Return to sender? Technological applications to mitigate e-commerce returns

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SafeShops.be
Confidence in online shopping

Returns in e-commerce: an economic and environmental problem driven by uncertainty

Online shopping is convenient for consumers, but challenging at the same time. The inability to closely inspect or touch and feel products before purchase limits the amount of product information available. As such, it increases the uncertainty or risk (De et al., 2013). Labelled in literature as a "market with imperfect information", following Akerlof (1970), the lens of information asymmetry has been applied to study e-commerce returns (Hong & Pavlou, 2014). Product uncertainty comprises two dimensions: quality uncertainty, or the degree to which consumers cannot assess products' attributes, and fit uncertainty, or the degree to which consumers cannot assess whether these attributes match their preferences (Hong & Pavlou, 2014; Sahoo et al., 2018). Examples for fit uncertainty are listed in Wang et al. (2016). For clothing: size, cut and shape; for shoes: width, arch support and flexibility; for hotels: noise levels of rooms and proximity to resources. Using consumer data of Chinese marketplace Taobao and international auction platform eBay, Hong and Pavlou (2014) found that fit uncertainty has a more influential effect on product returns than quality uncertainty.

Logistics and product-related risks that occur between product purchase and reception can influence returns as well (Ahsan & Rahman, 2021). Examples include improper billing, wrong product delivery or product damage. Yet, product defects are not even among the top three reasons for returns of online purchases, reported the Wall Street Journal in 2008 (Lawton, 2008). Contrary, McKinsey research in the United States found that 70% of returns are caused by poor fit or style (Ader et al., 2021). Fashion and footwear are most vulnerable to returns following product uncertainty. As Nestler et al. (2021) point out, they suffer from significant sizing variations, due to different sizing systems (Alpha, Numeric, Confection); uneven definition of size systems (S, M, L for garments); country conventions (EU, FR, IT, UK); different specifications for the same size according to the brand; different ways of converting a local size system to another; and "vanity sizing" in which brands deliberately adapt their nominal sizes to target specific consumer segments (Nestler et al., 2021). For example, the catalogue size to physical size convention for Reebok is: 6 = 15cm, 7 = 17cm, 8 = 21cm, while that for Nike is: 6 = 16cm, 7 = 18cm, 8 = 22cm (Sembium et al., 2017).

Consequently, consumers either hesitate to place online orders or adopt strategies for reducing uncertainty. “Bracketing” is one such strategy, i.e., ordering multiple sizes or colours of the same article and returning those that did not match their criteria (Nestler et al., 2021). Pei and Paswan (2018) differentiate between legitimate and opportunistic return behaviour. Legitimate reasons include defects, fit issues and change of mind, while opportunistic reasons include returns after using the products for a specific event, also called “wardrobing”. Walsh et al. (2014) found that most online retailers have return rates of more than 50%, although specialist retailers tend to have lower return rates than generalist retailers. Book, music and video retailers (less than 5%) and electronics retailers (less than 10%) report low return rates (Walsh et al., 2014). A McKinsey Returns Management Survey in the United States noted a 25% return rate for clothing, compared to 20% overall (Ader et al., 2021).

In interpreting return rates, it is important to note that companies and researchers typically employ one of three calculation methods (El Kihal et al., 2021). These methods are based on number of returned items; returned items’ revenue; or returned items’ profit contribution. El Kihal et al. (2021) find that return rates calculated via these methods differ on average by 24.3%, complicating comparisons. In contrast, the research finds that return rates develop similarly over time, allowing for meaningful time-series comparisons, regardless of the method. Over the past years, e-commerce returns have been growing significantly, reaching up to 50% increase year over year for certain categories (Nestler et al., 2021). Throughout the pandemic, returns increased along with online purchases (Ahsan & Rahman, 2021).

Product returns are associated with high costs, estimates vary by context and product category. In general, returns processing is found twice as expensive compared to delivery (Jack et al., 2019; Wallenburg et al., 2021). Every return costs 10% to 15% of the ordered products on average (Walsh & Möhring, 2017). For shoes with a prime cost of €30 and an overall return rate of 28%, Gustafsson et al. (2021) established a return cost of 17% of the prime cost. For this, they include costs associated with product handling; tied-up capital; inventory holding; transportation; and order-picking. Jack et al. (2019) argue, however, that the size or cost of items has little impact on the cost of returns. This is logical enough, as the number of staff members required and the amount of infrastructure such as cages, transport and space for pallets and boxes remains roughly the same regardless of the nature of items returned (Jack et al., 2019). The researchers point out the exception of very large items.

Jack et al. (2019) developed a cost calculator for returns of online retailers, considering information on sales; returns; and resales, as well as cost of sales; transaction costs including postage and packing; rate of returns; operation and net margin; number of items shipped from online sales; and average wages. Applying the model to a single item, i.e., a grey cardigan that costs €29 and sells for €89, they find a maximum return rate of 66% before the item fails to produce any contribution to net profit. For a typical online consumer, the maximum return rate before failing to produce any contribution to profit is 77%. The researchers conclude as well that even very small changes to the rate of return can improve profits (Jack et al., 2019). In agreement, Nick Robertson, the chief executive officer of online fashion retailer ASOS said a 1% fall in returns would immediately add 10 million pounds to the company's bottom line (Thomasson, 2013). At least six people are involved in the returns process (Cullinane et al., 2017). Less than half of returns are resold at full price (Cantini et al., 2021; Frei et al., 2019).

