Avoiding high return rates in retail. An explorative study under the aspect of customer acceptance.

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Abstract:

Along with the development of e-commerce, product returns have developed to a common perk. The actions a retailer can take to reduce them can either be by adjusting the return policy or by identifying and analysing return reasons. According to Ratchford *et al. [9], there has been a need to investigate how online retailers can reduce returns. Besides that, it has been interesting to have a look at the age of customers, since young customers tend to be major drivers of online re-tailing [2] survey in Germany was applied to generate data. According to the results measures suggested by literature are not accepted by customers. Furthermore, the results show no correlation between the age of customers and the acceptance of certain return tools. The results allow a derivation of suggestions regarding the measures online retailers can take if they strive for a reduced return rate.*

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1 Introduction

In recent years, the growing development of e-commerce has fundamentally changed retail dynamics, offering a large level of convenience to customers and meaningful opportunities for online retailers [3]. However, this digitally driven development has also brought up various operational challenges, one of them being high product return rates. In the United States alone, product returns are accountable for an estimated amount of USD 761 billion in lost sales, with an average of USD 90 billion worth of goods being returned each year [4; 5]. One of the striking things about these figures is that online orders have a significantly higher return rate than traditional in-store purchases, namely almost twice as high at 21 percent of the online sales value [4]. Not only are these product returns costly for retailers, but they also lead to logistical and environmental challenges and customer relationship management concerns. There are two different ways to deal with these challenges regarding product returns: either retailers become more effective, or they reduce product returns.

Although existing literature on product returns covers various managerial strategies to reduce product return rates reaching from improved product presentation to having stricter return policies, there is limited empirical research and evidence on how customers accept and perceive these tools. Especially the influence of customers' age on the acceptance of tools to reduce return rates has not been researched properly yet. Therefore, the goal of this explorative study is to gain insights on which measures aimed at reducing product returns are accepted by customers, setting a clear focus on tools that are meant to tackle customer centric return reasons. Furthermore, this paper also analyses whether the customers' age and incentives like rewarded reviews have an influence on customers' tool acceptance level. It also investigates how stricter return policies may affect customers' return behaviour.

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2 Literature Review

2.1 Method and Focus of the Literature Review

This study can be classified into the science fields of retail management, behavioural economics and reverse logistics. It begins with a review of the recent literature that contributes to the field of product returns. The literature review is crucial to provide an overview of the research topic to identify trends and uncover research gaps [6]. For a systematic approach, it is recommended to search for a literature framework by using various search methods such as data-base searches, table-of-content scans, citation searches, and complementary searches [7]. Here, database search with e.g. *Google Scholar*, *ScienceDirect* and *Resurchify* contributes to this framework for each scientific field identified before. To ensure that the sources used are up to date, this paper mainly uses papers from the years 2020 to 2025. The next step involves further screening of the previously identified papers to separate relevant sources from those that are irrelevant for further review. This procedure typically begins with a superficial se-lection based on papers' titles or their abstracts. Afterwards, a more detailed screening takes place based on full text review [7]. This selection leads to 20 journals that are used for this study. All these identified papers addressing product returns meet the requirement of being double blind peer-reviewed journals. Furthermore, most of them are either ranked in the *VHB JOURQUAL3* complete list or in the latest *VHB 2024* ranking. For better classification in the scientific context, it is crucial to assign this study about product returns to specific scientific fields beforehand. In that regard, this work can be classified into the science fields of retail management, behavioural economics and reverse logistics.

