Spring 6-10-2017

HOW ONLINE CUSTOMER REVIEWS AFFECT SALES AND RETURN BEHAVIOR – AN EMPIRICAL ANALYSIS IN FASHION E-COMMERCE

Tobias Lohse
RWTH Aachen University, lohse@time.rwth-aachen.de

Jan Kemper
RWTH Aachen University, Aachen, kemper@win.rwth-aachen.de

Malte Brettel
RWTH Aachen University, brettel@time.rwth-aachen.de

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Research in Progress

Lohse, Tobias, RWTH Aachen University, Aachen, Germany, lohse@time.rwth-aachen.de

Kemper, Jan, RWTH Aachen University, Aachen, Germany, kemper@win.rwth-aachen.de

Brettel, Malte, RWTH Aachen University, Aachen, Germany, brettel@time.rwth-aachen.de

Abstract

The goal of this study is to get a better understanding of the relationship between online customer reviews (OCRs), product returns and sales after returns in online fashion. Furthermore, we generate deeper insights about the moderating role of mobile shopping usage, product involvement and brand equity in this context. We answer our research questions by empirically analyzing a unique data set from a European fashion e-commerce company. This study links a wide range of transaction data (2.5 billion page clicks, 46 thousand different products, 700 brands, 40 product categories, 72 million sold and 33 million returned items) with a large set of OCRs (0.9 million). Our results show that positive OCRs can lead to lower return rates, higher sales after returns, and better conversion rates. Considering higher search costs on mobile devices, we reveal a weaker impact of OCRs in the mobile than in the desktop sales channel. Furthermore, in line with involvement theory, we see a significant impact of product involvement in this context such as the influence of positive OCRs is stronger for high-involvement products than vice versa. Moreover, we find support for statements from brand signaling literature, that OCRs matter more for weak than for strong brands.

Keywords: eWOM, Online Customer Reviews, Product Returns, Mobile Shopping, Product Involvement, Brand Equity

1 Introduction and Related Literature

The field of e-commerce has experienced a significant sales growth in the last decade (U.S. Department of Commerce, 2016) with the fashion segment as one of the main growth drivers (BBC News, 2014). Especially the mobile commerce has reached a significant contribution level in this sector and is expected to account for about 50% of global e-commerce revenues in 2018 (Xu et al., 2016). At the same time, online retailers are facing substantial profitability headwinds due to high return rates (Petersen and Kumar, 2009). In some cases, return rates greater than 25% are no exception (Hess and Mayhew, 1997) costing firms an estimated $100 billion per year by product depreciation and logistics (Anderson et al., 2009). Thus, retailers are open for measures like additional user-generated product information and online customer reviews (OCRs) to mitigate the financial headwinds from returns.

OCRs belong to the most powerful tools in marketing communication in these days (King et al., 2014). They are an important information source to deal with large product assortments like in online stores as they allow customers to evaluate products prior to purchase and to minimize disconfirmation upon delivery (Cui et al., 2012). Their main characteristics are an unprecedented volume and reach compared to offline (Dellarocas, 2003), a viral dispersion effect across different platforms (Godes and Mayzlin, 2004) and an on-demand availability (Dellarocas and Narayan, 2007). Many e-commerce players like Amazon have used OCRs since more than two decades for marketing reasons (Bloomberg Businessweek, 2009). The high level of trust and credibility which consumers usually attribute to

OCRs (Bickart and Schindler, 2001) and the strong influence of OCRs on the purchase decision of consumers (Filieri, 2014) can be seen as main reasons.

Consequently, the influence of OCRs on retailers' commercial performance also attracts many researchers (Gu et al., 2012). The appropriate literature is dominated by papers discussing the relationship between OCRs (esp. rating valence) and sales (Chevalier and Mayzlin, 2006; Godes and Mayzlin, 2004; Ho-dac et al., 2013). Even if the findings of prior studies are mixed, the majority reveals a positive, significant relationship between OCRs and sales. However, none of these studies discuss the new challenges and changing circumstances of higher search cost due to an increasing share of customers using mobile devices. Moreover, regarding high return rates and costly logistic processes in e-commerce, it is surprising that almost none of the existing studies focus on the relationship between OCRs and returns or sales after returns. To the best of our knowledge, only two studies discuss the influence of OCRs on product returns in e-commerce. Minnema et al. (2016) find that a better rating valence induces a higher purchase probability, but also a higher return probability. In contrast, Sahoo et al. (2015) reveal that positive OCRs can help consumers to make better purchase decisions leading to lower product returns. However, this field of research is still rather unexplored. In addition, the moderating role of mobile intensity, product involvement, and brand equity are totally unknown in this context. This seems critical for two reasons: First, the increasing share of customers using mobile devices for online shopping changes the way how customers can evaluate products significantly. Second, product categories and brands are the two main dimensions in an online shop such that retailers should establish category-, brand- or device-specific strategies to use OCRs as marketing instrument in the most effective way (Ho-dac et al., 2013; Kostyra et al., 2016).

