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Taking Advantage of Algorithmic Preference to Reduce Product Returns in E-Commerce

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Abstract

Reimbursement of repair costs is a way to motivate customers to keep defective products instead of returning them. However, there is no research-based guidance on how retailers should frame repair costs reimbursement offers in terms of who decides on the size of the reimbursement and makes the offer—an employee or a machine. To guide further IS research and suggest ways that help e-commerce businesses to improve repair costs reimbursement effectiveness to decrease product return rates, the present research draws on literature on offer sources and on insights from a qualitative and an experimental study. We find that artificial intelligence-based (vs. human-based) repair costs reimbursement offers promote fairness perceptions, which, in turn, affect important customer outcomes—the likelihood to accept the offer and digital negative word of mouth. The results can guide e-commerce businesses' returns-prevention efforts and IS research.

Keywords: E-commerce, Product returns, Algorithmic preference

Introduction

Assume the following situation: A customer buys a product (e.g., long sleeve shirt) from an online retailer. After limited (or before the first) usage the customer detects a product defect (e.g., defective seams), which she/he reports to the retailer by email; the email is accompanied by a picture of the defective product. To prevent the product from being returned, the online retailer sends an email and offers the customer a repair costs reimbursement (i.e., a reimbursement that represents only a fraction of the original price)[1] so that the customer takes responsibility for getting the product repaired. Figure 1 depicts an example email offering repair costs reimbursement sent to the customer after she/he reported the product defect. Such offers, if accepted, have the potential to reduce product returns and are therefore in line with the European Union's upcoming "proposal on common rules promoting the repair of goods" (EU 2023), with the goal of prioritizing repairs over replacements. Once received, the customer has a choice: accepting the offer (hence keeping the product and getting it repaired) or declining it and returning 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 repair costs reimbursement offers accepted as possible to avoid reverse logistics and the ensuing costs (Dutta et al. 2020).

Although repair costs reimbursement offers are a potentially useful returns-prevention approach (Walsh and Möhring 2017), which is advocated for by industry experts (e.g., Bruch 2022), little is known about the efficacy of repair costs reimbursement. Specifically, given the potential hassle involved on the customer side (i.e., it may be more convenient to send the faulty product back instead of finding appropriate repair

[1] We note that a reimbursement is a payment made to the customer who has incurred an expense on behalf of the paying entity (i.e., online retailer). A refund, on the other hand, is a payment that one party makes to another as a result of overpayment or returning a product.

services, especially when free product returns are offered), there is little academic and practical guidance on how to increase the efficacy of repair costs reimbursements. This is an important oversight, given that defective or damaged products are among the top three reasons for product returns (together with "item didn't fit" and "item didn't match expectations"; Consumer Survey 2021). Accordingly, this research is motivated by a practical problem and aims to investigate strategies to increase the acceptance of reimbursement offers.

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Dear Mrs. XX

Thank you for your message.

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

#Repair defective seams

This will cost around £12. Please contact us if the repair costs are higher,
otherwise a reimbursement can only be made over the amount mentioned.

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

Many greetings,
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Figure 1. Example Email Offering Repair Costs Reimbursement

Many online retailers offer a free return policy to reduce consumers' perceived risk prior to ordering; however, this advantage is offset by the fact it leads to unnecessary ordering and increased return rates (Walsh and Möhring 2017). Making customers a repair costs reimbursement offer poses a viable alternative to free returns and likely results in a higher net benefit for the retailer. Importantly, in e-commerce practice, online retailers can frame the source of the repair costs reimbursement offer as human-made or not (Adam et al. 2022; Ge et al. 2021). 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 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). For example, a trained algorithm can analyze the captured images of the returned products to detect and localize defects (or missing parts) and select products suitable for reselling. In a similar vein, AI can be used to assess repair costs and make offers aimed at making customers keep the defective products and deal with the repair themselves.

