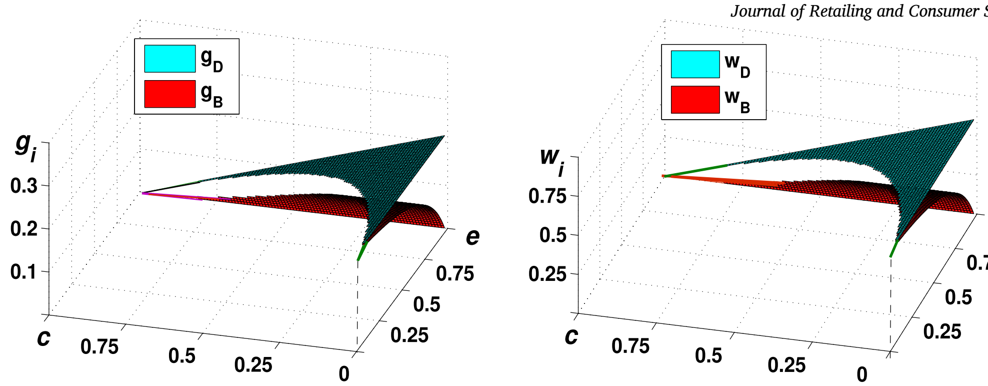
Proposition 3. *The adoption of DTs technology leads to a greater incentive for the manufacturer to improve quality, i.e., $g_B < g_D$, which is associated with an increase in the wholesale price, i.e., $w_B < w_D$.*

Many prior studies have explored the implications of DT adoption in the manufacturing sectors. For instance, Li et al. (2024) and Zhang et al. (2025) argued that DT technology enhances quality by utilizing dynamic fidelity models to analyze shop-floor uncertainties and performance fluctuations, optimizing reconfiguration designs. McKinsey & Company (2024) expected that implementing a DT system in manufacturing would result in improved product-market fit (20-50%), product performance (15-60%), and workplace productivity (30-50%). Likewise, Proposition 3 indicates that the adoption of DT technology in the retail sector can also lead to improved product design quality during manufacturing, consequently enhancing the manufacturer's wholesale price.

Observing $w_B < w_D$, and consistent with existing literature on DT technology in the manufacturing, one might expect that implementing DT technology not only enhances product design quality but also fosters revenue growth for manufacturing firms. However, as previously mentioned, Corollary 1 reveals that, although implementing DT technology in the retail sector can indeed enhance product design quality and wholesale price at the manufacturing stage, it is not always beneficial to the manufacturer. Specifically, as illustrated in Fig. 4(b), an increase in the unit cost of adopting c leads the manufacturer to decrease the lower wholesale price, meaning $\partial w_D/\partial c < 0$.

Next, we present a proposition comparing the manufacturer's optimal decisions.

Proposition 4. *The adoption of DTs technology results in a higher selling price, i.e., $p_B < p_D$.*



(a) Comparing g_D and g_B (b) Comparing w_D and w_B

Fig. 4. Comparing manufacturer's decisions under both models (with $k = 0.7$, $r = 0.2$).

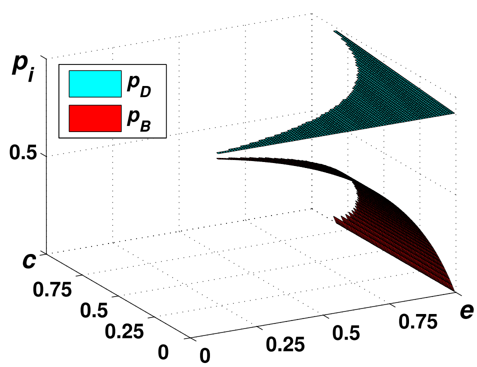


Fig. 5. Comparing selling price under both models (with $k = 0.7$, $r = 0.2$).

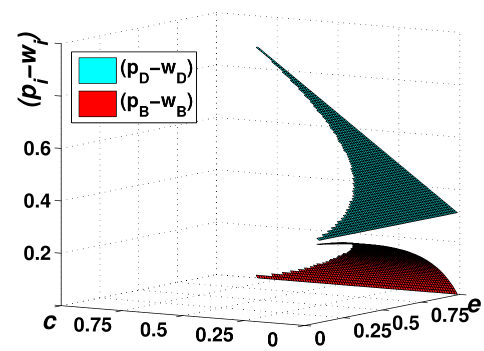


Fig. 6. Comparing retailer's marginal revenues under both models (with $k = 0.7$, $r = 0.2$).

As demonstrated in Proposition 3, the adoption of DTs technology provides the manufacturer with a greater incentive to enhance quality, i.e., $g_B < g_D$, which, in turn, is associated with an increase in the wholesale price, i.e., $w_B < w_D$. Consequently, such a higher wholesale price should naturally lead to a higher retail price, $p_B < p_D$ in Fig. 5.

Drawing upon Propositions 3 and 4, we derive the following corollary, which sheds further light based on Corollary 1.

Corollary 2. *Implementing DTs at the retail sector enables the retailer to pursue higher marginal revenues, i.e.,* $(p_D - w_D) > (p_B - w_B)$.