Product returns are reducing profits of manufacturers and retailers by 3.8% per average (Petersen and Kumar, 2009) and just a one percent decrease in the return rate could help a large retailer to reduce its logistic costs by $17 million in average per year (Minnema et al., 2016). Consequently, a better understanding of the relationship between OCRs, returns, and sales after returns can help to improve retailers' financial performance significantly. This leads us to the following research questions which we aim to answer in this study: (RQ1) How do positive OCRs influence product returns? (RQ2) Do positive OCRs increase sales after returns? (RQ3 and RQ4) How does mobile intensity moderate the influence of OCRs on product returns and sales after returns? (RQ5 and RQ6) How far does the level of product involvement affect the relationships between OCRs, returns, and sales after returns? (RQ7 and RQ8) To which extent does brand equity influence the impact of OCRs on returns and sales after returns? The overall research model with all research questions is summarized in Figure 1.

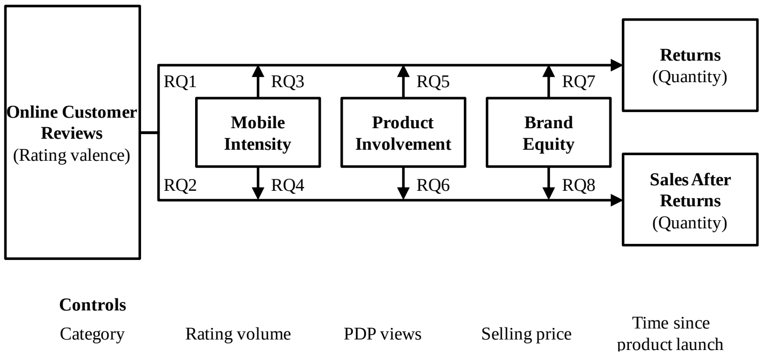

Figure 1. Overall research model with research questions

In our paper, we follow specific research calls to optimize firm-consumer interactions and to get a better understanding of product return behavior (Anderson et al., 2009; Kang and Johnson, 2009; Petersen and Kumar, 2009) especially in the context of mobile shopping (Einav et al., 2014; Wang et al., 2015). We mainly contribute to existing research in the areas of uncertainty reduction theory

(Berger and Calabrese, 1975) and search cost (Stiglitz, 1989) by connecting the research streams about OCRs, product returns, and mobile shopping.

We answer our research questions by empirically analyzing a unique data set from a European fashion e-commerce company. Almost all studies in the field of OCRs are dealing with webcrawled outside-in data (Chevalier and Mayzlin, 2006; Sun, 2012). In contrast, we link a wide range of actual transaction data (> 70 million sold items) with a large set of OCRs (~ 0.9 million). This unique data set allows us to improve the understanding about customers' purchase and return behavior significantly.

2 Data and Methodology

2.1 Data

We were able to obtain a unique data set from a leading fashion e-commerce company selling shoes- and apparel products across the European market to analyze our research questions. The online retailer is well-known for his lenient product return policy. Customers receive their products generally for free as long as they do not order via overnight delivery. The return procedure is also for free and any purchased item can be handed back to the retailer with no restriction and no further reason up to 100 days after purchase. Satisfaction surveys of the retailer show that this zero-priced return policy is one of the most appreciated service functionalities from customers' point of view.