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. Two streams of research offer some nascent yet contradictory results: Algorithm appreciation and algorithm aversion research (Dietvorst et al. 2018; Hou et al. 2021). These co-existing streams suggest that there is no general superiority of AI over human decision making: Acceptance of AI-based decisions largely depends on the error proneness of algorithms, the context such as whether it is utilitarian or hedonic, on who is the human agent (e.g., an expert), and on whether or not an algorithm may replace human labor (e.g., Castelo et al. 2019; Dietvorst et al. 2015; Park et al. 2022; You et al. 2022). Perhaps this is why Jauernig et al. (2020) surmise that people do not dislike algorithms per se, but appreciate the discretionary scope of human deciders. Hence, while there is consensus that AI facilitates process automation and diminishing costly touchpoints in e-commerce (Bawack et al. 2022), as well as evidence for general algorithm aversion (e.g., Daschner and Obermaier 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 repair costs reimbursement offer on customer offer acceptance. Literature findings are complemented by qualitative insights based on interviews with e-commerce managers. Using insights from the offer sources literature and the interviews, we derive hypotheses that are tested against empirical data. Using a scenario-based experiment, we find AI-based (vs. human-based) repair costs reimbursement offers to positively affect customers' perceptions of distributive fairness, which refers to the comparison a customer makes of his or her outcome (e.g., offered reimbursement, hassle) to another's (i.e., online retailer) outcome (Ferguson et al. 2014; Franke et al. 2013). Distributive fairness, in turn, is positively associated with the likelihood of customers accepting the offer and negatively with their intention to engage in digital negative word of mouth behavior, which refers to expressing dissatisfaction online by posting bad experiences on social media (Pfeffer et al. 2014). The results thus provide support for the mediational role of distributive fairness. Interestingly though, the reimbursement offer size, which could be perceived as a proxy for severeness of the damage, but also as a value signal, does not interact with the offer source (i.e., AI- vs. human-based) to affect distributive fairness. The results provide a starting point for the consideration of differential effects of repair costs reimbursement offer sources on important customer outcomes.

This research makes at least three contributions to the IS literature. First, we introduce the notion of customers' 'algorithmic preference' or 'appreciation' in relation to online retailers' repair costs reimbursement offers. Second, we theorize and empirically confirm that customers faced with a repair costs reimbursement offer are more likely to accept AI-based to human-made decisions and that AI- (vs. human-) based offers are less likely to elicit digital negative word of mouth (NWOM). Third, we find that the size of the reimbursement offer does not moderate the effect of offer source on distributive justice perceptions. These findings can guide future empirical IS research and managerial decisions in e-commerce organizations.

Background, Interview Insights, and Hypotheses

Product Returns and Approaches to Preventing Them

E-commerce firms are confronted with product returns in unabated numbers; in the U.S. alone more than $800 billion worth of products are returned to vendors each year (NRF 2022). In response to this continuing challenge, e-commerce businesses explore the efficacy of different approaches to reducing product returns (Sahoo et al. 2018; Walsh et al. 2014). For example, Walsh and Möhring (2017) differentiate monetary instruments such as discounts or gifts for not returning products, customer-based instruments such as virtual try-ons, and procedural instruments such as cycle-time optimization.

A growing number of vendors though 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 result in 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.

Qualitative Insights into Product Returns Practices

As part of our research effort, we conducted qualitative interviews with five German e-commerce managers to gain further insights into novel approaches to preventing product returns. The interviews, which lasted between 30 and 45 minutes with an average of 35 minutes, were transcribed, coded, and content analyzed using the MAXQDA software and a top-down (i.e., deductive) process (Krippendorff 2018). To code deductively, we used a priori categories from the literature on returns prevention (e.g., Walsh and Möhring 2017).

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 (i.e., inspection), 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 repair costs reimbursements. 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. £22/$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, managing director). Because damaged and defective products make up a relatively large percentage of all products returned (Consumer Survey 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. The reverse logistics process set in motion by the customer's decision to return a product comprises five distinct steps: collection, transport, reception, inspection, and sorting (Nibedita 2021).

To limit returns-related costs (e.g., shipping costs), some online retailers have begun to use a two-step 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 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 with more than 20 years of experience in e-commerce, the latter approach "is what most online retailers (that offer a repair costs reimbursement) employ" (Mike, 42 years, senior director). 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 repair costs reimbursement to the customer; the reimbursement 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 repair costs reimbursement offer, she/he keeps the product; the vendor does not have to take the faulty product back (i.e., no reverse logistics is necessary) and the case is closed. If customers decline the offer, they will return the product to the vendor in order to get a full refund or a new replacement product; in both cases, reverse logistics is required. Obviously, it is in the online retailer's interest that the customer accepts the repair costs reimbursement offer and keeps the faulty product. However, what firms can do to increase the likelihood that customers retain the faulty product has received little research attention.