Confronted with a relatively higher wholesale price set in Model D, i.e., $w_D > w_B$, the retailer has an incentive to raise the retail price even further, i.e., $(p_D - w_D) > (p_B - w_B)$. That is, observing $\partial w_D/\partial c < 0$ in Proposition 3, Corollary 2 further illustrates that, an increase in the unit cost of adopting c leads the manufacturer to decrease the lower wholesale price, meaning $\partial w_D/\partial c < 0$. That is, the retailer-owned DTs prompt the retailer uses it as a lever to capture a portion of the manufacturer's revenue derived from quality improvement, i.e., $(p_D - w_D) > (p_B - w_B)$. The retailer does so for two reasons: First, in a decentralized supply chain with independent retailers and manufacturers, the classic double marginalization problem arises: As each independently seeks to maximize profits, the retailer charges higher prices. Second, as previously established in Model D, we assume that the retailer utilizes DT, which provides complete product quality information and effectively eliminates the loss of misfit-related returns. Consequently, even considering any potential loss of $e(-rp)$ in U_B, the consumer's expected utility of U_D in Model D remains higher. This increased expected utility, in turn, leads to higher selling price in Model D than in Model B. Fig. 6 illustrates the result in Proposition 5.

As Corollary 2 indicates, implementing the DT system at the retail sector is associated with a higher selling price premium for the retailer; however, such a higher price premium could not only potentially squeeze the manufacturer's wholesale price, but also reduce overall product sales: A comparison of sales volumes under both models is presented in the following proposition.

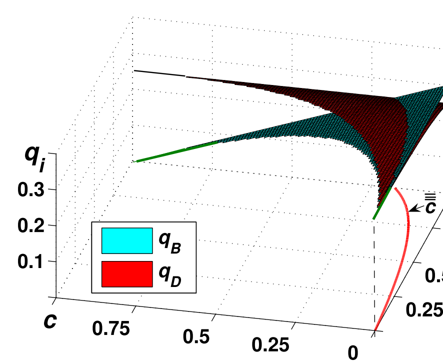


Fig. 7. Comparing quantities under both models (with $k = 0.7$, $r = 0.2$).

Proposition 5. *When* $c > \bar{\bar{c}}$, *Model D yields a lower sales volume than Model B, i.e.,* $q_B > q_D$. *Conversely, the opposite is true.*

Fig. 7 confirms the traditional wisdom that higher selling prices may result in lower sales volumes. That is, a pronounced marginal cost of adopting the DT technology, i.e., $c > \bar{\bar{c}}$, inevitably leads to a price increase, which in turn causes a decrease in sales volumes. Then, for the manufacturer, when the unit cost of adopting the DT system exceeds a certain threshold ($c > \bar{\bar{c}}$), the negative impact of reduced sales volume outweighs the positive impact of a higher price premium.

However, Fig. 7 also reveals that, when $c < \bar{\bar{c}}$, Model D yields a higher sales volume for two reasons: On one hand, implementing DT technology at the retail sector eliminates the loss of misfit-related returns and increases consumers' willingness-to-pay, potentially leading to higher sales volumes despite a higher selling price. On the other hand, as Proposition 3 demonstrates, the adoption of DT technology incentivizes the manufacturer to improve quality (i.e., $g_B < g_D$), which further enhances consumers' willingness-to-pay and potentially boosts sales volumes even with a higher price point.

6. Extensions

6.1. Privacy concerns and customer truth

Our analysis thus far mainly discusses the implications of retailer-owned DTs based on the trade-offs between customer experience, misfit returns reduction, and investment costs. It's important to note that while retailers can improve the customer experience with more accurate content recommendations, doing so requires collecting and using large volumes of sensitive data (Duan et al., 2022; Palinski et al., 2025). This raises potential privacy issues and can erode consumer trust in retailer-owned DTs.[2]

We then extend Model D to Model DP (denotes the scenario with privacy concerns and customer truth) to account for two important aspects. First, we represent the consumers' utility concerning the portion of information that remains un-leaked, using the expression $(1-s)d$. Here, d denotes the amount of personal information, while s indicates the consumer's privacy concerns, thus, $(1-s)d$, representing the un-leaked portion, decreases as s increases, inversely mirroring the decline in acceptance and truthfulness (Duan et al., 2022; Palinski et al., 2025).[3] On the other hand, to further elaborate on challenges retailers face in the extensive data collection, we assume that maintaining this data incurs a cost of fd^2 (Chen and Duan, 2022; Yin et al., 2010). Therefore, we can rewrite the demand functions in Eq. (3) as follows.

$$q_{DP} = \begin{cases} 1+g+(1-s)d-p & \text{if } p < 1+g+(1-s)d \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

To focus clearly on the issues of privacy concerns and consumer trust, we normalize the manufacturer's quality investment scaling parameter, k, to one.[4] As such, the manufacturer's and the retailer's problems are as follows.

$$\begin{aligned} &\max_{w_{DP}, g_{DP}} \ \pi^M_{DP} = w_{DP} q_{DP} - g^2 \\ &\max_{d_{DP}, p_{DP}} \ \pi^R_{DP} = (p_{DP} - w_{DP} - c) q_{DP} - f d^2 \end{aligned} \tag{7}$$

Using standard backward induction provides the outcomes in Model DP. To highlight the implications of privacy concerns and customer truth, comparing the outcomes in Model DP with those of Model B in §4.1 and provides the following proposition.