The comprehensive data set covers the entire sales period of 2015. It contains information for 46,178 different SKUs (stock-keeping units), 71,523,144 sold and 33,001,296 returned SKUs along 40 different product categories (e.g., jeans, sneaker) and 701 different brands (e.g., Nike, Converse) across three different sales channels (desktop, mobile website, mobile application). Moreover, the data set includes 875,918 OCRs (237,913 from 2014 or earlier) and 2,462,323,455 product detail page (PDP) views. A PDP view is defined as one user click to access the PDP coming, for instance, from the catalog page or search engines like Google. This gives us the opportunity to discuss the influence of OCRs in terms of conversion. Finally, we use the share of "branded" purchases as a proxy for SKU-specific brand equity and shoppers goal-directedness (Janiszewski, 1998; Schellong et al., 2016). This score is calculated automatically as the result of an integrated click stream analysis and represents the share of purchases mainly driven by the brand (e.g., direct brand search via Google or brand filter on the retailers' webpage) compared to the total amount of sales for each SKU with a value range from 0 to 1.

Specifically, sales, returns, sales after returns, conversion rates, and OCRs (numerical rating with 1-5 stars as well known e.g. from Amazon and prior research like Sun (2012)) are measured for each SKU individually. In addition, we observe customers' shopping behavior on mobile devices as mobile intensity (purchases via mobile devices over total sales for each SKU). Finally, we control for different factors like product category (Gu et al., 2012), sales price (Minnema et al., 2016), rating volume (Liu, 2006) and time range since product launch (Chevalier and Mayzlin, 2006) whose influence on the OCRs-sales/returns relationship is known. Table 1 represents descriptive statistics for the main variables.

To study the moderating impact of mobile shopping behavior we cluster the mobile intensity variable in three groups (MIC: 1/low, 2/middle, 3/high). Priors studies classify low- and high-involvement products based on the extent of risk perceived by consumers (Baum and Spann, 2014; Wells and David, 1996). As the level of product involvement is supposed to be higher for more expensive products (Prelec and Loewenstein, 1998), we take the average sales price per category as an indicator to split the 40 different product categories into three different levels of product involvement (Involvement: 1/low, 2/middle, 3/high). Ho-dac et al. (2013) approximate the level of brand equity by publicly available advertising expenditures on the general brand level. We extend this method by using a bottom-up approach that allows us to track the brand equity and customers' goal-directedness while shopping on SKU-level individually. To analyze and interpret interaction effects we also split the brand score variable into three different levels (BSC: 1/low, 2/middle, 3/high).

Variable	Mean	SD	Min	Max
Sales (in units)	1,549	2,106	501	160,085
Returns (in units)	714	907	18	45,931
Mobile sales (in units)*	1.00	1.65	0.06	125.40
Mobile intensity (in % of total sales)*	1.00	0.31	0.14	2.56
Rating valence (1-5 stars)	4.30	0.40	1.40	5.00
Rating volume	18.97	37.67	5	3,106
PDP views*	1.00	1.38	0.03	74.8
Conversion rate*	1.00	0.65	0.01	11.21
Sales Price (in EUR)	47.04	34.36	3.74	411.15
Buying Price* (in EUR)	1.00	0.72	0.01	8.87
Brand Score (0-1)	0.19	0.11	0.01	0.58
Time since product launch (in months)	22.88	9.11	11.00	94.00

Notes: For confidentiality reasons the mean values of selected variables (*) are set to 1;
SD, Min, and Max are proportional to these standardized values; SD = Standard deviation

Table 1. Descriptive statistics for main variables in the data set

2.2 Methodology

Within our estimation approach, we analyze the data set in order to discuss RQ1-RQ8 and to analyze the influence of OCRs on customers' purchase and return behavior with mobile intensity, product involvement and brand equity as moderators. To operationalize this approach we combine and extend leading papers from this research area (Gu et al., 2012; Ho-dac et al., 2013; Minnema et al., 2016; Sahoo et al., 2015). Specifically, we follow prior research for our estimation approach by applying a 2SLS log-log-regression model with instrumental variables (Amblee and Bui, 2011; Clemons et al., 2006; Jabr and Zheng, 2014). To discuss RQ1, we use rating valence as a predictor of returns under consideration of different control variables. Therefore, Model 1 is presented by:

$$
\begin{aligned}
\text{Log(Returns)}_i &= \beta_0 + \beta_1 \cdot \text{Log(RatingValence)}_i + \beta_2 \cdot \text{Log(RatingVolume)}_i \\
&+ \beta_3 \cdot \text{Log(SPricePredict)}_i + \beta_4 \cdot \text{Log(PDPViews)}_i \\
&+ \beta_5 \cdot \text{Log(TimeSPLaunch)}_i + \beta_6 \cdot \text{Log(BrandScore)}_i \\
&+ \beta_7 \cdot \text{Log(MobileIntensity)}_i + ß_8 \cdot \text{Log(Sales)}_i + \sum_{k=9}^{48} ß_k \cdot \text{Category}_{ik} + \varepsilon_i
\end{aligned}
\tag{1}
$$

