How to reduce product returns – Should the machine make the offer for partial refunds?

Abstract

As exemplary returns-prevention instrument, partial refunds as a way to motivate customers to keep defective products instead of returning them, are being used by an increasing number of online retailers. However, there is no research-based guidance on how retailers should frame partial refund offers in terms of who decides on the size of the refund and makes the offer—an employee, the company, or a machine. This lack of research may translate into a possibility of failure because online retailers may employ sub-optimal offers. Thus, a better understanding of customer acceptance of human-made vs. machine-made (i.e., algorithmic or artificial intelligence-based) decisions is required. To guide further IS research and suggest ways that online retailers might improve partial refund effectiveness and thereby decrease product return rates, the present research draws on insights on offer sources from extant research. Based on this analysis of past research and equity theory, propositions about how partial refund offers made by humans (vs. the company vs. algorithmic) may influence customers' acceptance of offers are presented. The proposed conceptual foundation can guide online retailers' returns-prevention efforts and research.

Keywords: Algorithmic decision making, artificial intelligence (AI), offer source, partial refund, product returns

Introduction

Assume the following situation: A customer buys a product from an online retailer. After limited (or before the first) usage the customer detects a product defect, which she/he reports to the retailer. To prevent the product from being returned, the online retailer sends an email and offers the customer a partial refund (i.e., a refund of only a fraction of the original price) so that the customer takes responsibility for getting the product repaired. The offer email is typically signed by a customer service agent (e.g., "Jack Smith") or the vendor's 'customer service team' (i.e., the 'company'). The customer then accepts the offer (and keeps the product) or declines it and returns the product to the retailer to get it replaced with a new immaculate product or a full refund. Clearly, it is the retailer's goal to get as many partial refund offers accepted as possible to avoid reverse logistics and the ensuing costs. Figure 1 depicts an example email offering partial refund sent to the customer after she/he submitted a picture of the product defect.

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Dear Mr. XX

Thank you for your message.

Please excuse the problems with your boots. In order to get your boots ready for use again as
quickly as possible, please take the boots to a shoemaker near you and have them carry out
the following work:

#Repair rubber edge

This will cost around $40. Please contact us if the repair costs are higher, otherwise a
refund can only be made over the amount mentioned. The shoemaker will explain to you the
reason for the higher costs.

Then send us a copy of the invoice and your bank details in reply to this email so that we
can refund you. For further questions we are at your disposal at any time.

Many greetings,
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Figure 1. Example email offering partial refund

Although partial refund offers are a potentially useful returns-prevention tool, little is known about the efficacy of partial refund offers depending on the source of the offer. Here source is defined "as the medium by which information is carried and/or the person who authored that information (Gunther et al. 2009, p. 750)". Past research suggests that the source of an offer is relevant because customers associate different levels of social presence with different offer sources. The level of social presence, in turn, determines the likelihood of acceptance of partial refund offers. Specifically, social presence theory suggests that the social presence of another human—whether actual, implied, or imagined—influences people's affective reactions (Herhausen et al. 2020). We thus argue that when customers associate a partial refund offer with low vs. high social presence (because it is perceived to be machine vs. human made), they are more inclined to accept it.

Importantly, in e-commerce practice, online retailers can frame the source of the refund offer as human-made or not. Specifically, an online retailer can present the offer as coming from a human employee (e.g., "Jack Smith") after she/he inspected the product or as the result of an inspection by the 'company' or of an AI (artificial intelligence) based inspection. The latter approach to inspecting defective products is not yet industry standard, but some retailers are already employing AI-based decision making for dealing with (potential) product returns (Janakiraman et al. 2016; Kapner and Ziobro 2021). Whether this approach will become the approach of choice for e-commerce businesses will largely depend on customers' responses to offers made (or said to be made) by AI. However, while there is consensus that AI facilitates process automation (and diminishing costly touchpoints) in e-commerce

(Bawack et al. 2022; Longoni and Cian 2022), little is known about consumer receptivity to AI and AI-based decisions in a product-returns context.