Proposition 6. *With privacy concerns: For any $f > \bar{f}$,*
(i) there exists a cost threshold of $\bar{c}_{DP}$, below which the retailer prefers to adopt DTs;
(ii) the manufacturer benefits from the retailer-owned DTs only when $c < \bar{\bar{c}}_{DP}$.

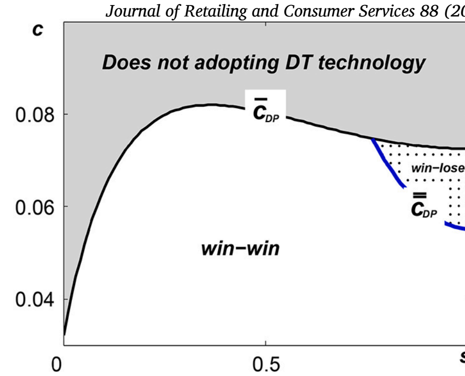


Fig. 8. Impacts of retailer-owned DT with privacy concerns (with $f = 0.4$, $k = 0.7$, $r = 0.2$, $e = 0.5$).

Corollary 3. *The value of $\bar{c}_{DP}$ exhibits an inverted U-shaped relationship with the consumers' privacy concerns, denoted by s.*

Proposition 6 confirms that our main conclusion appears to be robust with respect to privacy concerns and customer truth: when $c < \bar{\bar{c}}_{DP}$, retailer-owned DTs benefit both the retailer and manufacturer, securing Pareto gains. Conversely, when $c > \bar{\bar{c}}_{DP}$ (indicating high DT implementation costs), DTs benefit the retailer but are unprofitable for the manufacturer, leading to a win-lose outcome. As Corollary 3 shown, Fig. 8 indicates that the retailers' incentives for DT adoption (i.e., $\bar{c}_{DP}$) peak near the median consumer privacy concern level ($\bar{s}$), resulting in an inverted U-shaped relationship between incentives and privacy concerns. More specifically, on one hand, in an extreme case where there are no consumer privacy concerns ($s = 0$), retailers fully reap the benefits of accurate content recommendations. This enables them to achieve appropriate returns without needing to excessively collect extensive data. However, on the other extreme, when privacy information is fully leaked and consumers exhibit strong privacy concerns ($s = 1$), retailers suffer from consumer distrust, leading to diminished incentives to collect extensive data. Consequently, the inverted-U relationship emerges from the interaction between retailers' incentives for data collection and consumer privacy concerns.[5]

6.1.1. Two-period dynamic model

Through a static analysis of market demand dynamics, we find that, if a retailer adopts a DT to proactively prevent subsequent consumer misfit and product return issues, this retailer-owned DT may lead to Pareto improvements or result in a win-lose situation. Recognizing the need to capture their dynamic impact, we extend Model D to a two-period dynamic model (Model DS) to illustrate how prior-period sales and returns might affect current return rates and adoption incentives.[6]

That is, since DT was lacking in period 1, any purchases made by consumers during that period will result in returns materializing, regardless of the retailer's adoption of DTs in period 2. Then, consistent with Das et al. (2025) and Yin et al. (2010), a consumer's utility in period 1 and period 2 under Model DS can be rewrite as follows.

$$\begin{aligned} U_1 &= (1-e)(v + g_1 - p_1) \\ U_2 &= (v + g_2 - p_2) + e(-rp_1) \end{aligned} \tag{8}$$

Based on the payment schemes in (8), we derive the inverse demand functions of both periods as follows.

---

[2] We sincerely thank an anonymous reviewer for pointing it out.

[3] Where $(1-s)d$ signifies that, for a given amount of personal information d, a higher proportion of leaked privacy information (s) leads to lower customer acceptance and diminished truthfulness.

[4] Relaxing this assumption would make the analysis more complex, yet it does not alter our findings. Notably, Shi et al. (2013) and Biswas et al. (2023) similarly employed such an assumption to streamline their analysis.

[5] We refer interested readers to Chen and Duan (2022) for a detailed analysis of the inverted-U relationship between consumers' privacy sensitivity and financial performance.

[6] We sincerely thank an anonymous reviewer for pointing it out.

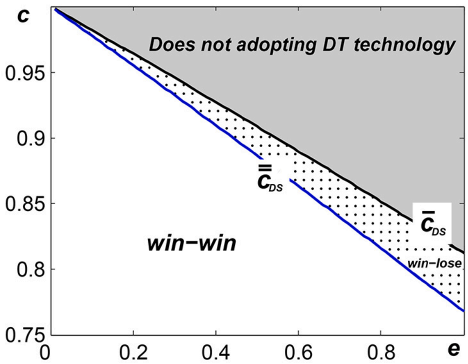


Fig. 9. Impacts of retailer-owned DT with previous-returns (with $k = 0.7$, $r = 0.2$).

$$p_1 = 1 + g_1 - q_1$$
$$p_2 = 1 - q_2 + g_2 + erq_1 - er - erg_1 \tag{9}$$

Then, we can rewrite the manufacturer's and the retailer's problems in period 2 as follows.