The question why online retailers employ the described approach to preventing returns was not comprehensively answered by the qualitative interview, which speaks to the novelty of the repair costs reimbursement offer-based approach. It is worth emphasizing though that customers who accept the retailer's repair costs reimbursement offer will earn zero net utility from accepting the offer. All their efforts will get them is a functioning product, something they could achieve by simply returning the defective product and requesting a replacement. In fact, given that the efforts associated with getting the product repaired represent time and other costs, one could even argue that customers are left with negative net utility, which makes it even less plausible that customers should accept such offers. The most likely explanation for this returns-prevention approach is that online retailers think they can take advantage of the endowment effect, which refers to customers' tendency to place greater value on items that they own compared to the value they would place on the same product if they did not own it (Kahneman et al. 1990). This endowment effect can be explained by loss aversion, that is, consumers' aversion to losses (e.g., caused by the prospect of relinquishing a product already in one's possession) (Thaler 1980).

While the use of repair costs reimbursement offers 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 investigate the efficacy of different offer sources or determine at what percentage of the original price customers find the online retailer's proposition acceptable. Economic theory would suggest that offer acceptance is correlated with the size of the repair costs reimbursement offer. However, it would not be financially prudent for retailers to simply maximize the size of the reimbursement 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 repair costs reimbursement offer could be a way to keep those costs down. Next, we offer research hypotheses (see Figure 2) and test them against empirical data.

Hypotheses

Online shoppers, or people in general, seek equity in every transaction they are party to (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. 2023). Therefore, for customers to respond favorably to a reimbursement offer, it is important that they perceive a transaction as equitable. If customers believe a transaction is unfair (e.g., because they feel they receive poor value for money) they will engage in avoidance behavior (Aquino et al. 2006).

The source of the offer is likely to affect the customer's inclination to accept the offer and their intention to engage in digital NWOM. 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 decision 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. Furthermore, Leventhal (1980) and others suggest 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 (Adams 2005; Newman et al. 2020). It therefore seems reasonable to assume that perceived distributive fairness can be positively influenced by online retailers' framing of the offer as being AI (vs. human) based. This notion is supported by research such as Helberger et al. (2020) who asked respondents whether human- or AI-based decisions would be fairer. One-third of respondents answered that they believed humans make fairer decisions, compared to 54% who thought AI-based decisions were fairer. This notion also chimes with research that reports that customers are more likely to accept expectancy-violating offers (e.g., an overpriced taxi fare) when offers are AI- versus human-based (Garvey et al. 2023). The reason given for this finding is that, unlike humans, AI systems are perceived to lack their own exploitative intentions. Distributive fairness, which is about the perceived fairness of outcomes allocated to different exchange partners in relation to the inputs (Franke et al. 2013), is an appropriate mediator in our study context because it can be theoretically linked to decisions made by different agents (AI vs. humans) as well as to customer outcomes. Accepting a repair costs reimbursement offer involves a time and effort investment on part of the customer (i.e., input) but also yields a reward in the form of getting to keep (and not returning) the purchased product.

The notion that online customers who have decided whether to accept a repair costs reimbursement offer exhibit an 'algorithmic preference' (vs. a preference for human-made or company-made decisions or even algorithm aversion) 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. Similarly, Daschner and Obermaier (2022) show when advice accuracy is at a threshold, behavioral algorithm appreciation is present.

We therefore 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). Thus:

Hypothesis 1: *Perceptions of distributive fairness are higher for AI-based versus human-based repair costs reimbursement offers.*

As stated, customers may question the appropriateness and fairness of human-made decisions, whereas they are less likely to perceive AI-based offers as arbitrary or unfair (Garvey et al. 2023). When perceptions of distributive fairness exist, they likely translate into customer intention and behavior, as evidenced by previous research. Specifically, people have a tendency to accept fair offers as reported in other relational contexts (e.g., Hong et al. 2017) and distributive fairness has been shown to predict NWOM (e.g., Bambauer-Sachse and Young 2023; Van Vaerenbergh et al. 2018). Extant findings therefore suggest a customer preference for repair costs reimbursement offers coming from machines instead of individual employees because they perceive AI-based offers as fairer. They further suggest that offer source-induced fairness perceptions drive customers' offer acceptance likelihood and intention to engage in digital NWOM. Especially digital NWOM is dangerous as it may thwart companies' efforts to lower product returns by offering reimbursements as well as their customer acquisition efforts. In other words, when customers perceive a repair costs reimbursement offer as fair, they are likely to accept it and unlikely to make negative statements in the digital realm about the online retailer and its return-prevention practices.