Frei et al. (2022) identify seven types of waste involved in product returns, i.e., over-processing of returned goods; inventory costs of returned goods; unnecessary transportation; unnecessary motion of people dealing with returns; delays due to badly integrated processes; defects of returned goods; and use of space by returned goods. As such, returns also severely impact the environment (Nestler et al., 2021). Unfortunately, unlike economic impacts, literature does not present detailed assessments of the environmental impacts of e-commerce returns. According to one estimate, returns in the United States alone create 5 billion pounds of landfill waste and 15 million tonnes of carbon emissions annually (Schiffer, 2019). More sustainable ways to manage returns can contribute to three of the United Nations Sustainable Development Goals, namely industries, innovation and infrastructure; sustainable cities and communities; and responsible production and consumption (Frei et al., 2019).

Most research on preventing e-commerce returns has focused on return policies. These policies can be classified as being lenient or restrictive along five dimensions: **time leniency** (e.g., 60 day vs. 30 day return policy), **monetary leniency** (e.g., offering 100% money back vs. 80% money back), **effort leniency** (e.g., no forms required vs. forms required), **scope leniency** (e.g., accepting returns on sale items vs. not), and **exchange leniency** (e.g., cash back vs. store credit) (Janakiraman et al., 2016). In the European Union, online retailers have to offer a return period of fourteen days to consumers (The Economist, 2013). Lenient return policies have thus become standard practice. They improve reputation, engagement, revenue, purchase rate, experience and repeat buying behaviour among consumers (Kedia et al., 2019). Bower and Maxham III (2012) found that customers who paid for their return decreased their post-return spending at a retailer 75% to 100% by the end of two years, while free returns resulted in post-return spending that was 158% to 457% of pre-return spending.

Nonetheless, the promise of free and easy returns also inevitably comes with high return rates (Kedia et al., 2019). "Product returns are, therefore, a conundrum, expensive on their own but less so than backfired attempts at avoiding them, which lead to unhappy customers taking their business elsewhere", summarise Wallenburg et al. (2021). Tackling this conundrum through meta-analysis, Janakiraman et al. (2016) observe a more pronounced increase in purchases stemming from lenient return policies than for returns. This suggests that return policies do in fact benefit retailers. Yet, they stress that leniency factors have differential effects on purchase and return. Specifically, both money leniency and effort leniency increase purchases to a greater extent than the other return policy factors. Contrary, leniency on time and exchange reduces returns more than other return policy factors, while leniency on scope increases returns. To curb returns, retailers are suggested to offer a restrictive return policy in terms of products eligibility for return, in combination with longer deadlines and accommodating exchange conditions (Janakiraman et al., 2016). Retailers such as Amazon and Zara have recently begun to tighten their policies to reduce return rates (Ryan, 2022; Schiffer, 2019).

Research on the causes linked to quality and fit uncertainty is still limited, but interest is growing. Companies and researchers believe that providing appropriate and precise information on products, potentially supported by technology (Cullinane et al., 2019), can prevent unnecessary returns (Leeuw et al., 2016; Walsh et al., 2014). It is reflected as well by venture capitalists' investments in companies that aim to reduce product uncertainties with internet-enabled tools (Cosgrove, 2022). Online retailers, such as Asos and Zalando, are hiring data analysts whose sole focus is to reduce returns (Schiffer, 2019). They improve information, production and delivery of products. These initiatives support mitigation, the first activity of the reverse logistics process that deals with returns (Cullinane et al., 2017). It constitutes the main topic of this report. In what follows, we discuss the successive reverse logistics activities (i.e., mitigation, gatekeeping, collection, sorting, disposal), introduce various mitigation instruments (i.e., monetary, procedural, customer-based) and summarise the research to date on the effectiveness of customer-based instruments to mitigate returns. An efficient returns process is essential in retailers' transition from a linear to a circular economy, which requires a range of initiatives and improvements. They are, however, out of the scope of this report, that is focused on commercial returns of online ordered products, after delivery but before usage by consumers.

The returns process: reverse logistics through five activities

In the research on reverse logistics for e-commerce returns, four essential activities are suggested: i.e., gatekeeping, collection, sorting and disposal. Cullinane et al. (2017) introduce a fifth one, mitigation. It constitutes all initiatives designed to reduce the return rate. **Mitigation** precedes all other activities in the reverse logistics process and is the main topic of this report. Therefore, this section concentrates on the four remaining activities. They are summarised in Figure 1, based on Frei et al. (2022). The second activity, **gatekeeping**, revolves around retailers' decision to accept a product to enter the returns process and the criteria determined to that end (Cullinane et al., 2017). Some researchers mention barriers to prevent consumers from returning (Leeuw et al., 2016; Wallenburg et al., 2021), although not all retailers set those up. The third activity, **collection**, is determined by the ways in which returns reach retailers. Different configurations are possible. They include third party couriers (e.g., home collection, collection and drop-off points), partner stores and own stores. Some retailers experiment with returns during delivery. It implies consumers to immediately fit their purchase after delivery, while the delivery person awaits their return decision at the door (Leeuw et al., 2016).