where Returns stands for the number of returned items for product i; RatingValence captures the average star rating (1-5) for product i; RatingVolume is the number of OCRs for product i; PDPViews represents the number of PDP views for product i; TimeSPLaunch stands for the time range in month since the launch of product i in the shop and our data collection in the autumn of 2016; BrandScore captures the share of branded purchases for product i; MobileIntensity equals the share of sold items by using a mobile device with mobile website and mobile application as sales channels for product i; Sales represents the number of sold items of product i and Category represents the appropriate fashion category for product i. Finally, we also control for the price of each product. However, we have to consider the threat of endogeneity between sales and price due to dynamic pricing systems (Granados et al., 2012; Greene, 2003). To counteract this risk, we use buying price as an instrumental variable for sales price and run an appropriate OLS procedure to calculate the predictor SPricePredict for each product i. For simplicity reasons, we do not present the additional Models 2-8 which are required to discuss RQ2-RQ8 in detail. They are basically adjustments of Model 1 just differing by specific interaction terms or sales after returns as the dependent variable.

We use RStudio (version 1.0.44) and R (version 3.3.2) for our calculations. The log-log regression models exhibit a reasonably good model fit and adjusted R² values between .57 up to .86. In order to avoid statistical problems such as multicollinearity, heteroskedasticity or endogeneity, we run several robustness checks and tests. The variance inflation factors for all variables in our main models, as presented in Table 2, are far below the threshold of 10 (Dormann et al., 2013). Thus, we assume that multicollinearity is not a problem in our sample. In order to check for heteroscedasticity, we perform Breusch-Pagan tests for every model (Breusch and Pagan, 1979). The hypothesis of a homogeneous variance structure is rejected in all cases ($p < .01$). Therefore, in line with Clemons et al. (2006) and Grüschow et al. (2015), we use Huber-White robust standard errors in all four models (Greene, 2003; White, 1980).

3 Results

The main goal of this study is to get a better understanding of the impact of OCRs on customers' shopping and return behavior in online fashion with a special focus on the moderating role of mobile intensity, product involvement, and brand equity. Table 2 reports the empirical results of the appropriate 2SLS log-log regression estimations to study RQ1 and RQ2.

		Model 1 (RQ1) DV: Returns				**Model 2 (RQ2)** DV: Sales after Returns			
	Variable	**ß**			**VIF**	**ß**			**VIF**
	Const.	-.08	.	(.04)		1.69	***	(.06)	
RQ1/2	LogRatingValence	-.95	***	(.01)	1.06	1.04	***	(.02)	1.06
	LogRatingVolume	-.02	***	(.01)	2.17	.26	***	(.01)	2.04
	LogSPricePredict	.25	***	(.01)	1.93	-.53	***	(.01)	1.62
	LogTimeSPLaunch	-.05	***	(.01)	1.56	-.17	***	(.01)	1.56
	LogPDPViews	.01	**	(.01)	2.82	.52	***	(.01)	2.00
	LogBrandScore	-.07	***	(.01)	1.42	.17	***	(.01)	1.37
	LogMobileIntensity	.07	***	(.01)	1.30	.17	***	(.01)	1.26
	LogSales	1.01	***	(.01)	2.27				
	Observations	46,178				46,178			
	Adj. R^2	.86				.66			

= p < .1, * = p < .05, ** = p < .01, *** = p < .001.

Notes: DV = Dependent variable; Huber-White robust std. errors in parentheses; Results for CG-specific variables are omitted for brevity

Table 2. Regression results for Model 1-2

Due to the chosen log-log method, all coefficients represent elasticities. The interpretation follows price elasticity from classic economic theory and is defined as the percentage change in demand because of a percentage change in price (Granados et al., 2012). The estimation results for Model 1 reveal a negative, significant impact of rating valence on the number of product returns (ß = -.95, $p < .001$). Thus, positive customer feedback can help to decrease the number of product returns. All control variables, such as rating volume (ß = -.02, $p < .001$), sales (ß = 1.01, $p < .001$), sales price (ß = .25, $p < .001$), time since product launch (ß = -.05, $p < .001$), number of PDP views (ß = .01, $p < .01$), brand score (ß = -.07, $p < .001$) and mobile intensity (ß = .07, $p < .001$) have also a highly significant impact on the level of product returns.