2.2 Retail management

Since online shopping has got more attention in recent years, e-commerce has experienced substantial growth. A closer look on numbers show that the global e-commerce volume amounted to USD 3,53 trillion in 2019 [8]. This number even increased to approximately USD 4,9 trillion in 2021. This trend also seems to continue further in the future since the total volume of global e-commerce is expected to surpass USD 7 trillion by 2025 [4]. According to *Zhao, et al.* [9] and *Masuch, et al.* [10] this substantial growth results from advancements achieved in information technology like the emergence and popularity when it comes to portable devices such as smartphones and tablets and further the availability of various platforms like Amazon. Moreover, *Ratchford, et al.* (2022) state that consumers gained more confidence when it comes to online shopping which also contributed to this trend. Further-more, the Covid-19 pandemic has led to meaningful and long-lasting influence on global e-commerce [1]. Along with this rapid development, product returns have developed to a common perk used by consumers. The total sum of product returns in the United States amount up to USD 761 billion being lost sales for retailers [4]. *Ratchford, et al.* (2022) state that product returns overall influence more than 30% of global online sales. In general, this large number of product returns in e-commerce is a major challenge for online retailers as product returns and its associated costs lower retailers' margins [2; 11].

Prior to looking at what measures can be used to overcome this trend; there will be a brief overview of possible reasons when it comes to returning a product. A possible way of dividing common return reasons is by considering them either to be company centric or customer centric. Company centric reasons are the ones that the retailer is accountable for, like damaged products, delayed delivery or poor quality shown in Table 1. Those kinds of return reasons can be controlled by the retailer and solved or reduced by management actions, like an improved quality audit for suppliers or training for employees regarding picking and packing [2].

Since customer centric return reasons are part of chapter 2.3, this chapter focuses on the company centric return reasons. As represented in Table 1, there are many different reasons that may result in product returns. These reasons can be separated into four different categories: unsuitable product, compromised delivery, deceptive advertisement and manipulated information. Furthermore, Table 1 also shows the specific return reasons and a short explanation on why a product return might occur.

Now that there is a brief overview of the possible company centric return reasons for products, it is also important to consider different ways of reducing these returns. Therefore, Table 2 shows different kinds of management measures that can be used to reduce product returns and what exact return reason gets tackled by them.

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Table 1. Company centric return reasons

Categories	Return reason	Explanation
Unsuitable product	product mismatch	Product differs from the picture regarding fit, color, design, etc.
	fake product	Product is fake, an older version or expired
	poor product quality	Product has a lower quality than expected
	damaged product	Product is damaged or defective upon delivery
Compromised delivery	delayed delivery	Delivery date varies from estimated date given by the retailer
	delivery delay in urgency	Delivery date varies from the estimated date given by the retailer. For example: product required for a special occasion
	manhandling of product	Unprofessional handling during delivery leads to product damage
	poor packaging	Proper packaging as a sign of the product quality
Deceptive advertisement	perceptual inaccuracy	Product fails to match prior expectation based on quality, size or performance
	misleading advertisement	Product differs from the information provided in the advertisement
Manipulated information	tampered information	Missing detail and truthfulness in provided information
	inadequate information	Given information leads to confusion of the customer
	no clear terms & conditions	Mismatch in terms & conditions bring uncertainty for the customer
	ambiguous refund practices	Inconsistent and random refund processes result in customer dissatisfaction

Source: Own representation based on [2, p. 5]

Table 2. Management measures to reduce company centric returns

Management measure	Company centric return reason
Open box delivery to enable customers to verify the product prior to delivery acceptance	product mismatch, damaged product
Customer feedback during return process to ensure better understanding of the customers' issue	product mismatch
Confirmation of the product specification prior to pick up by or dispatch to the customer	product mismatch
Audit of current suppliers and maintenance of standardized product quality	fake product, poor product quality
Realistic estimation of delivery time and, if needed, earlier shipping process	delayed delivery
Transparency in communication regarding occurrence of delays	delayed delivery
Extra fee for urgency delivery process to realize categorization during the shipping process	delivery delay in urgency
Sensitization of involved personnel in the packing and shipping process regarding product handling	manhandling of product
Usage of ample shock bearers	poor packaging
Product showcase includes different models and implementation of augmented reality (AR)	perceptual inaccuracy
Refrain from confusing advertisement and unrealistic promises	misleading advertisement
Reconciliation of product code with the invoice and provision in original packaging	tampered information
Verification of provided information on the website and its supplementation with additional standardized size charts and brand specific size charts	inadequate information
Presence of simple and crisp return policies that are displayed clearly on the website	no clear terms & conditions, ambiguous refund practices