The fourth activity, **sorting**, involves inspection of each returned product individually. Sorting activities can be organised centralised, at the returns centre, or decentralised, at the place of collection (Leeuw et al., 2016). Retailers can choose to rely on specialised third party providers or manage the activities themselves (Cullinane et al., 2019). Essential at this stage is to record return codes, use these records to gain insights and improve production and delivery processes accordingly (Frei et al., 2022). The fifth and final activity is **disposal**, which determines where returned products end up. It has three basic outcomes: the product is fit for resale and can be placed again on shelves or into stock; the product can be made fit for resale after rework; or the product is not fit for resale. When products are not resold, they are discarded, recycled or disposed of in alternative channels. Such alternatives include manufacturers, charities, 'jobbers' and auctions (i.e., physical or online). Many retailers now have their own outlet or second-hand channel, where returns can be sold. Increasingly, software solutions are being developed to support retailers in their disposal activities (Frei et al., 2020).

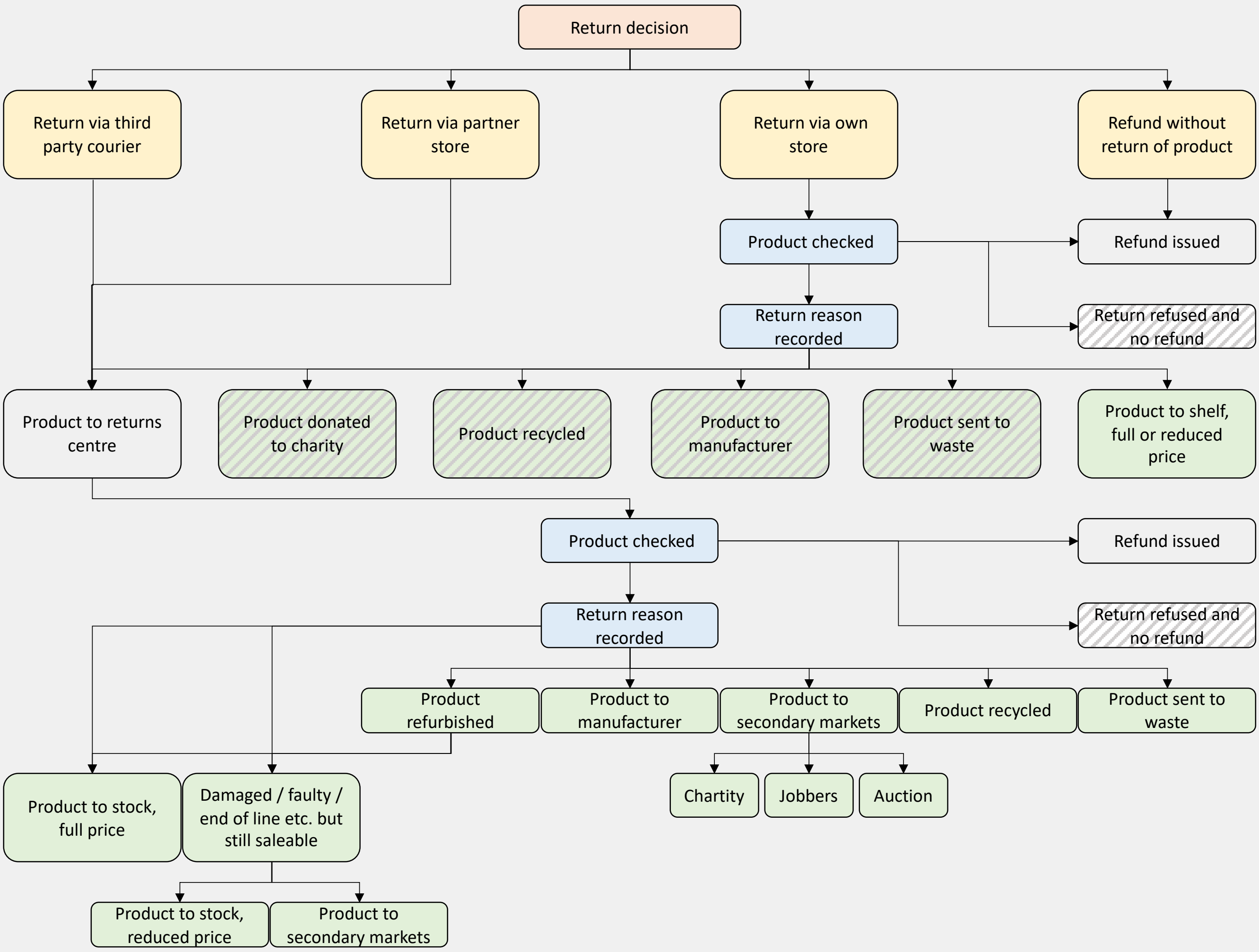

Figure 1. Generic process map of e-commerce returns, based on Frei et al. (2022). Gatekeeping activities in orange, collection activities in yellow, sorting activities in blue, disposal activities in green, hatched boxes represent minor activities.