The results of Model 2 show that rating valence has a positive, significant impact on sales after returns (ß = 1.04, $p < .001$). Consequently, positive OCRs can help to increase the number of sold items that are not returned and the appropriate conversion rate as our model also includes the number of PDP views. Again, the control variables rating volume (ß = .26, $p < .001$), sales price (ß = -.53, $p < .001$), time since product launch (ß = -.17, $p < .001$), volume of PDP views (ß = .52, $p < .001$), brand score (ß = .17, $p < .001$) and mobile intensity (ß = .17, $p < .001$) are highly significant.

Table 3 gives us a comprehensive overview of the analyses regarding the moderating impact of the usage of mobile devices, product involvement and brand equity on the relationship between OCRs and product returns as well as sales after returns as formulated in RQ3-RQ8.

		Model 3 (RQ3) DV: Returns	**Model 4 (RQ4)** DV: Sales after Returns	**Model 5 (RQ5)** DV: Returns	**Model 6 (RQ6)** DV: Sales after Returns	**Model 7 (RQ7)** DV: Returns	**Model 8 (RQ8)** DV: Sales after Returns
	Variable	**ß**	**ß**	**ß**	**ß**	**ß**	**ß**
	Const.	-.09 . (.05)	1.54*** (.08)	-.02 (.07)	2.60 *** (.08)	-.01 (.04)	1.47 *** (.07)
	LogRatingValence	-.92 *** (.03)	1.10*** (.04)	-1.18*** (.04)	.96 *** (.05)	-.86 *** (.01)	1.00 *** (.02)
	LogRatingVolume	-.02 *** (.01)	.26 *** (.01)	.03 *** (.01)	.22 *** (.01)	-.02 *** (.01)	.27 *** (.01)
	LogSPricePredict	.25 *** (.01)	-.53 *** (.01)	.32 *** (.01)	-.62 *** (.01)	.27 *** (.01)	-.55 *** (.01)
	LogTimeSPLaunch	-.06 *** (.01)	-.17 *** (.01)	-.18 *** (.01)	.02 * (.01)	-.05 *** (.01)	-.18 *** (.01)
	LogPDPViews	.01 ** (.01)	.53 *** (.01)	.04 *** (.01)	.47 *** (.01)	.01 * (.01)	.53 *** (.01)
	LogBrandScore	-.07 *** (.01)	.18 *** (.01)	-.11 *** (.01)	.28 *** (.01)	.04 *** (.01)	.04 *** (.01)
	LogMobileIntensity	.08 *** (.01)	.15 *** (.01)	.07 *** (.01)	.23 *** (.01)	.07 *** (.01)	.17 *** (.01)
	LogSales	1.01 *** (.01)		.96 *** (.01)		1.01*** (.01)	
RQ 3/4	LogRatingVal : MIC 2	-.02 (.03)	-.05 (.03)				
RQ 3/4	LogRatingVal : MIC 3	-.04 (.03)	-.12 * (.05)				
RQ 5/6	LogRatingVal : Involvement 2			.10 * (.05)	.41 *** (.06)		
RQ 5/6	LogRatingVal : Involvement 3			-.06 (.06)	.23 *** (.07)		
RQ 7/8	LogRatingVal : BSC 2					-.27 *** (.03)	.20 *** (.05)
RQ 7/8	LogRatingVal : BSC 3					-.19 *** (.04)	-.13 *** (.04)
	Observations	46,178	46,178	46,178	46,178	46,178	46,178
	Adj. R^2	.86	.66	.82	.57	.86	.67

. = $p < .1$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$.