Source: Own representation based on [2, p. 13]

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Even though these measures help retailers to reduce their product returns, it is unlikely that a retailer will not have any returns at all. Thus, it is important to think about terms and conditions when it comes to product returns, so called return policies. Return policies can be categorized as lenient and strict policies. A lenient policy is characterized by free returns with a long period to return without charging any fees to the customer and allowing so called "change of mind returns". Afterwards, there are rather restrictive return policies that include a return fee, a smaller time frame to return [12, p. 509 ff.] or reject returns [13, p. 7]. Lenient return policy have negative and as well as positive aspects for the retailer. The positive side is that it increases the number of purchases and repurchases because it is associated positively and fair to the consumer. Furthermore, it increases the trust of the consumer and stands as a signal of quality which attracts customers. On the other side lenient policies are abused by customers and lead to higher return rates and higher costs since they can purchase goods with almost no restrictions and consequences [12]. Strict return policies set incentives to reduce intended returns by increasing the effort for a customer to return goods in form of time effort or fees [14]. Hence, they are beneficial for online retailers regarding reverse logistics costs, and they can further contribute to profitability when chosen correctly [15], [16].

2.3 Behavioural economics

This chapter focuses on customer centric reasons for product returns. Those are reasons that originate from the customers' side and cannot be directly controlled by the retailer, like impulsive buying and regretting afterwards [2]. To develop measures that reduce returns based on customer centric reasons, it is important for online retailers to know and understand the psychological reasons for product returns and their underlying theories. Bringing the reasons and theories into a structure obtains a systematic approach to identify appropriate measures that can lead to a reduced return rate.

The reason why customers return products purchased online can be explained by three theories. *The expectation confirmation theory*, *the theory of cognitive dissonance* and *the theory of planned behavior*. *The expectation confirmation theory* by *Oliver* [18] states that the customers' expectation of a product can be either confirmed or disconfirmed. In case the customer's expectation is confirmed, the customer is satisfied. In the event of a disconfirmed expectation (e.g. product fits differently than expected), it can turn out to be either positive and lead to satisfaction as well or negative and lead to dissatisfaction and return [2;17]. *The theory of cognitive dissonance* by *Festinger* [18] describes the creation of a psychological tension whenever an individual's behaviour mismatches its beliefs and thoughts (e.g. purchase because of certain information of a product which turns out to be wrong). According to this theory, humans generally seek to lower their dissonance by taking some action. Consequently, if a customer develops cognitive dissonance because of inconsistencies between the expected beliefs of the product and the actual product, the customer tends to return it. *The theory of planned behavior* by *Ajzen* [19] states that a person's intention is driven by his attitude, subjective norms and perceived behavioural control. The intention then results in certain behaviour. That means that a customer with the attitude and belief to return a product is likely to do so. An example would be an impulsive purchase and regret it afterwards which leads to the attitude of returning the product before it even arrived [1;19].

Even though customer centric reasons, which are shown and explained in Table 3, cannot be directly controlled by the online retailer, there are some suggested management actions for retailers that might reduce customer centric return reasons shown in Table 4.