Retailers generally have limited control over returns. Despite forecasting based on previous returns (Frei et al., 2022), it remains difficult to predict which products will be returned when, in what quantity and in what condition. Moreover, products often come back in non-standard packaging (Ader et al., 2021). These circumstances lie at the basis of a reverse logistics process that is fragmented, subscale and overall inefficient. In response, retailers are advised to streamline processes (Frei et al., 2022), collect and employ consumer data on their products and services (Frei et al., 2020); invest in optimised systems and technologies; assign accountability for returns to a specific unit or department (Ader et al., 2021); and designate a dedicated returns director (Frei et al., 2022).

Monetary, procedural and customer-based instruments to mitigate returns

Based on research by Walsh et al. (2014) and Walsh and Möhring (2017), Table 1 presents three categories of preventive instruments to e-commerce returns. **Monetary instruments** provide financial incentives to consumers to keep the ordered products or reduce the risk of purchase (Shulman et al., 2010). **Procedural instruments** affect return likelihood in the post-order phase by complicating returns or improving shipping (Walsh et al., 2014). **Customer-based instruments** influence consumers before and during the order process by communicating information (Walsh et al., 2014). The table was complemented by examples from recent articles. For procedural instruments, Neerman (2019) describes oversized tags to prevent wardrobing behaviour, used by Zalando for more expensive items. Retourvignet is a similar initiative offering self-adhesive stickers, hang tags, seals and leaflets to prevent consumers from using products, prior to returning them for a full refund. These initiatives are summarised under the anti-wardrobing label. For customer-based instruments, Ahsan and Rahman (2021) refer to social media and augmented reality; from El Kihal and Shehu (2022) who mention detailed product descriptions and chatbots; and from Yang and Xiong (2019) who discuss three-dimensional visualisation and mix-and-match of product images. Ahsan and Rahman (2021) also point out that big data, machine learning, artificial intelligence and blockchain are important technologies to be harnessed to mitigate returns. In an article on The New Retail Reality, Wasserman (2021) uses the term "extended reality" to comprehend augmented reality, virtual reality and 3D technology.

Table 1. Overview of mitigation instruments, based on Walsh et al. (2014) and Walsh and Möhring (2017) and complemented by the author. Instruments in bold are discussed in the next paragraphs.

Monetary instruments	Procedural instruments	Customer-based instruments
Restocking fee	Safety packaging	**Virtual try-on**
Money-back guarantee	Cycle-time optimisation	Augmented reality
Discount (for not returning)	Return advice	Avatar
Gift (for not returning)	Different return channels	**Customer review**
Prepayment	Contacting serial returners	**Product advice**
Restriction of order volume	Banning serial returners	Height/size chart
Shipping cost	Not providing return label	Detailed product description
	Final package inspection	Product-availability information
	Personalised package extras	Customer hotline
	Hassle cost	**Alternative product visualisation**
	Anti-wardrobing labels	3D product visualisation
		Products mix-and-match
		Zoom technology
		Social media
		Chatbots
		Visual packaging

While the majority of research has focused on monetary instruments, fewer studies have examined instruments that are procedural or customer-based (Walsh & Möhring, 2017). On the latter, De et al. (2013) point out that different technologies provide different types of information, which potentially influence product returns differently in turn. Moreover, marketing instruments are informative as well. They can therefore influence returns just as much, although they are not designed for that purpose. El Kihal and Shehu (2022) investigate newsletters, catalogues, coupons, free shipping, paid search, affiliate advertising and image advertising. They find that marketing instruments either have no impact or increase returns substantially. The researchers advocate to take returns into account as key indicator when evaluating and deciding on marketing instruments (El Kihal & Shehu, 2022).

Some researchers have studied mitigation instruments as a proactive action when return probability is high (Kedia et al., 2019; Li et al., 2018). Examples include popping up chatbots to provide guidance or offering discount coupons for not returning. Such initiatives require to generate probability predictions in real-time and at check-out, as well as thorough knowledge of the effectiveness of various instruments. As a reactive action, Tran (2022) explores customer profiling technologies to classify legitimate returners from opportunistic ones. Based on records of previous transactions and consumers' personal identification, statistical models decide whether or not to accept a return.

Customer-based instruments to mitigate returns: a review on effectiveness

From the customer-based instruments to prevent returns, as listed in Table 1, only a few have been studied for effectiveness. Literature covers the impact of virtual try-on, customer reviews, product advice, alternative product photos, zoom technology and visual packaging on e-commerce returns. Customer reviews received most attention from researchers so far, while product advice showed most diversity in approaches. The results are summarised in the next paragraphs.

Some definitions

Virtual try-on enables consumers to select and/or personalise three-dimensional virtual models, to mirror actual looks and fit products on the virtual self (Yang & Xiong, 2019).

Augmented reality enables consumers to add virtual data or images to the real world, to interact with virtual products in a real-world environment (Berman & Pollack, 2021).

Avatars are standard customer models that provide product information (Gustafsson et al., 2021; Walsh et al., 2014).

Customer reviews are virtual sources of opinions about and experiences with products, available on both retail and non-retail websites, that provide product information (Walsh & Möhring, 2017).

Customer hotlines are service assistants, that consumers can call in case of product questions (Frei et al., 2022).

Alternative product photos allow consumers to look at products or models wearing products from different angles or in different settings (De et al., 2013).

3D product visualisations use three-dimensional computer graphics instead of two-dimensional images, they allow consumers to simulate use, view colour options and manipulate the environment of products (Wodehouse & Abba, 2016).