Notes: DV = Dependent variable; Huber-White robust std. errors in parentheses; Results for CG-specific variables and the main effects of the interaction variables (MIC, Involvement, BSC) are omitted for brevity

Table 3. Regression results for Model 3-8

The results of Model 3 does not reveal any significant difference between the three stages of mobile intensity regarding the impact of OCRs on product returns (MIC 1 vs. MIC 2: ß = -.02, $p > .1$; MIC 1 vs. MIC 3: ß = -.04, $p > .1$). In contrast, the results of Model 4 show a significant interaction effect regarding mobile intensity (MIC 1 vs. MIC 3: ß = -.12, $p < .05$). Hence, the positive impact of OCRs on sales after returns is stronger in the desktop sales channel than in the mobile application or the mobile website. The outcome of Model 5 shows that involvement has only a limited interaction effect on the relationship between OCRs and returns (Involvement 1 vs. Involvement 2: ß = .10, $p < .05$; Involvement 1 vs. Involvement 3: ß = -.06, $p > .1$). Further, the estimation of Model 6 shows a significant moderator impact of product involvement (Involvement 1 vs. Involvement 3: ß = .23, $p < .001$). Thus, the positive impact of OCRs on sales after returns is higher for items with a higher level of product involvement. The estimation approach of Model 7 underlines that the impact of OCRs on product returns is higher for strong brands than for weak brands (BSC 1 vs. BSC 3: $ß = -.19$, $p < .001$). Finally, the results of Model 8 show a significant interaction between rating valence and brand score on sales after returns (BSC 1 vs. BSC 3: $ß = -.13$, $p < .05$). Consequently, positive OCRs matter more for weak brands.

4 Discussion and Conclusions

Our study provides several contributions and implications for the literature and practitioners. By analyzing a large set of actual transaction data we contribute to the literature in the areas of OCRs, product returns, and mobile shopping. Specifically, we extend prior research in at least four ways. First, our findings underline the general hypothesis motivated by uncertainty reduction theory (Berger and Calabrese, 1975) that positive OCRs can lead to lower returns, higher sales after returns, and better conversion rates. Consequently, we show, that OCRs are a powerful marketing instrument to lower customers' product uncertainty, that they are facing constantly in the e-commerce sector (Dimoka et al., 2012). Second, we reveal a significant moderator effect of mobile intensity considering the relationship between rating valence and sales after returns. Thus, the positive sales impact of OCRs is lower in the mobile sales channel (mobile application, mobile website) in comparison to the desktop. This might also be explained by higher search cost on mobile devices as customers have to invest more time and effort to lower their level of product uncertainty in the same way as they can do it by using a normal desktop computer (Wang et al., 2015). Third, in line with involvement theory (Zaichkowsky, 1985) we see a significant impact of product involvement in this context. The influence of positive OCRs on sales after returns is stronger for high-involvement (e.g., winter jackets) than for low-involvement products (e.g., socks). Fourth, even if positive OCRs have a higher impact for strong brands regarding customers' return behavior we find also support for statements from brand signaling literature, that OCRs matter more for weak than for strong brands regarding sales after returns. Thus, weak brands can substitute their lack of marketing measures and strong quality signals by positive OCRs to drive customers' purchase probability (Erdem and Swait, 1998; Ho-dac et al., 2013; Montgomery and Wernerfelt, 1992).

From the managerial perspective, our findings are very relevant for those responsible as they offer a way to reduce costly product returns and to increase sales after returns. More specifically, we provide a better understanding how to allocate marketing budgets regarding OCRs. First, search costs for customers using mobile devices are higher due to limited screen capacities. Considering the rising share of mobile commerce, the mobile OCR functionalities should be simplified and optimized. Second, OCRs matter more for high-involvement than for low-involvement products such that OCR strategies should focus more on high-involvement goods. Third, as OCRs matter more for weak brands regarding the overall sales performance, the appropriate brand managers should consider a significant role for OCRs in their marketing strategy. In conclusion, retailers should establish sales channel, device, category, brand or even product-specific strategies on how to deal with OCRs in their online shop. Regarding our results, one overarching approach using OCRs as an efficient marketing instrument cannot be seen as the most effective strategy.

The meaningful findings of our study notwithstanding, we naturally face some limitations. First, the empirical analysis is based on a very large data set. However, the data covers only one firm from one industry. Replications of our study with different e-commerce players in one industry or even across different industries would be useful. Second, as large online retailers have customers from different parts all over the world with a very heterogeneous cultural background, practitioners, as well as researchers, are eager to get deeper insights about the specific online shopping behavior. Thus, the area of cross-cultural research provides sufficient motivation to discuss the relationship between OCRs, sales and returns sales along different countries, cultures or even continents. Finally, the combined analysis of quantitative and qualitative parts of OCRs offers also a fruitful area for further research.

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