Table 3. Customer centric return reasons

Categories	Return reason	Explanation
Buyer's regret	Expectation Disparity	Customer perceives a mismatch of price and quality of a product
	Bad experience from personnel involved	Bad service quality from customer care in case of queries and complaints
Wardrobing	Trial order	Purchase a product to try it on or out to maybe buy it in the future
	Dishonest activity	Return a product after using it, also known as "deshopping"
Buyer's spontaneity	Impulsive buying	Buying a product under influence or by mistake and regretting is afterwards
	Peer influence	Returning a product after reading bad reviews or after a friend advised against it

Source: Own representation based on [2, p. 9]

Table 4. Management measures to reduce customer centric returns

Management measure	Customer centric return reason
Offering a rental program for products	Trial order, dishonest activity
Offer 360-degree view of the product for a better matching with the customer's expectation	Trial order, expectation disparity
Use augmented reality for try on and better product inspection	Trial order, expectation disparity
Monitor customers and their return activities and put those with frequent return activities on blacklists or block them	Trial order, Impulsive buying, dishonest activity
Encourage customer to write product reviews with pictures or videos	Trial order, expectation disparity
Training for own personnel and for the personnel of delivery partners who have direct contact to customers	Bad experience from personnel involved

Source: Own representation based on [2, p. 13 f.]; [20, p. 34]; [8, p. 152]; [2, p. 171 f.]

Another very common categorization, besides company and customer centric reasons, is the one between planned und unplanned returns. For these categories many synonyms are used, like intended and unintended returns or opportunistic and legitimate returns [8, p. 152]. Planned returns include the reasons within the categories "wardrobing" and "buyer's spontaneity" in Table 3. [2, p. 3]. Unplanned returns include reasons within the category "buyer's regret" in Table 2 and all the company centric reasons from Table 1 [2, p. 6 ff.]. Unplanned returns can be explained by the expectation confirmation theory and the cognitive dissonance theory, while planned returns are explained by the theory of planned behaviour ([2, p. 3]). Figure 1 summarizes the findings regarding the underlying theories for return behaviour and the different categories for return reasons. Such a systematic framework can be the base for online retailers to create proper measures to reduce returns by addressing the reasons and underlying theories.

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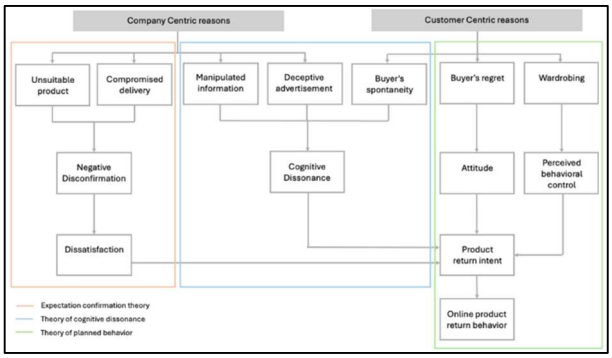


Figure 1. Systematic framework of online product return behaviour
Source: [2, p. 11]

2.4 Reverse logistics

Reverse Logistics is described by *Fleischmann* as "the process of planning, implementing and controlling the efficient, effective inbound flow and storage of secondary goods and related information opposite to the traditional supply chain direction for the purpose of recovering value and proper disposal" [21]. This includes the collection of returned products, the redistribution to the retailers, the product inspection which includes recovery or disposition and the restocking process. Since return rates have increased, retailers are overwhelmed by handling reverse logistics because of the complexity due to many stakeholders and different location, time and customer needs [8]. Additionally, consumer returns are attached to the uncertainty of a customer's decision. The uncertainty is even higher in e-commerce compared to physical store retailing because the consumer cannot inspect the product before purchasing it. Hence, there is also uncertainty regarding the capacities needed for reverse logistics processes [13].

An efficient management of reverse logistics implies the efficient use of resources and capacities and is key for a sustainable business [22]. It can be a source of competitive advantage or just an improvement in competitiveness [23] since it increases customer satisfaction due to faster return processing and refund payment [13] and reduces costs for the retailer [22]. But there are not only economic advantages. *Karl* as well as *Ayree & Adaku* mention that retailers with efficient reverse logistics management also profit from environmental advantages [13],[23] - [25].