Products mix-and-match allow consumers to virtually select and view several products together (Yang & Xiong, 2019).

Zoom technology allows consumers to inspect finer product details (De et al., 2013).

Chatbots are virtual assistants using artificial intelligence and machine learning, that consumers can contact in case of product questions (Rossmann et al., 2020).

Visual packaging allows to communicate information to consumers, more than merely protect the product (Wallenburg et al., 2021)

Virtual try-on

Yang and Xiong (2019) report the findings of two studies testing virtual fitting rooms. They analyse data from field experiments, in collaboration with two women's clothing retailers in China. In the first study, consumers were able to try on clothes on a virtual model, either standardised or personalised using their own photos and body measurements. Considering the retailer's average return rate of 8.6%, the researchers indicate that the launch of the virtual fitting room induced a reduction of 56.8% in return rate. The data did however not allow to differentiate between consumers using a personalised or non-personalised virtual model. Therefore, in the second study, consumers were provided a non-personalised standardised virtual model only, in a first phase, followed by a personalised virtual model only, in a second phase. Consumers who entered the virtual fitting rooms were asked to scan their full body to create a personalised avatar that matched her face and body. Relative to an average return rate of 6.5%, the introduction of non-personalised and personalised virtual fitting rooms reduced return rates by 29.4% and 54.1% respectively (Yang & Xiong, 2019). Figure 2 provides an example of a virtual fitting room as provided by Zeekit's technology.

Figure 2. Zeekit's technology to dress anyone virtually in any item of clothing found online.

This study confirmed the hypothesis that virtual try-on technology provides consumers with a more realistic view of how clothing actually looks on them, typically not the same as on models from promotional photos or other product visualisations. It alleviates concerns raised in the consumer focus group discussions of Kim and Forsythe (2008), in which virtual fitting rooms were considered fun and useful for promoting multiple sales, as consumers enjoy putting various items together on the virtual model, but not suitable to provide reliable information on clothing's actual fit. Still, studies highlight the technological challenges in realistically rendering clothing for virtual try-on, mostly conducted in computer graphics research (Guan et al., 2012; Han et al., 2018; Hsiao & Grauman, 2020) (Figure 3).

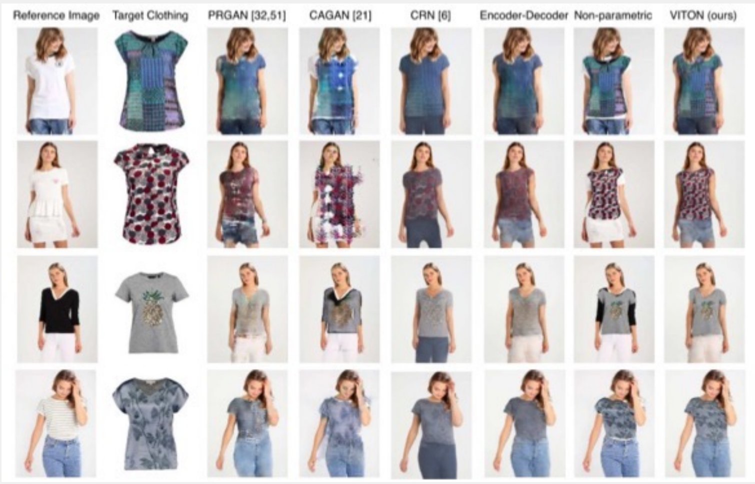

Figure 3. Different methods to effectively render the target clothing on to a person (Han et al., 2018).

Virtual try-on providers:

FIT:MATCH

Zeekit

Fit Analytics

True Fit

WAIR

triMirror

Lalaland

Customer review

Customer reviews are the most researched instrument in literature to mitigate returns. Mostly, they consist of a numeric rating that primarily addresses product quality and a text that provides information on product fit (Sahoo et al., 2018). Based on data from Taobao and eBay, Hong and Pavlou (2014) examined the effect of product forums on return behaviour. They focus specifically on experience goods, as opposed to search goods, as their value cannot be ascertained before purchase. Examples of experience goods include clothes, wines and cosmetics. The researchers found that the use of product forums moderates the effect of experience goods on uncertainty, enabling consumers to better match their personal preferences with product attributes (Hong & Pavlou, 2014). Walsh and Möhring (2017) examined the effect of reviews on returns as well, based on field experiments with a premium clothing manufacturer and retailer headquartered in Germany. Extending the previous findings, their study demonstrates a decreasing return rate of 49%, highlighting the risk-reducing and spending-increasing potential of customer reviews in an online shopping setting.

Taking a closer look at customer review characteristics, Minnema et al. (2016) study return decisions with data from an online retailer in the electronics and furniture product category. They examine three characteristics in particular: **volume** (i.e., number); **variance** (i.e., dissensus); and **valence** (i.e., overall evaluation) of customer reviews. Although the researchers did not find a significant effect of review volume on returns in general, they did determine that a higher review volume creates a lower return probability in the furniture category. Similarly, although review variance did not produce significant results in general, a higher review variance does generate a lower return probability for furniture. When it comes to review valence, the study showed that a point increase in review valence increases the return probability by 11.2% (electronics) and 10.3% (furniture). This means that if the set of reviews available at the moment of purchase is more positive than the long-term average, return probability increases. As such, a temporary high rating inflates expectations about the product, that are ultimately not met. Contrary, a higher average valence over the product life cycle, exhibits a lower return probability in the electronics category. In this way, the findings indicate that review ratings also reflect product quality. Minnema et al. (2016) add that the effect of review valence on return decisions is stronger for cheaper products, while reviews in general are particularly effective for novice consumers.