Hypothesis 2: *The effect of AI-based versus human-based repair costs reimbursement offers on a) offer acceptance likelihood, and b) digital negative word-of-mouth (NWOM) is mediated by perceptions of distributive fairness.*

The fact that AI- versus human-based decisions may interact with other variables to influence downstream variables suggests the need to explore the boundary conditions under which such decisions influence distributive fairness. A key aspect in designing mechanisms to lower product returns is reimbursement size. Economic literature as well as literature on discounts have identified prices and discounts as important signals (Grewal et al. 1996). For example, the higher a promotional discount, the higher the likelihood of purchase (Raghubir 1998). In a similar vein, the reimbursement size is a signal in multiple ways: On the one hand, it (implicitly) signals severity of the damage, on the other hand it also signals trust because higher reimbursement size suggests that the amount offered is sufficient to get the product repaired. Specifically, given that a defective product generates no utility for the customer (Hsiao and Chen 2012), a high reimbursement amount (which implies a big repair is needed) may indicate to customers an inability to gain full utility from the product, which could make them less willing to accept the offer.

However, we assume that online retailers can increase offer acceptance by taking advantage of customers' general responsiveness to financial incentives and offers (e.g., Sussman and O'Brien 2016). Based on past research that suggests that when a retailer's repair costs reimbursement offer is perceived as too low the customer will reject it, that is, exhibit 'negative reciprocity' (Peterburs et al. 2017), we surmise that a higher reimbursement size signals "value". The literature dealing with service failures and service recovery compensations emphasizes the important role of monetary compensations in shaping customers' fairness perceptions (e.g., Albrecht et al. 2019). In this context, Orsingher et al. (2010, p. 183) propose "that the promise of compensation will evoke preconsumption mental imagery, where the consumer vicariously experiences the satisfaction of the redress before the actual experience" (i.e., receiving the compensation). Although a reimbursement is not the same as a monetary compensation, redress or refund, reimbursements (especially high vs. low) likely elicit similar feelings, especially when the reimbursement offer is thought to be AI-based. We thus expect the reimbursement size to interact with the offer source to affect distributive fairness.

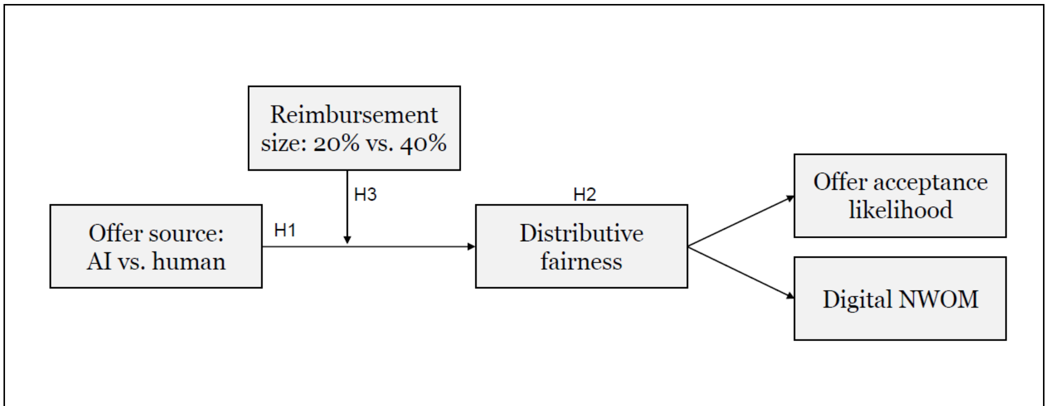

Figure 2. Conceptual Model

Consequently, when an offer is made by the AI system (vs. human) a high (vs. low) offer should promote (diminish) perceptions of distributive justice (Grgić-Hlača et al. 2018). 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). Applied to the present context, these insights suggest that offer source and reimbursement offer size interact to affect customers' distributive fairness perceptions.

Hypothesis 3: *Reimbursement size will moderate the effects of AI-based versus human-based repair costs reimbursement offers on offer acceptance likelihood and digital NWOM, through distributive fairness, such that these mediation effects will be more (less) pronounced for high (low) reimbursement size.*

Method

Study Design, Procedure, and Participants

To study the effect of AI-based versus human-based calculations of repair cost reimbursement offers, we conducted a scenario-based online between-subject experiment. Scenario-based experiments are widely used when participants would otherwise be exposed to unnecessary hassle (e.g., Albrecht et al. 2017), and are therefore appropriate in situations with product returns. The scenario described a purchase of a pair of outdoor hiking boots at a price of £200. The fictitious online shop offered free shipping and product returns. In the scenario, the right boot was damaged, and the online retailer offered to reimburse repair costs, following a shoe repair organized by the customer (see Appendix B). As our main hypotheses concern two dimensions, 1) AI versus human-based calculation of repair costs and 2) reimbursement size as a proxy for the product defect, we utilized a 2 (AI vs. human) × 2 (reimbursement size high vs. low) between-subject design. Reimbursement size was manipulated by differentiating a low repair costs reimbursement offer (i.e., 20% of the original price, £40) and a high offer (i.e., 40%, £80) after consulting both shoe repair services and emails real-life online retailers had sent out in comparable cases.