$$\max_{w_2, g_2} \pi^{M}_{DS2} = w_2 q_2 - k g_2^2$$
$$\max_{q_2} \pi^{R}_{DS2} = (p_2 - w_2 - c) q_2 \tag{10}$$

Note that, in period 1, both players' objective is to maximize his total two-period profit (Das et al., 2025; Li et al., 2025a, 2025b). Therefore, both players' problems in period 1 are,

$$\max_{w_1, g_1} \pi^{M}_{DS} = \pi^{M}_{DS1} + \pi^{M*}_{DS2} = w_1 q_1 - k g_1^2 + \pi^{M*}_{DS2}$$
$$\max_{q_1} \pi^{R}_{DS} = \pi^{R}_{DS1} + \pi^{R*}_{DS2} = (p_1 - w_1) q_1 + \pi^{R*}_{DS2} \tag{11}$$

Using standard backward induction provides the outcomes in Model DS. Given that the retailer does not adopt DTs in Period 1 but does in Period 2, comparing the outcomes in period 2 with those of in period 1 allows us to highlight the implications of prior-period sales and returns in the following proposition.

Proposition 7. *With prior-period sales and returns:*
(i) there exists a cost threshold of $\bar{c}_{DS}$, below which the retailer prefers to adopt DTs;
(ii) the manufacturer benefits from the retailer-owned DTs only when $c < \bar{\bar{c}}_{DS}$.

Corollary 4. *The value of $\bar{c}_{DS}$ decreases prior-period returns of e, i.e., $\partial \bar{c}_{DS}/\partial e < 0$.*

Besides confirming our main result in Proposition 7, Corollary 4 further indicates that prior-period returns deter the retailer from adopting DTs services (see, Fig. 9). The reasons behind this can be interpreted as follows. Note that, since DT was lacking in period 1, any purchases made by consumers during that period will result in returns materializing, regardless of the retailer's adoption of DTs in period 2. That is, if consumers purchase products in period 1 and find them unsuitable for their needs, they will return the products, leading to a compensation in period 2. As such, the higher the prior-period returns of e, the greater the damage to the retailer's profit in period 2, which makes the retailer more reluctant to adopt DT services in period 2.

Recalled that, Propositions 1 and 2 indicate that $\partial \bar{c}/\partial e > 0$, meaning that, anticipating greater subsequent product returns, retailers are more likely to adopt DT technology as preventive measures to avoid the negative effects from consumer uncertainty. In contrast, Corollary 4 reveals that, $\partial \bar{c}_{DS}/\partial e < 0$, meaning that, confronting greater product returns from the previous period, retailers are less likely to adopt DT technology as a remedial mechanism to compensate for the negative effects from consumer uncertainty. In addition, from the profitability perspective, we also suggest both the retailer and the manufacturer should take other appropriate measures to avoid the negative consequences that arise from previous-period product returns.

7. Conclusions and discussions

Prior research has explored the implications of DT adoption in the manufacturing sectors (see, e.g., Zhang et al. (2025) and references therein), but has largely ignored retailer-owned DT services. However, rather using DTs to enhance operational efficiency in manufacturing, retailers like Walmart, Kroger, IKEA, and Amazon adopt DTs to improve customer experience and reduce misfit returns by creating virtual replicas of products, services, and marketing environments.

Hence, this research investigates how retailer-owned DT service is shaped by the trade-off between customer experience, misfit returns reduction, and investment expenditures and as well as investigate its impact on the manufacturer's equilibrium decisions and profits. Specifically, we develop two models based on the retailer's choice to adopt DT or not: The first is a benchmark model, Model B, where the retailer sells products without DT, and consumers may return products due to misfit. The second is Model D, where the retailer adopts DT. In this model, the retailer sells products equipped with DT, which provides complete product information to fulfill the customer experience and effectively eliminates the loss from misfit-related returns.

Our models capture three key aspects of retail-owned DTs: First, implementing DT technology enables retailers to fulfill customer experience and effectively eliminates the risk of misfit-related returns during the sales process. Second, the complexity and advancement of DT services are positively correlated with its costs, including hardware, sensor configuration, software platforms, and operations (Ankitha, 2025); consequently, the retailer, as the primary adopter, would bear these costs. Third, although the retailer may own the DT system, the manufacturer can still benefit from it within the supply chain.

We now address the managerial questions raised at the beginning of this paper.

What are the necessary conditions for retailers to adopt DTs?

We find that, there exists a cost threshold of $\bar{c}$, below which the retailer is willing to adopt DTs. Put differently, our analysis confirms that the substantial creation costs of DTs can deter some companies from adoption, casting doubt on the actual benefits (Ankitha, 2025; RisingMax, 2024). Moreover, Proposition 1 reveals that higher values of misfit rates (e) and/or the return loss rates (r) encourage the retailer to adopt DTs technology. Then, we recommend that retailers should classify products when adopting DT technology: For products with high misfit rates and/or high return losses, implementing DTs can enhance customer experience and reduce returns. Conversely, DTs may not be cost-effective, and thus, their adoption is not advised.

Thus, when implementing DT technology, we recommend that retail managers should pay particular attention to considering misfit returns: For products with high misfit losses and/or high return rates, managers should be aware that adopting retailer-owned DT would be beneficial for retailers, as it can enhance customer experience and reduce returns. Conversely, for products with minimal misfit issues and low return losses, managers at the retail level should note that the adoption of DTs may not be cost-effective and is therefore not advised.