Investigating customer review characteristics as well, Sahoo et al. (2018) analyse data from a North-American specialty retailer. Throughout three brands, the retailer's assortment covers clothing, accessories and furniture. On review volume, the researchers find that the probability of return decreases by 1%, for 10 additional reviews. This finding is in line with conclusions of Minnema et al. (2016) for furniture. Consumers buy more substitutes when fewer reviews are available, increasing their return probability. On review valence, the researchers establish that the time-varying average rating has a negative impact on the probability of return. Thus, products with higher ratings are less likely to be returned than products with lower ratings. However, the probability of return increases when the average rating is higher than justified. These findings are again in agreement with Minnema et al. (2016). Sahoo et al. (2018) also studied the type of product review that has most potential for reducing returns. Reviews voted by consumers as "helpful", decrease product returns: a 10% increase in "helpful" reviews is associated with a 0.4% decrease in return probability. Contrary, reviews from retailer-identified "top reviewers", typically determined based on number of contributions, generate the opposite effect. A 10% increase in reviews from "top reviewers" is associated with a 0.2% increase in return probability. As such, the study shows that the availability of more reviews and the presence of more "helpful" reviews, provide better information and lead to fewer product returns.

Using data from a European online fashion retailer, Lohse et al. (2017) join conclusions of Minnema et al. (2016) and Sahoo et al. (2018) regarding review valence. They find that positive reviews help to decrease the number of returns. The study contributes by differentiating between devices, revealing a weaker impact of customers reviews in the mobile than in the desktop channel. According to the researchers, consumers have to invest more time and effort to lower their level of product uncertainty in the same way as they can on desktop computers (Wang et al., 2015). They also see a significant impact of product involvement, whereby customer reviews are stronger for high-involvement products. Finally, Wang et al. (2016) perform field experiments in the clothing category. The researchers nuance conclusions of Lohse et al. (2017), by indicating that consumers can benefit from negative customer reviews as well. They demonstrate the importance of the type of information shared in customer reviews and argue that expressions of both **valence and reference** are essential (Figure 4). Valence reflects consumers' subjective evaluations and can be specified as true to size, runs large or runs small. Reference is defined as a consumers' self-description and can include their body size. The researchers estimate that an additional 10% increase in the availability of both valence and reference information in reviews, leads to a 1.6% decrease in return rates. Reviews that include valence information only are effective, if a sufficient number of reviewers indicate consistent opinions.

Figure 4. Fit-related information in an actual online review (Wang et al., 2016).

These studies confirm that customer reviews complement retailer-provided data and reduce return rates, particularly when unbiased, rich in subjective and reference information as well as fairly consistent. As such, they can outweigh the costs of implementing and maintaining an online review system and the challenges in managing fake reviews and unauthorized content (Walsh & Möhring, 2017). Minnema et al. (2016) recommend online retailers to not only encourage very satisfied consumers to write reviews, while Sahoo et al. (2018) caution to reward consumers who contribute a significant amount of reviews and suggest encouraging other consumers to do so as well.

Product advice

Online retailers try to support consumers by providing advice in passive or active forms (Hajjar et al., 2021). Three studies investigated the impact of size recommendation instruments, either on product returns or on advice accuracy. The first is called "SizeFlags" and is developed within Zalando (Nestler et al., 2021) (Figure 5); the second is titled "CompareDimensions" and is tested on Amazon (Cantini et al., 2021); and the third is embedded in Amazon (Sembium et al., 2017). Size recommendations are challenging due to data sparseness, "cold starts" in which products have no past purchases and consumers buying for multiple personas, within their households or as gifts (Sembium et al., 2017).

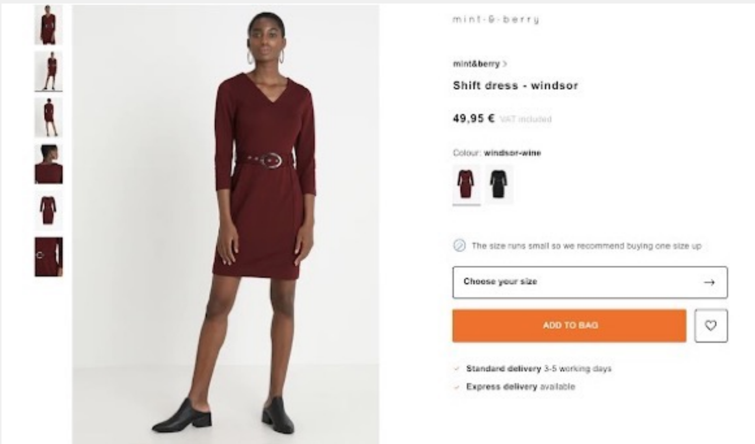

Figure 5. Zalando's SizeFlags technology to flag when items are likely too small or too big.