We recruited participants from prolific academic, a crowdsourcing platform that has been used for scenario-based experiments previously. We targeted a sample size of around 100 respondents per cell and received 409 complete answers. After eliminating responses that either failed an attention check question ("Please provide the sum of 4+4") or to recall the respective scenario correctly, we arrived at a dataset of n = 390 responses with cell sizes ranging from 92 to 101. Of the respondents, 192 were male, 192 were female, and six preferred to not disclose their gender. The mean age was 39.11 years (SD = 12.81). We further assessed the realism of our scenario using one item ("Situations like that can happen in real life"; 7-point Likert scale, 1=fully disagree to 7=fully agree). The scenario was rated as realistic (M=4.67, SD=1.67).

Measures and Validity Tests

We measured the concepts depicted in our conceptual model with multi- and single-item measures. For distributive fairness, we adapted three items from Maxham and Netemeyer (2002), which also have been used in service failure settings previously (Walsh et al. 2022), measured on a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Construct reliability is appropriate, given a Cronbach's α of .93. For our dependent variables, offer acceptance likelihood and digital NWOM, we used single-item measures with likelihood scales that range from 0% to 100%, in accordance with other studies interested in behavior-like outcomes (e.g., Dose et al. 2019).

We also assessed demographics (e.g., age, gender), and four additional factors that act as control variables. The control variables were selected based on arguments from e-commerce literature (Chiu at al. 2014). For example, as to gender, Hack and Lammers (2009) report that fairness perceptions of women (vs. men) are more important for determining behavioral outcomes. In addition, as respondents with a higher sense for the environment may value a repair more than a carbon-dioxide-heavy product return because this is more congruent to their believes, we control for environmental consciousness, using four items adapted from Roberts and Bacon (1997); Cronbach's α is .89. We also assessed online shopping frequency with a single item anchored at 1=never to 5=always, because shopping frequency reflects respondents' familiarity with product returns. Potentially, respondents with frequent purchases are less likely to accept repair offers due to their expectancy of free product returns. We further included offer appropriateness by asking: "How do you perceive the amount offered in comparison to the costs of the boots?". Answer options ranged from 1=highly inappropriate to 5=highly appropriate. With this measure, we aimed to capture respondents' evaluation of repair cost calculation accuracy. Finally, we included a measure to capture respondents' perceived effort involved in the scenario because effort reflects the "input-side" of distributive fairness (Franke et al. 2013). We asked for agreement or disagreement with the statement: "For customers, the benefit of bringing the boots to a shoemaker outweighs the required effort" on a 7-point Likert scale.

To assess the quality of the measurement instruments, we applied a confirmatory factor analysis (CFA) for our two multi-item measures, distributive fairness, and environmental consciousness, using the AMOS package and a maximum likelihood estimator. The fit values used involve chi-square value divided by degrees of freedom, goodness-of fit index (GFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The results indicate that the data fit the model well: χ^2 =

10.382, df = 13 (χ^2/df = .80), GFI = .99, RMSEA = .01, SRMR = .02) (Hu and Bentler 1999). Average variance extracted (AVE) is greater than .50 for each construct, and, in support of discriminant validity, AVE exceeded the squared inter-construct correlation for the multi-item measures (Fornell and Larcker 1981).

A common threat to all survey-related research is that independent and dependent variable correlate simply because they have been measured in a similar way, and not because they correlate in reality; a problem known as common method variance (CMV). Although our study rests on an experimental design, where CMV is very unlikely, still, some of our measured variables could potentially share variance. Accordingly, we applied ex-ante and ex-post procedures to limit this threat. In designing our survey, we aimed for different scale anchors and ranges for constructs of interest (Podsakoff et al. 2013). For example, while distributive fairness, our mediator, was measured on a seven-point Likert scale, our dependent variables were measured as likelihoods, with percentages ranging from 0-100. In addition, we tested the amount of CMV present in this study by applying the measured latent marker variable (MLMV) technique, which assume that there is a single cause of common method bias for all variables (Lindell and Whitney 2001). A marker variable then has to be chosen (and to be integrated in the survey), that "share(s) negligible or no substantively meaningful variance with the variables suspected of CMV bias" (Simmering et al. 2015, p. 475). In line with previous research (e.g., Renner et al. 2021), we chose marker variables that were theoretically unrelated to all other constructs, and which were also assessed on a seven-point-Likert scale to mimic the same source of bias. The items used appear in Appendix A. In line with Williams et al.' (2010) MLMV approach, we compared a CFA model without the marker variable with one that contained the marker variable as an additional construct. This additional construct consists not only of the marker variable items, it also has links to all other items. In case of high CMV, the factor loadings for all non-marker variables would drop in a model with marker variable. In our case, none of the indicators changed by more than .10 (standardized). Hence, we conclude that CMV is unlikely to affect this study's results. Finally, we conducted a series of checks to ensure that our random assignment of respondents to the scenarios worked. As a manipulation check, we let respondents recall what their scenario was about (see Appendix B). Also, we conducted analyses of variance for age, gender (1=female, 0=all others), shopping frequency, and the marker variable. In all cases, no significant differences were observed, which indicates that cells are not biased in any of these dimensions.