There are many approaches to bring more efficiency into the reverse logistics system. *Karl* emphasizes the importance of forecasting systems for returns. Forecasting is essential to overcome the uncertainty of returns and hence, increase plannability to reduce re-active planning and the inefficient use of resources and capacities. Consumer return forecasts usually focus on the return volume. The total return volume can be further segmented in various ways, e.g. by products or by different types of returns like used, damaged or unused products because of different processing requirements. To forecast returns, retailers need a broad data collection as well as suitable information and communication technology for processing the data. Especially for online retailers it is convenient to collect proper data since they have access to data about customers and their purchase and return behavior [13].

Another way to increase efficiency is to adjust the reverse logistics network. *Thibbotuwawa et al.* [22] suggest online retailers include Initial Collection Centers (ICC) in their reverse logistics network to bundle returns before sending them back to the warehouses. For that bundle effect, there should be decision-making processes within the ICCs to differentiate the returns regarding their destination, e.g. goods that will be sold again enter the warehouse and goods that will be disposed are transported to a landfill. A crucial aspect in designing the reverse logistics network is to identify the optimal location of the ICCs. *Thibbotuwawa et al.* [22] created a programming model that provides retailers with the optimal number of ICCs and their location by analyzing the consumer market. It then allocates the return volume to the ICCs. Considering these aspects, designing a reverse logistics network will increase the transportation efficiency which leads to lower costs [22].

2.5 Research gap & research questions

The main research gap identified is whether the various tools proposed by retailers to reduce return rates are accepted by customers. Besides that, other authors give the following suggestions for further research.

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According to *Ratchford et al.*, there is a need to research on how online retailers can reduce returns and how a more detailed and accurate description of product characteristics and sizes, detailed pictures and videos, consumer reviews with pictures and videos, apps or technologies that assist in finding the right size can contribute to a lower return rate [2, p. 172]. It is also interesting to have a closer look at the age when conducting research on online returns since young customers (Generation Y and Generation Z) tend to be the major driver of online retailing because of their stronger trust in online shopping and smarter handling of digital activities compared to the older generations [2, p. 2]. Another important aspect for further research is mentioned by *Ahsan & Rahman* which claim that research on strict return policy is rare [8, p. 150].

Based on that, the following study will focus on answering the following four research questions:

RQ 1 To what extent are certain tools to reduce product return rates, caused by customer centric reasons, accepted by customers?

RQ 2 To what extent does the customers' age have an influence on their acceptance of tools to reduce product return rates?

RQ 3 How does a rewarded tool usage influence the customers' acceptance level of this used tool?

RQ 4 How do stricter return policies affect the return behaviour of customers?

The centre of this study is the acceptance of customers regarding different tools which are suggested by literature to help online retailers to reduce returns (RQ1). The focus lays on those tools that should reduce returns caused by customer centric reasons since they are harder to control for retailers, which makes it more valuable to gain further insights in this category. The second and third research questions (RQ2 & RQ3) extend the first one by analysing the influence on the acceptance of two important aspects which are the customer's age and rewarding the customer for the usage of certain tools. Lastly, research question four (RQ 4) addresses a stricter return policy. The aim is to find out whether there would be an effect on the return behaviour of customers if online retailers implement stricter return policies and how that effect would look like.

3 Methods

This study adopts a questionnaire survey approach to answer the research questions. The software solution to conduct the survey was "*Limesurvey*". In total, the survey includes seven questions. For the first question the participants had to enter their age, while the remaining six questions addressed the acceptance of different tools to reduce return rates. These six questions could be answered by a *Likert* scale. A four-point *Likert* scale was intentionally chosen to eliminate a neutral midpoint and require respondents to indicate a directional tendency (forced-choice). This methodological design was implemented to prevent midpoint bias and ensure that the captured data clearly reflected positive or negative orientations, aligning with the study's objective to measure explicit attitudinal directions.

Before conducting the survey, there was a short pre-testing phase where two people went through the questionnaire. Their feedback led to the adjustment of questions three and six where further explanation regarding augmented reality and the renting program for a better understanding and answering were needed.