How does the retailer-owned DTs affect the manufacturer's profitability?

Proposition 2 and Corollary 1 first indicate that the manufacturer would benefit from the retailer's DT only when $c < \bar{\bar{c}}$. That is, we identify that Pareto gains can arise from promoting efficiency gains by eliminating the loss of misfit-related returns when $c < \bar{\bar{c}}$ (see, Proposition 2). Thus, the manufacturer welcomes an efficient retailer's implementation of DT technology, as it may incentivize the retailer to proactively invest in the DT system, thus reducing its unit cost (c). This conclusion may align with the results in the report of the "Digital Twin Market

Size, Share, and Trends", which states that retailers' investment in DT technology not only eliminates the loss of misfit-related returns but also promotes the adoption of related technologies, thereby providing manufacturers with more efficient solutions (MarketsandMarkets, 2025). However, Corollary 2 shows that the substantial implementation costs ($c > \bar{\bar{c}}$) associated with retailer-owned DTs render it unprofitable for the manufacturer. From a practical perspective, this argument is partly supported by the attitudes of some manufacturers. These manufacturers are concerned that the digital twin systems implemented by some smaller retailers, due to the significant investments required and the retailers' inability to keep up with product and sales scale, may lead to a decline in their profits. This, in turn, reduces their willingness to participate in their DT systems (Forbes, 2023).

Then, although implementing DT technology at the retail sector can secure Pareto gains when $c < \bar{\bar{c}}$, we still suggest that manufacturers should exercise caution when participating in retailers' DT systems. This is especially true for those "inefficient retailers" with $c > \bar{\bar{c}}$, implementing the DT system at the retail sector would harm the manufacturer's profits and lead to a win-lose outcome for the retailer and manufacturer.

What are the implications of retailer-owned DTs on the optimal decisions of both the retailer and manufacturer?

To test our hypothesis that retailers might utilize DT systems to capture a share of the manufacturer's revenue gained from quality improvements, our analysis intends to investigate the implications of optimal decisions of both parties on their profitability. In particular, although implementing DT technology in the retail sector can indeed enhance product design quality and wholesale price at the manufacturing stage (see, Proposition 3), retailers are incentivized to raise the retail price even further (see, Proposition 4 and Corollary 2) which in turn reduces the optimal sales volume (Proposition 5). Obviously, for the manufacturer, when the unit cost of adopting the DT system exceeds a certain threshold ($c > \bar{\bar{c}}$), the negative impact of reduced sales volume outweighs the positive impact of a higher price premium.

How do the potential privacy concerns and previous-period misfit returns affect the equilibrium decisions and profits?

Extending our models to consider low customer privacy concerns and/or dynamic scenarios involving previous misfit returns, besides confirming the robustness of our main finding, we first find an inverted U-shaped relationship between these incentives and privacy concerns. This argument is partly supported by Chen and Duan (2022), who provided a detailed analysis of the inverted-U relationship between consumers' privacy sensitivity and financial performance. Second, our analysis reveals that, unlike acting as preventive measures to avoid subsequent misfit returns, if a retailer confronts greater product returns from the previous period, they are less likely to adopt DT technology as a remedial mechanism to compensate for the negative effects stemming from consumer uncertainty. Then, we suggest that both the retailer and the manufacturer should take other appropriate measures to avoid the negative consequences arising from previous-period product returns.

We suggest several promising directions for future investigation. First, prior researches have studied implications of DTs in manufacturing (e.g., Zhang et al. (2025) and references therein), however, we assume that the manufacturer does not invest in DT technology or consider the possibility of collaborating with the retailer in its development and implementation. Future research could build upon this study by examining scenarios where the manufacturer does invest in DT technology or considers such collaboration on DT implement. Second, our research findings provide several promising directions for future research. First, the retailer-owned DT may lead to Pareto improvements or result in a win-lose situation. Based on this finding, we welcome future research to offer a mechanism (e.g., contracts, subsidies, or cooperative schemes) to align manufacturer-retailer incentives. Second, our analysis reveals an inverted U-shaped relationship between these incentives and privacy concerns. We believe this finding generates a series of empirically testable hypotheses and welcome future research to explore the empirical correlations stemming from this result. Third, our models focus on the trade-off between the costs of implementation and the benefits of reducing returns related to product misfits. However, future research could also explore other potential benefits of DT systems, such as performance monitoring, improved logistics efficiency, and organizational change management. Finally, our model currently considers a single product, where consumer experiences vary based on the probability of misfit. Future research could expand upon this by examining the uniform adoption of DTs across all retail contexts or product categories, acknowledging that different types of products and consumer segments experience varied impacts.

CRediT authorship contribution statement

Qin Yang: Writing – original draft. **Lin Sun:** Writing – review & editing. **Xu Wu:** Visualization, Funding acquisition. **Youwei Li:** Supervision.

Declaration of competing interest

All authors declare no conflicts of interest regarding the publication of this manuscript.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jretconser.2025.104478.

Data availability

No data was used for the research described in the article.