Hypotheses Testing

We start by analyzing the main effect of offer source on offer acceptance measured as a binary variable (acceptance yes/no). A chi-square test indicates that there is a significant difference in acceptance between the AI and human condition: The chi-square statistic is 5.4435 ($p < .05$.), supporting the argument that AI-based reimbursement offers can lower product return rates. To test hypotheses 1-3, we used the SPSS macro PROCESS (Models 4 and 7; with 5000 bootstrap samples), which is based on OLS regression but also uses bootstrapping to calculate significance levels for indirect effects (Hayes 2022).

Specifically, we first regressed distributive fairness on the independent variables AI decision making (1 = AI yes; 0 = human) and repair cost size (1 = £80; 0 = £40), their interaction, and the following controls: age, gender (1 = female, 0 = all others), shopping frequency, environmental consciousness, appropriate repair cost calculation, and perceived effort involved (PROCESS model 7, first part). For the interaction term, we used mean centered values. Results are depicted in Table 1 (including controls) and Figure 3 (main effects only).

We first report the effect of the independent variable on the mediator, distributive fairness (see Figure 3). The effect of AI-based reimbursement offer on distributive fairness is positive and significant ($b = .34$, $p < .05$; with 95% confidence interval that does not contain "zero"), in support of H1. Of the controls, age, appropriate cost calculations, and perceived effort involved also have a significant effect. H2 proposed an indirect effect of AI-based reimbursement cost offers on a) offer acceptance likelihood and b) digital NWOM. The results of the second part of the mediation analysis are displayed in Table 2 and Figure 3.

	Distributive Fairness			
	Coefficient	SE	p	95% CI [LL; UL]
Antecedents				
AI (vs. human)	.34	.15	.0209	[.05; .64]
High (vs. low) reimbursement size	-.22	.15	.1429	[-.51; .07]
AI x reimbursement size	.42	.30	.1623	[-.17; 1.01]
Controls				
Age	-.02	.01	.0024	[-.03; -.01]
Gender (1=female, 0 all others)	-.05	.15	.7425	[-.34; .25]
Environmental consciousness	.05	.06	.4564	[-.07; .17]
Online shopping frequency	-.02	.11	.8569	[-.24; .20]
Appropriate costs	.83	.07	.0000	[.69; 98]
Perceived Effort	.22	.04	.0000	[.14; .30]
	R^2 = .37, F(9, 380) = 25.01, p < .001			
	Note: CI = confidence interval; LL = lower limit; UL = upper limit.			

Table 1. Results of AI-based Reimbursement Offer on Distributive Fairness

Distributive fairness has a significant effect on both offer acceptance likelihood (b = 14.02, p < .001) and digital NWOM (b = -4.68, p < .001). In addition, the direct effect of AI-based reimbursement offers on the outcome variables is no longer significant. An additional mediation analysis with PROCESS model 4 (i.e., without the first stage moderation of reimbursement size), indicates significant indirect effects of AI-based reimbursement offers on both offer acceptance likelihood (b = 4.84, 95% CI [.65, 9.13]) and digital NWOM (b = -1.62, 95% CI [-3.39, -.21]), in support of H2a and H2b.