SizeFlags applies to clothing and brings out indications when items are likely too small or too big (Nestler et al., 2021). As such, the size flags provide article-specific sizing characteristics, instead of personalised recommendations. To do so, the researchers use return data from past purchases, expert knowledge from fashion models with relatively standard body sizes as well as computer vision techniques. Field experiments on shoes demonstrated a 3.8% reduction in size-related returns, 4.3% for "too small" and 6.6% for "too big" size flags. CompareDimensions allows consumers to understand and evaluate the real dimensions of a product, by adding reference images of items they are more familiar with (Cantini et al., 2021). Applied to a range of products in field experiments, including furniture and electronics, the researchers found 17.5% greater accuracy among consumers using the tool. Focusing on critical products, that are criticised in customer reviews because of their misleading dimensions, average accuracy increased by 24%. The researchers found an improvement of 27% for items smaller than expected and of 11% for products larger than expected. Sembium et al. (2017) provide a novel model for recommending product sizes, based on past product purchases and returns data. Applied on shoe datasets, the researchers demonstrate an improvement of 0.5% in fit transactions, translating into a reduction of the same magnitude in number of returns.

Product advice providers:

- https://comparesizes.com/
- http://pective.com/
- https://phonesized.com/

Alternative product photos

Alternative photos allow consumers to evaluate products from different angles, whereas colour swatch enables them to see products in other available colours (De et al., 2013). Both instruments have been assessed in literature on their ability to reduce returns. Using data from Taobao and eBay, Hong and Pavlou (2014) employ the number of pictures provided for each product listing in their study. They conclude that more visual information reduces uncertainty among consumers and accordingly results in fewer returns. Interestingly, the study by De et al. (2013) contradicts this finding. Analysing data from a women's clothing company, they find that a higher use of alternative photos is associated with more returns. A one unit increase in alternative photo usage by consumers, increases the odds for returning a product by 5%. Explaining these findings, the researchers differentiate between two types of information provided by alternative photo technology: factual and impression-based. In this context, factual information includes rotation, or the ability to see how products look from all sides, assumed helpful for consumers. Impression-based or evaluative information enables contextualisation, or the placement of products in settings to simulate how they can be used, potentially creating unrealistic expectations. Despite providing factual information as well, colour swatch has an insignificant impact on returns, indicating its added value for visualisation is limited.

Building on these findings, De et al. (2013) advise online retailers to carefully consider which material to include in the set of alternative photos. They recommend enabling consumers to post their own pictures of the product, to assist in forming realistic pre-purchase expectations. Considering the findings of both studies, the impact of alternative products photos is determined to a large extent as well by the product category, in which clothing is more sensitive and search goods are less. The potential of alternative product videos is however not yet covered in scientific research.

Zoom technology

Analysing data from a women's clothing company, De et al. (2013) studied the impact of zoom technology on product returns. Zoom allows consumers to inspect finer details of the focal product, including fabric, pattern, print, stitches and small decorative features such as buttons. By investigating the number of times the zoom technology was used by a consumer, the researchers found that a one unit increase in zoom usage is associated with a 7% decrease in the odds for returning. Accordingly, the study confirms the importance of enhancing factual product information, as conveyed by zoom.

Visual packaging

While safety packaging was considered in the original overview by Walsh et al. (2014) and Walsh and Möhring (2017) as a procedural returns-reducing instrument, visual packaging was initially not included. Wallenburg et al. (2021), however, found that too little attention was paid to product presentation at the time of order fulfilment. To the researchers, packaging is not only a functional element that ensures damage-free delivery, but also informs consumers about retailer and product. For online retailers, they argue that packaging may serve as a surrogate for store layout and ambience. The researchers initiated a study in collaboration with an online clothing accessory retailer in Germany, focusing on purchases of handbags only. Following brain scanning studies that showed that consumers are influenced by the way items are presented, with more "premium" product presentation associated with higher evaluations, they introduce two adaptations. First, the semi-premium packaging condition introduces luxurious wrapping paper and a personalized card, while keeping the outer box unchanged. The second, premium packaging condition keeps the upgraded inner packaging, but enhanced the outer box as well. The researchers found that products shipped with premium packaging indicates a 6.6% lower probability of return compared to ordinary utilitarian packaging. A 2.8% decrease in return rates was found using semi-premium packaging. According to the researchers, the added cost of the premium packaging to the retailer was less than 10¢ per shipment. (Wallenburg et al., 2021).

Concluding remarks

Table 2 summarises the findings in research on the effectiveness of customer-based instruments to mitigate returns. From the literature, it appears that some instruments reduce uncertainty among online consumers, leading to lower return rates, while others intensify expectations, leading perhaps to more sales but also to disproportionately more returns (El Kihal & Shehu, 2022). Factual information proved to decrease returns, while impression-based information demonstrated an increasing effect (De et al., 2013). From the overview of customer-based returns-reducing instruments in Table 1, only a few have been studied on their effectiveness in scientific research: virtual try-on, customer review, product advice, alternative product photos, zoom technology and visual packaging. It leaves ample room for further exploring these instruments in different contexts as well as investigating other instruments, including augmented reality (Figure 6), social media and chatbots.