We address this void by theorizing the effect of source of the fault inspection and of the partial refund offer on customer offer acceptance. Literature findings are complemented by qualitative insights based on interviews with five German e-commerce managers. Using insights from the offer sources literature and the interviews, we derive research propositions that provide a starting point for the consideration of differential effects of partial refund offer sources on important customer outcomes. This conceptual piece makes at least three contributions to the IS literature. First, we introduce the notion of customers' 'algorithmic preference' in relation to online retailers' partial refund offers. Second, we theorize that customers faced with a partial refund offer are more likely to accept AI-based to human-made (or company-made) decisions. Third, we develop research propositions that can guide future IS research.

Background and Interview Insights

E-commerce firms are confronted with product returns in unabated numbers; in the U.S. alone more than $66 billion worth of products are returned to vendors (CBRE 2021). In response to this continuing challenge, online retailers explore the efficacy of different approaches to reducing product returns (Sahoo et al. 2018). For example, a growing number of vendors are using AI-supported disposition engines to bring down returns-related costs (Cui et al. 2020). With disposition engines, online retailers' employees can scan an item and follow real-time instructions to determine the most profitable path of the item. Not only does this make a better business decision, it also reduces time and overhead investment (Ray 2020). However, disposition engines are used to optimize decisions for products that are already returned (e.g., decision to sell the product to disposal firm after costs of refurbishing have been assessed); they are not used to prevent the customer from returning (defective) products though. Indeed, most current returns management systems focus on dealing with rather than preventing returned products.

In e-commerce practice, all products that customers return are screened to determine whether they can be resold 'as-is', repaired (and resold), sold to a third party or disposed of altogether (Bijmolt et al. 2021; Wilson et al. 2022). This screening process, also known as 'gatekeeping', takes place after the customer returns a product. However, online retailers may also apply gatekeeping to defective products that the customer intends to return (i.e., before the product is actually returned). In this context, one of our five interview experts, who is co-founder of an online shop that specializes in gifts, emphasized the importance of preventive measures, such as offering partial refunds. The following vignette illustrates the approach his e-commerce business takes: "Our company estimates the average full costs of a product return at €25 (approx. $27). Therefore, handling returned products that are priced below those costs makes no business sense. We rather let the customer keep the product and write off the loss than incur preventable additional costs" (Alexander, 44 years).

Although faulty and "not as described" products make up only 10% of all products returned (Dopson 2021), they result in high handling costs for online retailers. Handling costs, which refer to costs associated with the physical handling of goods (Brijs et al. 2004), come about because faulty products that customers decide to return necessitate costly reverse logistics efforts.

To limit returns-related costs (e.g., shipping costs), some online retailers have begun to use a two-step approach for dealing with faulty products: 1) They ask customers to describe the product fault and to email a picture of the 'problem' (e.g., picture of burst stitching of the sole of a boot, jammed zipper of a coat). The pictures of the faulty products then undergo either automated inspection (whereby by the picture of the faulty product is compared to pictures from a picture database) or human visual inspection (Guo et al. 2020). According to one industry expert, the latter approach "is what most online retailers (that offer partial refunds) employ" (Mike, 42 years). 2) Based on the customer's emailed picture and the inspection, the online retailer then determines the extent of the product fault and offers a partial refund to the aggrieved customer; the refund amount is typically based on what it would cost the customer to get the problem fixed (e.g., to get a cobbler to stitch the sole to the upper part of the boot or a tailor to put in a new zipper). If the customer accepts the partial refund she/he keeps the product; the vendor does not have to take the faulty product back and the case is closed. If customers decline the partial refund, they will return the product to the vendor in order to get a full refund or a new replacement product (see Figure 2). Obviously, it is in the online retailer's interest that the customer accepts the partial refund and keeps the faulty product. However, firm measures to increase customer retention of the faulty product has received little research attention.