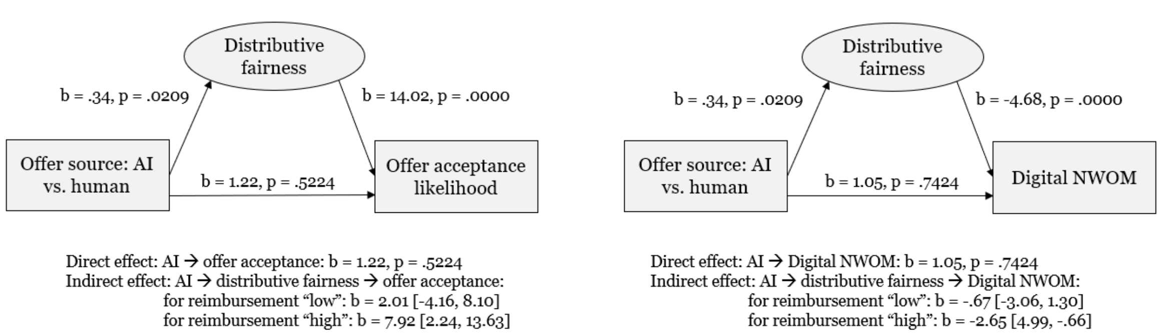

Figure 3. Mediation Results

Finally, we turn to Table 2 to assess the moderation proposed in H3. The interaction of AI-based reimbursement offers and reimbursement size has no significant effect on distributive fairness. Hence, we must reject H3 because of a missing first-stage moderation. In addition, results of a moderated mediation analysis (PROCESS model 7) lend further support for the rejection of H3: The 95% confidence interval for the index of moderated mediation did contain zero (Offer acceptance likelihood: index = 5.91, 95% CI: [-2.36, 14.38]; Digital NWOM: index = -1.97, 95% CI: [-4.93, .82]), suggesting that there were no differences between the indirect effects at different levels of the moderator.

Discussion

Summary and Managerial Implications

E-commerce firms continue to invest in the automation of processes in all operational areas (Zhang et al. 2021) although important tasks (e.g., inspection of returned products) are still often performed by humans, as our qualitative data illustrate. 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 (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.

	Offer Acceptance Likelihood		***Digital NWOM***	
	Coefficient (SE)	p	Coefficient (SE)	p
Antecedents				
AI (vs. human)	1.22 (1.91)	.5224	1.05 (3.18)	.7424
Distributive fairness	14.02 (.64)	.0000	-4.68 (1.07)	.0000
Controls				
Age	-.14 (.08)	.0608	.15 (.13)	.2307
Gender (1=female, 0 all others)	-2.83 (1.91)	.1386	-3.13 (3.18)	.3260
Environmental consciousness	.50 (.78)	.5136	.05 (1.27)	.9668
Online shopping frequency	.41 (1.41)	.7729	2.76 (2.35)	.2408
Appropriate costs	3.25 (1.05)	.0023	-5.25 (1.76)	.0030
Perceived effort	1.19 (.54)	.0278	-.37 (.90)	.6816
	$R^2 = .72$		$R^2 = .16$	
	Conditional indirect effect of AI through distributive fairness			
	Coefficient (Boot SE)	95% CI	Coefficient (Boot SE)	95% CI
Reimbursement size low	2.01 (3.08)	[-4.16; 8.10]	-.67 (1.09)	[-3.06; 1.30]
Reimbursement size high	7.92 (2.87)	[2.24; 13.63]	-2.65 (1.11)	[-4.99; -.66]
Index of moderated mediation	5.91	[-2.36; 14.38]	-1.97	[-4.93; .82]

Table 2. Results of Moderated Mediation for Offer Acceptance Likelihood and Digital NWOM

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. Our findings suggest that AI-based offers are perceived to be fairer and that customers' fairness perception promote offer acceptance likelihood and suppress intention to engage in digital NWOM. 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, such as (financially) rewarding customers for not returning products (Gelbrich et al. 2017), 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 repair costs reimbursement 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). We show that framing an offer as coming from an AI system leads to favorable effects on key downstream variables. 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.

Future Research

We realize that that this research contrasts with some previous studies that find that algorithmic (vs. human) decisions may be perceived as less trustworthy and can evoke negative emotions (Glikson and Woolley 2020; Lee 2018). However, drawing on equity theory, nascent extant research, qualitative insights, and the results of an experiment, we found support for our theorizing and the notion that e-commerce customers are more amenable to repair costs reimbursement offers coming from the AI system than from a human. Despite these insights, there remain issues deserving of continued research attention.