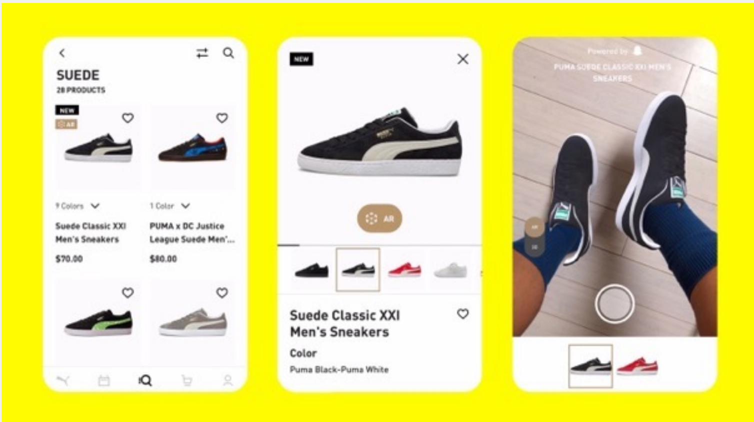

Figure 6. Snapchat's "Dress Up" feature for in-app augmented reality fashion and virtual try-on experiences.

Table 2. Summary of effectiveness of customer-based instruments to mitigate returns. Positive effect in green, negative effect in red.

INSTRUMENT	CATEGORY	CONTEXT	FINDING	REFERENCE
VIRTUAL TRY-ON USING A PERSONALISED OR NON-PERSONALISED VIRTUAL MODEL	Clothing	China	Reduces returns by 56.8%	(Yang & Xiong, 2019)
VIRTUAL TRY-ON USING A NON-PERSONALISED MODEL	Clothing	China	Reduces returns by 29.4%	(Yang & Xiong, 2019)
VIRTUAL TRY-ON USING A PERSONALISED MODEL	Clothing	China	Reduces returns by 54.1%	(Yang & Xiong, 2019)
CUSTOMER REVIEW VIA PRODUCT FORUMS	Clothing, wines and cosmetics	China and USA	Moderates uncertainty	(Hong & Pavlou, 2014)
CUSTOMER REVIEW	Clothing	Germany	Reduces returns by 49%	(Walsh & Möhring, 2017)
CUSTOMER REVIEW VOLUME (I.E., NUMBER)	Furniture	Europe	Higher review volume = lower return probability	(Minnema et al., 2016)
CUSTOMER REVIEW VARIANCE (I.E., DISSENSUS)	Furniture	Europe	Higher review variance = lower return probability	(Minnema et al., 2016)
CUSTOMER REVIEW VALENCE (I.E., OVERALL EVALUATION)	Electronics and furniture	Europe	Higher review valence = higher return probability	(Minnema et al., 2016)
CUSTOMER REVIEW VALENCE (I.E., OVERALL EVALUATION)	Electronics	Europe	Higher average review valence = lower return probability	(Minnema et al., 2016)
CUSTOMER REVIEW VOLUME	Clothing, accessories and furniture	North-America	Higher review volume = lower return probability	(Sahoo et al., 2018)
CUSTOMER REVIEW VALENCE	Clothing, accessories and furniture	North-America	Higher review valence = lower return probability	(Sahoo et al., 2018)
CUSTOMER REVIEW VALENCE	Clothing, accessories and furniture	North-America	Higher review valence than justified = higher return probability	(Sahoo et al., 2018)
CUSTOMER REVIEW VOTED AS "HELPFUL"	Clothing, accessories and furniture	North-America	Higher review volume = lower return probability	(Sahoo et al., 2018)
CUSTOMER REVIEW FROM "TOP REVIEWERS"	Clothing, accessories and furniture	North-America	Higher review volume= higher return probability	(Sahoo et al., 2018)
CUSTOMER REVIEW VALENCE	Clothing	Europe	Higher review valence = lower return probability	(Lohse et al., 2017)
CUSTOMER REVIEW VALENCE AND REFERENCE	Clothing	-	Higher review valence and reference = lower return probability	(Wang et al., 2016)
PRODUCT ADVICE WITH SIZEFLAGS	Clothing	Europe	Reduces returns by 3.8%	(Nestler et al., 2021)
PRODUCT ADVICE WITH COMPAREDIMENSIONS	Furniture and electronics	-	Improves accuracy by 17.5%	(Cantini et al., 2021)
PRODUCT ADVICE WITH RECOMMENDATIONS	Shoes	USA	Improves fit by 0.5%	(Sembium et al., 2017)
ALTERNATIVE PRODUCT VISUALISATION WITH PHOTOS	Clothing, wines and cosmetics	China and USA	Reduces uncertainty	(Hong & Pavlou, 2014)
ALTERNATIVE PRODUCT VISUALISATION WITH PHOTOS	Clothing	-	Higher photo volume = higher return probability	(De et al., 2013)
ALTERNATIVE PRODUCT PHOTOS WITH COLOUR SWATCH	Clothing	-	Insignificant	(De et al., 2013)
ZOOM TECHNOLOGY	Clothing	-	Higher zoom usage = lower return probability	(De et al., 2013)
VISUAL PACKAGING WITH PREMIUM MATERIAL	Handbags	Germany	Reduces returns by 6.6%	(Wallenburg et al., 2021)
VISUAL PACKAGING WITH SEMI-PREMIUM MATERIAL	Handbags	Germany	Reduces returns by 2.8%	(Wallenburg et al., 2021)

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