References

Adivar, B., Hüseyinoğlu, I.Ö.Y., Christopher, M., 2019. A quantitative performance management framework for assessing omnichannel retail supply chains. J. Retail. Consum. Serv. 48, 257–269. https://doi.org/10.1016/j.jretconser.2019.02.024.

Agrawal, V.V., Kavadias, S., Toktay, L.B., 2016. The limits of planned obsolescence for conspicuous durable goods. Manuf. Serv. Oper. Manag. 18, 216–226. https://doi.org/10.1287/msom.2015.0554.

Ankitha, V., 2025. Digital twin cost for development explained. https://www.toobler.com/. (Accessed 27 April 2025).

Arya, A., Mittendorf, B., Sappington, D.E.M., 2007. The bright side of supplier encroachment. Mark. Sci. 26, 651–659. https://doi.org/10.1287/mksc.1070.0280.

Biswas, D., Jalali, H., Ansaripoor, A.H., De Giovanni, P., 2023. Traceability vs. Sustainability in supply chains: the implications of blockchain. Eur. J. Oper. Res. 305, 128–147. https://doi.org/10.1016/j.ejor.2022.05.034.

Cao, Y.N., Ding, R.L., Yu, Y.G., Yin, Z., 2025. Consumer self-optimization in a virtual showroom experience and its implications on online product return strategies. Transp. Res., Part E, Logist. Transp. Rev. 194. https://doi.org/10.1016/j.tre.2024.103951.

Chai, J.W., Yan, W., Li, Y.W., Palmer, M., Huang, Q.L., 2020. Selling vertically differentiated products under one channel or two? A quality segmentation model for differentiated distribution channels. J. Oper. Res. Soc. 71, 1180–1198. https://doi.org/10.1080/01605682.2019.1605469.

Chang, L.Y., Wang, C.X., Zhang, Q., 2025. Optimal channel structure for vertically differentiated products. Transp. Res., Part E, Logist. Transp. Rev. 193. https://doi.org/10.1016/j.tre.2024.103860.

Chen, C., Duan, Y., 2022. Impact of personalization and privacy concerns on information disclosure and pricing. J. Retail. Consum. Serv. 69, 103099. https://doi.org/10.1016/j.jretconser.2022.103099.

Culot, G., Orzes, G., Sartor, M., 2019. Integration and scale in the context of industry 4.0: the evolving shapes of manufacturing value chains. IEEE Eng. Manag. Rev. 47, 45–51. https://doi.org/10.1109/EMR.2019.2900652.

Das, M., Jana, D.K., Alam, S., 2025. Strategic product launch and pricing: maximizing profitability in a dynamic consumer market. In: Roy, P.K., Cao, X., Li, X., Bhattacharya, A. (Eds.). Springer Nature Singapore, Singapore, pp. 353–367.

Denning, S., Mckinney, J.R.E., Shao, L., 2016. The evolution of gift cards in secondary markets and money services. J. Int. Finance Stud. 16, 27–32. https://doi.org/10.18374/JIFS-16-2.4.

Duan, Y., Liu, P., Feng, Y., 2022. Pricing strategies of two-sided platforms considering privacy concerns. J. Retail. Consum. Serv. 64, 102781. https://doi.org/10.1016/j.jretconser.2021.102781.

Forbes, 2023. Why some manufacturers are reluctant to join retailers' digital twin revolution. https://www.forbes.com/sites/forbestechcouncil/2023/04/12/why-some-manufacturers-are-reluctant-to-join-retailers-digital-twin-revolution/. (Accessed 5 July 2025).

Grieves, M., 2015. Digital twin: manufacturing excellence through virtual factory replication. https://www.researchgate.net/publication/275211047.

Howard, J., Sheth, J., 1969. The theory of buyer behavior. J. Am. Stat. Assoc. 331, 1406–1407. https://doi.org/10.2307/2284311.

Hu, S., Zhu, S.X., Fu, K., 2023. Optimal trade-in and refurbishment strategies for durable goods. Eur. J. Oper. Res. 309, 133–151. https://doi.org/10.1016/j.ejor.2023.01.032.

Huang, S.H., Wang, G.X., Lei, D., Yan, Y., 2022. Toward digital validation for rapid product development based on digital twin: a framework. Int. J. Adv. Manuf. Technol. 119, 2509–2523. https://doi.org/10.1007/s00170-021-08475-4.

IBM, 2021. What is a digital twin? https://www.ibm.com/think/topics/what-is-a-digital-twin. (Accessed 17 April 2025).

Jia, W.J., Wang, W., Zhang, Z.Z., 2023. From simple digital twin to complex digital twin part II: multi-scenario applications of digital twin shop floor. Adv. Eng. Inform. 56, 101915. https://doi.org/10.1016/j.aei.2023.101915.

Kanyal, R., Patra, S., 2025. Promised hassle time management in online retailing with fraudulent and regretful customers. J. Retail. Consum. Serv. 82, 104100. https://doi.org/10.1016/j.jretconser.2024.104100.

Kelly, H., 2022. Why you need digital twins in your ecommerce strategy. https://www.modelry.ai/blog/why-you-need-digital-twins-in-your-ecommerce-strategy. (Accessed 18 April 2025).