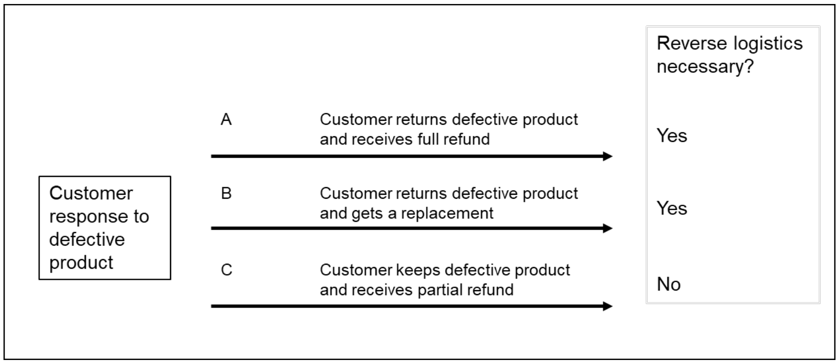

Figure 2. Defective products and reverse logistics implications

More specifically, while the use of partial refunds in relation to potential product returns (specifically, as a means to discourage product returns) could become common practice within the e-commerce industry, no research has been conducted to date to determine at what percentage of the original price customers find the online retailer's proposition acceptable. Economic theory would suggest that offer acceptance is strongly correlated with the size of the partial refund offer. However, it would not be financially prudent for retailers to simply maximize the size of the refund offers. On the contrary, it is in their interest to prevent customers from returning products at the lowest possible costs. Framing the source of the refund offer could be a way to keep those costs down.

However, past research has not empirically examined whether customers' willingness to accept partial refunds depends on who conducts the product inspection and who determines the size of the partial refund. We would argue that this is an important oversight because the source (and size) of the partial refund offer likely differentially impact key customer outcomes, such as service recovery satisfaction, trust and repurchase intention. Next, we offer research propositions and discuss implications of varying refund offer sources for e-commerce researchers and practitioners.

Research Propositions

Online shoppers, or people in general, seek equity in every transaction they are party to (e.g., Bagozzi 1975; O'Shaughnessy and O'Shaughnessy 2005). In particular, equity theory posits that the customer's level of satisfaction derived from a transaction is a function of the perceived fairness of the exchange (Bagozzi 1975; Schaarschmidt et al. 2021). Therefore, for customers to respond favorably to an offer, it is important that they perceive a transaction as equitable. If customers believe a transaction is unfair (e.g., because price is too high) they will engage in avoidance behavior (Aquino et al. 2006). Applied to the present context, these insights suggest that when a retailer's partial refund offer is perceived as too low (i.e., unfair) the customer will reject it, that is, exhibit 'negative reciprocity' (Peterburs et al. 2017). This reasoning is supported by experimental economics research using ultimatum games, which shows that most accepted offers are between 30% to 40% of the amount at stake or 'pie' (Ho and Su 2009).

Besides the size of the partial refund offer, the source of the offer is likely to affect the customer's inclination to accept the offer. Friestad and Wright's (1994) persuasion knowledge model assumes that the consumer considers the source of a message or offer in decoding it; when the source is a vendor, the consumer factors this in while assessing the message content or offer. Building on Friestad and Wright's (1994) model and past research, we posit that customers associate different levels of objectivity and fairness with different offer sources. The pertinent literature suggests that the decision on whether to accept an offer is based on the perceived trustworthiness (e.g., Swan and Nolan 1985; Wongkitrungrueng et al. 2020) and fairness of the offer. Leventhal (1980) and others (e.g., Adams 2005; Newman et al. 2020) suggest that individuals perceive decision-making procedures to be fair when the procedure ensures a maximum degree of consistency as well as the absence of personal bias. It therefore seems reasonable to assume that perceived fairness can be influenced by online retailers' framing of the offer as coming from an individual company employee (i.e., human made), the company or an algorithm. In other words, it matters to customers by whom the offer is made. A customer, confronted with the question of how to deal with a defective product, might display different degrees of favorability toward offers coming from different sources. We posit that customers are more likely to accept offers that they view as devoid of human subjectivity, because they perceive such offers to be consistent (e.g., intertemporally consistent) and free of personal bias. Indeed, convincing research suggests that although some consumers view AI critically (Kieslich et al. 2022; Longoni et al. 2019) and may display an 'algorithm aversion' (Castelo et al. 2019), consumers generally trust machine-provided recommendations (Yeomans et al. 2019) and algorithmic decision making in many decision contexts (e.g., Logg et al. 2019; Starke et al. 2021). Importantly, customers may question the appropriateness and fairness of human-made decisions, whereas they are less likely to perceive AI-based refund offers as arbitrary. This reasoning suggests that customers would prefer partial refund offers to come from machines instead of individual employees or the 'company'. The notion that online customers who have decided whether to accept a partial refund offer exhibit an 'algorithmic preference' (vs. a preference for human-made or company-made decisions) is corroborated by research from related fields. For example, Bai et al. (2021) report that warehouse workers consider work assignments (pick lists) by algorithms fairer than those by human managers. The arguments in this section suggest the following three research propositions:

Proposition 1: The higher the partial refund offer (i.e., the greater the fraction of the original price is offered) the greater the customer's likelihood of offer acceptance.

Proposition 2: Customers are more likely to accept an online retailer's partial refund offer when the customer perceives the offer to be AI based (vs. based on an employee's or the company's decision).

Proposition 3: The effect of partial refund offer size on the likelihood of offer acceptance is moderated by offer source, such that when customers perceive the offer to be AI based (vs. based on an employee's or the company's decision) increasing refund offer size increases the likelihood of customers' offer acceptance.

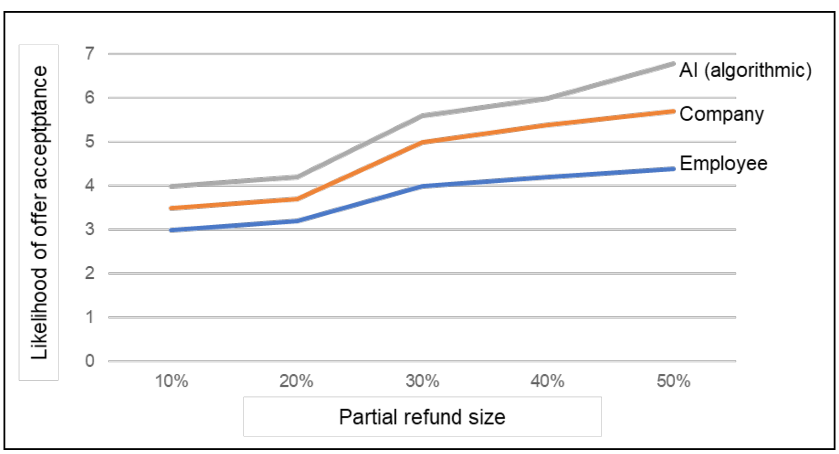

Figure 3. Possible 3-way interaction of offer source, partial refund size and likelihood of offer acceptance.

Based on the above theorizing, we might expect three nonlinear functions, depicted in Figure 3. This plot illustrates that for refund decisions made by an employee (who advises the customer in the offer email that she/he (vs. the company vs. an algorithm) decided on the offer size), the effect of partial refund size on likelihood of offer acceptance is weaker than that for refund decisions made by the 'company' or AI. The likely reason for this comparatively weaker relationship is the social presence of the employee which may trigger thoughts and feelings of bias and arbitrariness in the customer. On this note, it would also be interesting to determine whether for refund decisions made by AI, the level of likelihood of offer acceptance reaches a plateau at lower compensation levels than for the company or employee. If this were the case the retailer could realize considerable savings by framing the offer so as to make it appear AI-based (see Figure 4, panel C).