Afterwards, the survey has been conducted in front of a DHL parcel station located within a "REWE" grocery store in Bretten, South Germany, on 17th, 19th and 22nd of April 2025. The target group consists of people that went to the parcel station to return any kind of products. People that were willing to participate in the survey had two options to answer the questions: either via a tablet on site or later via QR-code. In total, 42 people participated in this survey.

To evaluate the gained answers, the statistical software tool "*SPSS*" was used for analysis using descriptive as well as inductive methods. During this process, the questions asked were assigned to certain variables that were named after the respective tool examined. In descriptive statistics, this study uses different ways of presenting the absolute frequencies of the various responses, such as bar charts and pie charts. The inductive statistics section relies on the *Spearman* rank correlation coefficient and simple linear regression. The *Spearman* rank correlation coefficient provides information on whether there is a statistically significant correlation between two ordinal or one ordinal and one metrically scaled variable [26, p.189 f.]. The findings of the Spearman rank correlation coefficient are then extended by the findings of simple linear regression, the aim of which is to predict the value of a dependent variable based on an independent variable. For this purpose, simple linear regression attempts to determine a regression line of the form $\hat{y} = b \cdot x + a$, which, if the data

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points of the answers were to be displayed in a scatter plot, could be placed through the centre of gravity of the data [27, p. 521 f.].

4 Results

The age groups are clustered according to the different generation types. Most of the participants belong to generation Z with 27 participants, followed by generation X with 10 participants and Y with 5 participants. (Figure 2).

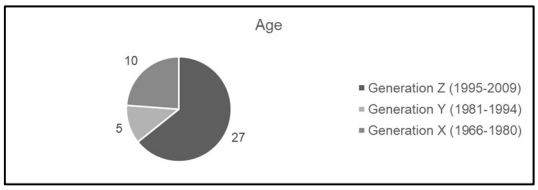


Figure 2. Absolute frequency distribution of the answers on Q1

Table 5 shows an overview of the questionnaire and the code for each question for the evaluation.

Table 5. Overview of the survey's questions and their coding

Question	Code
Q2: How likely would you use a 360-degree-view of products from online retailers for a better product inspection to reduce returns?	360-degree-view
Q3: How likely would you use augmented-reality-tools for a better inspection of products offered by online retailers to reduce returns?	AR-tools
Q4: How likely would you write a review (incl. pictures and videos) of a product from an online retailer to help other customers with their purchase decision and therefore reduce returns	Review
Q5: How likely would you write a review (incl. pictures and videos) of a product from an online retailer if you receive a coupon or discount for that?	Rewarded review
Q6: How likely would you use renting programs for products offered by online retailers, which you don't want to keep after usage, to reduce returns?	Rental
Q7: To what extent does the following statement apply to you? Strict return policies such as monitoring of high frequent return activities and therefore charging extra fees would encourage me to return less.	Strict policies

Figure 3 presents the frequency distribution of the participants' answers to each question. A closer look on the highest frequencies indicates that "very likely" was answered the most for stricter policies with 18 participants, followed by promoted reviews with 16 participants and AR-tools with 12 participants. For the answer "likely" there are 28 participants for the 360-degree-view tool, followed by promoted review with 20 participants and strict policies with 6 participants. 20 participants answered "unlikely" for the tools Review and Rental, followed by AR-tools with 17 participants. The answer "very unlikely" was chosen the most for Review with 10 participants, followed by strict policies with 4 participants and rental as well as 360-degree-view with 3 participants.

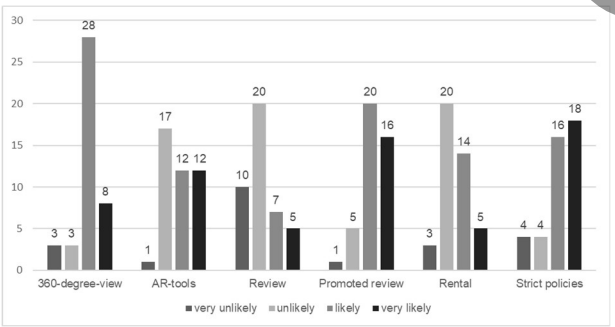


Figure 3. Overview of the absolute frequency distribution of the participants' answers

Table 6 shows Spearman's rank coefficient to each of the six questions as well as its corresponding significance level.