Khouja, M., Hammami, R., 2023. Optimizing price, order quantity, and return policy in the presence of consumer opportunistic behavior for online retailers. Eur. J. Oper. Res. 309, 683–703. https://doi.org/10.1016/j.ejor.2023.01.035.

Kokkonen, K., Hannola, L., Rantala, T., Ukko, J., Saunila, M., Rantala, T., 2023. Preconditions and benefits of digital twin-based business ecosystems in manufacturing. Int. J. Comput. Integr. Manuf. 36, 789–806. https://doi.org/10.1080/0951192X.2022.2145022.

Kumar, A., Chakraborty, S., Bala, P.K., 2023. Text mining approach to explore determinants of grocery mobile app satisfaction using online customer reviews. J. Retail. Consum. Serv. 73, 103363. https://doi.org/10.1016/j.jretconser.2023.103363.

Li, Y.L., Tsang, Y.P., Wu, C.H., Lee, C.K.M., 2024. A multi-agent digital twin-enabled decision support system for sustainable and resilient supplier management. Comput. Ind. Eng. 187, 109838. https://doi.org/10.1016/j.cie.2023.109838.

Li, J., Chen, Y., Liao, Y., Shi, V., Zhang, H., 2025a. Managing strategic inventories in a three-echelon supply chain of durable goods. Omega-Int. J. Manag. Sci. 131, 103204. https://doi.org/10.1016/j.omega.2024.103204.

Li, Z., He, P., Xu, H., 2025b. Optimizing cooperation mechanisms for augmented reality (AR) services: balancing product returns, pricing, and customer satisfaction. J. Retail. Consum. Serv. 85, 104263. https://doi.org/10.1016/j.jretconser.2025.104263.

Lim, K., Van Dang, L., Chen, C.H., 2024. Incorporating supply and production digital twins to mitigate demand disruptions in multi-echelon networks. Int. J. Prod. Econ. 273. https://doi.org/10.1016/j.ijpe.2024.109258.

Lin, J.X., Choi, T.M., Kuo, Y.H., 2024. Online retailing operations: is it wise to offer free sample trial and money-back guarantee together? Prod. Oper. Manag. 33, 2158–2176. https://doi.org/10.1177/10591478241268603.

Liu, H., Zhang, P.L., Cheng, H.Q., Hasan, N., Chiong, R., 2025. Impact of AI-generated virtual streamer interaction on consumer purchase intention: a focus on social presence and perceived value. J. Retail. Consum. Serv. 85, 104290. https://doi.org/10.1016/j.jretconser.2025.104290.

Liu, J.Q., Yuan, R., Feng, S., 2023. Whether to offer return-freight insurance or open a physical showroom: a strategic analysis of an online retailer's decisions. J. Retail. Consum. Serv. 75. https://doi.org/10.1016/j.jretconser.2023.103498.

Liu, Q.S., 2023. The impact of consumer's regret on firms' decisions in a durable good market. J. Econ. 139, 125–157. https://doi.org/10.1007/s00712-023-00819-w.

Marketsandmarkets, 2025. Digital twin market size, share, industry trends report 2030. https://www.marketsandmarkets.com/Market-Reports/digital-twin-market-225269522.html. (Accessed 24 May 2025).

McKinsey & Company, 2024. What is digital-twin technology? https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-digital-twin-technology. (Accessed 17 April 2025).

Meritalk, 2024. Commerce finalizes $285m CHIPS 'digital twins' funding. https://meritalk.com/articles/commerce-finalizes-285m-chips-digital-twins-funding/. (Accessed 11 July 2025).

Meyer, C., Schwager, A., 2007. Understanding customer experience. Harv. Bus. Rev. 2, 116–126.

Olsder, W., Martagan, T., Tang, C.S., 2022. Improving access to rare disease treatments: subsidy, pricing, and payment schemes. Manag. Sci. 69, 5256–5274. https://doi.org/10.1287/mnsc.2022.4634.

Palinski, M., Jusypenko, B., Hardy, W., 2025. Behind the screens. Privacy and advertising preferences in VoD -the role of privacy concerns, persuasion knowledge, and experience. J. Retail. Consum. Serv. 84, 104233. https://doi.org/10.1016/j.jretconser.2025.104233.

Pantano, E., Serravalle, F., Priporas, C.V., 2024. The form of AI-driven luxury: how generative AI (GAI) and large language models (LLMs) are transforming the creative process. J. Mark. Manag. 40, 1771–1790. https://doi.org/10.1080/0267257X.2024.2436096.

Pei, F., Xia, X.D., Qian, X.F., Yan, A., 2025. Extended warranty strategy analysis for online platform marketplace considering product reliability transparency. Comput. Ind. Eng. 199, 110642. https://doi.org/10.1016/j.cie.2024.110642.

Rahman, S.M., Chowdhury, N.H., Bowden, J., Carlson, J., 2025. Metaverse platform attributes and customer experience measurement. J. Retail. Consum. Serv. 83, 104159. https://doi.org/10.1016/j.jretconser.2024.104159.

Risingmax, 2024. Digital twin development cost - 2024. https://risingmax.com/blog/digital-twin-development-cost. (Accessed 1 May 2025).

Rokonuzzaman, M., Iyer, P., Harun, A., 2021. Return policy, no joke: an investigation into the impact of a retailer's return policy on consumers' decision making. J. Retail. Consum. Serv. 59, 102346. https://doi.org/10.1016/j.jretconser.2020.102346.