A)	**B)**	**C)**
Dear Mrs. XX Thank you for your message. Please excuse the problems with your boots. In order to get your boots ready for use again as quickly as possible, please take the boots to a shoemaker near you and have them carry out the following work: #Repair rubber edge *I calculated this will cost around $40*. Please contact us if the repair costs are higher, otherwise a refund can only be made over the amount mentioned. The shoemaker will explain to you the reason for the higher costs. Then send us a copy of the invoice and your bank details in reply to this email so that we can refund you. For further questions we are at your disposal at any time. Many greetings, *Jack Smith* *Customer Service Department* *[online retailer name*	Dear Mrs. XX Thank you for your message. Please excuse the problems with your boots. In order to get your boots ready for use again as quickly as possible, please take the boots to a shoemaker near you and have them carry out the following work: #Repair rubber edge *We calculated this will cost around this will cost around $40*. Please contact us if the repair costs are higher, otherwise a refund can only be made over the amount mentioned. The shoemaker will explain to you the reason for the higher costs. Then send us a copy of the invoice and your bank details in reply to this email so that we can refund you. For further questions we are at your disposal at any time. Many greetings, *Jack Smith* *Customer Service Department* *[online retailer name]*	Dear Mrs. XX Thank you for your message. Please excuse the problems with your boots. In order to get your boots ready for use again as quickly as possible, please take the boots to a shoemaker near you and have them carry out the following work: #Repair rubber edge *Our artificial intelligence system calculated this will cost around $40*. Please contact us if the repair costs are higher, otherwise a refund can only be made over the amount mentioned. The shoemaker will explain to you the reason for the higher costs. Then send us a copy of the invoice and your bank details in reply to this email so that we can refund you. For further questions we are at your disposal at any time. Many greetings, *Jack Smith* *Customer Service Department* *[online retailer name]*

Figure 4. Framing the source of the partial refund offer

Discussion

E-commerce firms continue to invest in the automation of processes in all operational areas. Clearly, processes automation and automating entire customer journeys brings about numerous benefits for e-commerce firms, such as the reduction of heterogeneity in customer-directed activities, simplification and removal of low-value, manual processes (Raman 2021; Tayeb 2022). In addition, AI-supported automation of the customer interface and front-office services may have other consequences, which facilitate the effectiveness of e-commerce firms' efforts to manage product returns more efficiently.

We believe this research effort is important from both a theoretical and managerial perspective. Conceptually, to gain a better understanding of the ways AI affords e-commerce businesses to predict and engage customers (Campbell et al. 2020), e-commerce scholars need to examine customer responses to AI-based compared to human-based offers. Managerially, this research is relevant because it is concerned with factors that decrease customer return rates and because it encourages online retailers to move beyond costly current approaches that achieve low return rates by treating defective products as complete write-offs or by taking them back, thereby incurring reverse logistics costs. Each defective product that customers wish to return represents a service failure. The source of a partial refund offer likely shapes customers' evaluation of the online retailers' service recovery efforts and as such will impact the customer's future relationship with the online vendor (Weun et al. 2004).

This research is premised on the assumption that e-commerce businesses can leverage AI to increase customer acceptance of partial refund offers with the goal of preventing returns of defective products. This research effort is a first step toward this goal. Building on the notions that partial refunds are financially better than full refunds (Shang et al. 2017) and that customers perceive AI-based offers to be less error-prone and contaminated by human bias (Morse et al. 2021), we suggest that online retailers should frame partial refund offers accordingly (see Figure 4, panel C). Given that a rejected offer prompts reverse logistics activities, which the online retailer will want to avoid, further research is needed to establish the conditions under which customers are most likely to accept partial refund offers in return for dealing with the defective product themselves. Toward this end, future research could vary the offer source and examine the satisfaction levels of customers that accept (i.e., retain the defective product) and that do not accept (i.e., return) the retailer's offer. For example, Butler and Highhouse (2000) show that individuals associate varying levels of anticipated regret with different sources, which influences their inclination to accept offers. Further, product characteristics may influence customers' likelihood of offer acceptance. For example, customers may be more likely to accept a poor offer (i.e., small fraction of the sales prices) in relation to scarce products (Fan et al. 2019). Also, it is worth remembering that customers have to make two separate decisions when being presented with a partial refund offer: whether to accept the offer and whether to use the partial refund toward getting the faulty product repaired. Future research could investigate whether customer satisfaction with the partial refund offer differs depending on how the refund is viewed, as a means to repair the product or as a windfall (i.e., an unexpected surplus). Finally, AI-based decisions (or those perceived to be AI-based) may invite unethical customer behavior (e.g., incorrectly claiming that product is defective) because customers perceive less anticipatory feelings of guilt toward machines than humans (Kim et al. 2022). Future studies could look at consumer characteristics in relation to offer (non-) acceptance to determine for which consumer segments the benefits of partial refund offers are outweighed by disadvantages, such as unethical or fraudulent returns claims.

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