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As the numbers show, all the available rank coefficients to the questions asked lay within the range of -0,284 to 0,087. Since the rank coefficient can have maximum values from -1 to +1, the coefficients to be seen are weak negative to weak positive correlations. In order to be able to make statements about the statistical verifiability, it is necessary to look at the significance level also shown in Table 6. The null hypothesis that there is no significant correlation between two variables can only be declined correctly if the significance level is below five percent. The numbers state that none of the researched correlations have a significance level below five percent while the promoted review via coupon is closest to this value with a significance level of 6,9 percent. As a result, there are no statistically significant correlations in the relationships analysed above, the null hypothesis applies.

Table 6. Overview of the results of Spearman's rank correlation

Variable (n=42)	360-degree-view	AR-tools	Review	Rewarded review	Rental	Strict policies
Spearman's rank coefficient	0,042	-0,118	0,087	-0,284	0,067	-0,066
Significance level	0,792	0,458	0,586	0,069	0,675	0,676

Table 7 gives a brief overview of the results of the linear regression. The table contains values of the R-square, significance level, constant, regression coefficient, standard error and t-value for each of the six questions regarding customer acceptance of measures to reduce return rates.

Looking at the numbers of the R-square value of each question, it is visible that the measured answers of the participants can be explained statistically from 0,3 to 2,5 per-cent. This circumstance does not represent a good value because, conversely 97,5 to 99,7 percent of variances cannot be explained with this regression model. Next up is an-other look at the significance level of each regression model. The implicit null hypothesis that the age of the test subjects has no influence on the respective variable under investigation can only be rejected again if the significance level is below 5 percent. However, since the significance values of the researched variables lie between 31,6 and 72,9 percent, the null hypothesis is assumed for all variables. The following rows constant, regression coefficient and standard error address the topic of the regression line. As an example for the other cases, a straight line with a y-intercept of 2,985 and a gradient of -0,005 can be laid through the existing data points in the variable AR-tools. As it is not possible to draw conclusions on the population from the given sample, the standard error specified for the regression coefficient must be considered for new test subjects outside the sample. In the case of the variable AR-tools this standard error would have a negative or positive influence on the coefficient of 0,011. Finally, the t-value indicates whether there is an effect different from zero and whether the regression coefficient can therefore be meaningfully included in the regression equation of the regression line. For this to be the case, however, the significance level must be considered again. Looking at the t-value of all variables, it is visible that there is an effect different from zero for all variables. However, remembering the significance levels already evaluated, none of these effects is statistically significant.

Table 7. Overview of the results of the simple linear regression

Variable (n=42)	360-degree-view	AR-tools	Review	Rewarded review	Rental	Strict policies
Spearman's rank coefficient	0,042	-0,118	0,087	-0,284	0,067	-0,066
Significance level	0,792	0,458	0,586	0,069	0,675	0,676

5 Conclusions

As the results of the statistical analysis of the participants' answers to the questionnaire have been described previously, this chapter now focuses on assigning the results to the research questions. Therefore, this chapter splits into the parts discussion, theoretical implications and further research and practical implications. During discussion, the different research questions are answered and then linked to the findings from the theory in the theoretical implications and further research section. Last, practical implications deal with the meaning of the results for online retailers in practice.