Sarkar, B., Amankou, K., Sarkar, M., Seo, Y.W., 2024. Online, offline, and buy-online-pick-up-in-store retail strategy under a dual-channel advertisement driven demand. J. Retail. Consum. Serv. 81, 103979. https://doi.org/10.1016/j.jretconser.2024.103979.

Shi, H.Y., Liu, Y.C., Petruzzi, N.C., 2013. Consumer heterogeneity, product quality, and distribution channels. Manag. Sci. 59, 1162–1176. https://doi.org/10.1287/mnsc.1120.1604.

Shulman, J.D., Coughlan, A.T., Savaskan, R.C., 2009. Optimal restocking fees and information provision in an integrated demand-supply model of product returns. Manuf. Serv. Oper. Manag. 11, 577–594. https://doi.org/10.1287/msom.1090.0256.

Siqueira, J.R., ter Horst, E, Molina, G., Losada, M., Mateus, M.A., 2020. A Bayesian examination of the relationship of internal and external touchpoints in the customer experience process across various service environments. J. Retail. Consum. Serv. 53, 102009. https://doi.org/10.1016/j.jretconser.2019.102009.

Sun, X.H., Zhang, F.L., Wang, J.J., Yang, Z.B., Huang, Z.G., Xue, R.J., 2025. Digital twin for smart manufacturing equipment: modeling and applications. Int. J. Adv. Manuf. Technol. 137, 4929–4946. https://doi.org/10.1007/s00170-025-15468-0.

Tao, R., Lan, Y., Zhao, R., Gao, R., 2025. Product line extensions and distribution channels in pharmaceutical supply chain. Eur. J. Oper. Res. 323, 490–503. https://doi.org/10.1016/j.ejor.2024.12.013.

Thomas, L.M., Dillenbeck, M.S., 2004. Best used by expiration date. Mark. Manag. 13, 53–55.

Van Doorn, J., Lemon, K., Mittal, V., Nass, S., Pick, D., Pirner, P., Verhoef, P., 2010. Customer engagement behavior: theoretical foundations and research directions. J. Serv. Res. 3, 253–266. https://doi.org/10.1177/1094670510375599.

Wan, X., Li, D., Chen, J., Lei, Y.Q., 2020. Managing customer returns strategy with the option of selling returned products. Int. J. Prod. Econ. 230. https://doi.org/10.1016/j.ijpe.2020.107794.

Wang, P., Li, K.Y., Du, Q.L., Wang, J.Q., 2024. Customer experience in AI-enabled products: scale development and validation. J. Retail. Consum. Serv. 76, 103578. https://doi.org/10.1016/j.jretconser.2023.103578.

Xie, Y.G., Liang, C.Y., Zhou, P.Y., Jiang, L., 2024. Exploring the influence mechanism of chatbot-expressed humor on service satisfaction in online customer service. J. Retail. Consum. Serv. 76, 103599. https://doi.org/10.1016/j.jretconser.2023.103599.

Xu, S.Y., Tang, H.J., Huang, Y.X., 2023. Inventory competition and quality improvement decisions in dual-channel supply chains with data-driven marketing. Comput. Ind. Eng. 183, 109452. https://doi.org/10.1016/j.cie.2023.109452.

Yang, J., Li, K.W., Huang, J., 2023. Manufacturer encroachment with a new product under network externalities. Int. J. Prod. Econ. 263, 108954. https://doi.org/10.1016/j.ijpe.2023.108954.

Yin, S., Ray, S., Gurnani, H., Animesh, A., 2010. Durable products with multiple used goods markets: product upgrade and retail pricing implications. Mark. Sci. 29, 540–560. https://doi.org/10.1287/mksc.1090.0545.

Zalando, 2024. Zalando enhances its virtual fitting room by enabling customers to create a 3D avatar with their body measurements. https://corporate.zalando.com/en/technology/zalando-enhances-its-virtual-fitting-room-enabling-customers-create-3d-avatar-their-body. (Accessed 18 April 2025).

Zhang, C., Tao, F., Qi, Q., Cheng, Y., Cheng, J., Wang, B., Nee, A.Y.C., 2025. Digital twin-based shop-floor reconfiguration design for uncertainty management. Int. J. Prod. Res. 1 (25). https://doi.org/10.1080/00207543.2024.2448605.

Zhang, F., Chen, H., Xiong, Y., Yan, W., Liu, M., 2021. Managing collecting or remarketing channels: different choice for cannibalisation in remanufacturing outsourcing. Int. J. Prod. Res. 59, 5944–5959. https://doi.org/10.1080/00207543.2020.1797205.

Zhao, C., Wang, X., Xiao, Y., Sheng, J., 2022. Effects of online reviews and competition on quality and pricing strategies. Prod. Oper. Manag. 31, 3840–3858. https://doi.org/10.1111/poms.13791.

Zhao, J.J., Liu, Q., Lee, M.K., Qi, G.Q., Liu, Y.F., 2024. Consumers' usage of errand delivery services: the effects of service quality and consumer perception. J. Retail. Consum. Serv. 81. https://doi.org/10.1016/j.jretconser.2024.104048.