This research is premised on the assumption that e-commerce businesses can leverage AI to increase customer acceptance of repair costs reimbursement 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 repair costs reimbursements are financially better for online retailers 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. 2022), we suggest that online retailers should frame repair costs reimbursement offers accordingly. 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 repair costs reimbursement offers in return for dealing with the defective product themselves. Toward this end, future research could vary the offer source and examine the distributive fairness and 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. Future research could also test additional mediators (beyond distributive fairness) of the offer source-outcomes relationships, such as the inferred intentions of the offering (AI or human) agent (Garvey et al. 2023). Similarly, additional moderators could be considered. Building on research that shows that perceived costs are not necessarily the same as actual (or true) costs (Cheng and Cryder 2018), true costs could be investigated as moderator. Further, product characteristics may influence customers' likelihood of offer acceptance. For example, customers may be more likely to accept a poor offer (i.e., reimbursement representing small fraction of the sales prices) in relation to scarce products (Fan et al. 2019). Moreover, we only distinguished two levels of repair costs reimbursement offers representing 20% and 40% of the purchase price. Future research could investigate if the notion of algorithmic preference holds for a greater number of offer levels. Specifically, it would be interesting to determine whether for reimbursement decisions made by AI (vs. human), the level of likelihood of offer acceptance reaches a plateau at lower compensation levels. If this were the case the retailer could realize considerable savings by framing the offer so as to make it appear AI-based. Neither did we differentiate between short and long repair time, which likely affects customers' willingness to have a defective product repaired (Fachbach et al. 2022), compared to returning it.

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. 2023). Future studies could look at consumer characteristics in relation to offer (non-) acceptance to determine for which consumer segments the benefits of repair costs reimbursement offers are outweighed by disadvantages, such as unethical or fraudulent returns claims. In addition, future research could investigate the effect of the quality of previous AI-based versus human based offers on offer acceptance likelihood (Saragih and Morrison 2022). Together, our conceptual and empirical consideration contribute to launching research initiatives that target the reduction of product returns by offering repair cost reimbursement.

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Appendix

A. Items and factor loadings

	Factor Loadings
Distributive fairness (adapted from Maxham and Netemeyer 2002) *7-point-Likert scale ranging from "fully disagree" to "fully agree"*	
Thinking about the offer made in the email, the outcome I received was fair.	.94
Thinking about the offer made in the email, the online retailer gave me what I needed.	.92
Thinking about the offer made in the email, I did not get what I deserved. (reverse)	.82
Offer acceptance likelihood *(from 0%=very unlikely to 100% very likely)*	
Thinking about the offer made in the email, how likely would you be to accept the offer made?	n.a.
Digital NWOM *(from 0%=very unlikely to 100% very likely)*	
How likely are you about warning other customers on social media about return practices at GLM online?	n.a.
Environmental consciousness (adapted from Roberts and Bacon 1997) *7-point-Likert scale ranging from "fully disagree" to "fully agree"*	
I normally make a conscious effort to limit my use of products that are made of or use scarce resources.	.76
If I have the choice, I will not buy products which have excessive packaging.	.84
When there is a choice, I always choose that product which contributes to the least amount of pollution.	.86
If I understand the potential damage to the environment that some products can cause, I do not purchase those products.	.81
Appropriate offer *5-point-Likert scale ranging from "highly inappropriate" to "highly appropriate"*	
How do you perceive the amount offered in comparison to the costs of the shoes?	n.a.
Shopping frequency *5-point-Likert scale ranging from "never" to "always"*	
How often do you shop online in general?	n.a.
Perceived effort *7-point-Likert scale ranging from "never" to "always"*	
For customers, the benefit of bringing the boots to a shoemaker outweighs the required effort.	n.a.
MARKER VARIABLE to assess forms of personal preferences. *7-point-Likert scale ranging from "fully disagree" to "fully agree"*	
Bears are amazing animals.	
Music is important to my life.	

B. Scenario descriptions

<table>
<tr><th><u>Employee-based offer</u></th><th><u>AI-based offer</u></th></tr>
<tr><td colspan="2">You bought a new pair of outdoor hiking boots at the GLM online shop which offers both free shipping and product returns. The boots cost you £200 and you start using them soon after they arrive. After one relatively short walk you notice that the rubber edge around the right boot is damaged. You write an email to GLM online to tell them about the defective boots. They answer the same day and ask you to email a picture of the ‘problem’ (i.e., picture of faulty rubber edge), which you do. You receive the following return email a day later:</td></tr>
<tr><td>Reimbursement size 40/80</td><td>Reimbursement size 40/80</td></tr>
<tr><td>Dear customer,

Thank you for your message.

We apologize for 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 [£80].

Upon completion of the repair, please email to us the shoemaker’s invoice and your bank details so that we can reimburse you the repair costs. For further questions we are at your disposal at any time.

Many greetings,
Joane Smith
Customer Service Department
GLM online</td><td>Dear customer,

Thank you for your message.

We apologize for 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 [£80].

Upon completion of the repair, please email to us the shoemaker’s invoice and your bank details so that we can reimburse you the repair costs. For further questions we are at your disposal at any time.

Many greetings,
Joane Smith
Customer Service Department
GLM online</td></tr>
</table>