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5.1 Discussion

The answer for RQ1 can be found in Figure 3 by looking at the evaluations on 360-degree-view, AR-tools, Review and Rental since those questions address solely the acceptance of the certain tools. Under the assumption that the answers "very likely" as well as "likely" imply that a tool is accepted and "unlikely" and "very unlikely" imply it is not accepted, the survey shows the following ranking. The 360-degree-view tool is the most accepted one with 36 participants accepting it and 6 participants not, followed by AR-tools in second place with 24 participants accepting it and 18 not. The third place is occupied by a rental system with 19 participants accepting it and 23 not. Writing product reviews is ranked in the last place with 12 participants accepting it and 30 participants not. Overall, the 360-degree-view tool as well as the AR-tool are accepted. The rental system and writing product reviews are not accepted.

The data and insights shown above in Table 6 and Table 7 can be used to answer RQ2 which deals with the influence of customers' age on their acceptance of tools to reduce product return rates. As Table 6 shows, none of the analysed spearman rank correlation coefficients show a statistically significant value. Therefore, there is insufficient evidence to justify rejecting the null hypothesis that there is no statistically significant relationship between the variables examined. This picture is confirmed when the results of the simple linear regression shown in Table 7 are also considered. Overall, the explanatory power of all the regression models analysed is very low and not significant in any case. This means that the null hypothesis, that age has no statistically significant influence on the variables analysed cannot be rejected. To conclude RQ2: according to this study, age does not have an influence on the acceptance of tools to reduce return rates.

RQ3 can be answered by having a look at the evaluations regarding Review and Pro-moted review. Since writing product reviews without a reward is not accepted but adding a reward shows a shift to being accepted leads to the conclusion that rewarding the usage of a tool increases the acceptance for the tool in this sample.

To answer RQ4 a look at the evaluation named Strict policy in Figure 3 is necessary. It is clear to see that there would be an effect if online retailers would implement a stricter return policy because 16 participants agree and 18 participants fully agree that the monitoring of high frequent return activities by online retailers and therefore charging extra fees would encourage them to return less. According to this study the answer is that implementing strict return policies will encourage most customers to return less products.

5.2 Limitations, theoretical implications and further research

The survey presented is exploratory in nature. Due to the small sample size (n=42) and its geographic concentration on in Germany, the generalizability of the findings is limited. The small sample size also limits the possibility of conducting more advanced statistical analyses and may affect the robustness of the findings. To gain a more comprehensive understanding, it is necessary to undertake a larger-scale survey involving a larger and more diverse sample involving broader geographic coverage and to investigate different consumer good categories However, the sample number is sufficient to ensure a qualitative result.

According to the results some of the management measures suggested by literature are not accepted by customers. The results of the study conducted by *Das & Kunja* in India led to the implication that retailers should offer a renting system for products [2, p. 14] while this study shows the opposite that customers won't accept and therefore probably won't use it. This example indicates that the acceptance for certain tools to reduce returns might deviate across different target groups. In case of no acceptance for renting products, it would be interesting to conduct further research on the reasons why customers would refuse to use a renting system for products that they want to have only for a single usage.

The results also show that there is no influence of the customer's age and the acceptance of certain tools while literature claims that young customers tend to have a higher technical affinity and are more enthusiastic concerning online shopping [2, p. 2] what causes the expectation that such tools are more accepted by young customer. However, the missing correlation in this study is explained by the fact that it is an explorative study and was conducted for a small sample. For a valid result on whether there is an influence, the conduction of a representative study is needed.

Further research is also needed on if adding a reward for the usage of a tool increases the acceptance for that tool, since this study shows an increase of acceptance for the example of writing reviews when adding a monetary reward. This correlation should be tested for various tools in the form of a representative study. Additionally, there should be more research on the value of the reward: What are the boundaries for a reward

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to be high enough to have a motivational impact for the customer and low enough to not threaten the retailer's profit? Is there even a span existing?

Further research questions are also interesting concerning stricter return policies. can be: How strict can a return policy be without putting the revenues of an online retailer at risk? How high could an extra fee for high frequent return activities be? How can frequent return activities be defined?

5.3 Practical implications

The results of the survey allow a derivation of suggestions regarding the measures online retailers can take if they strive for a reduced return rate.

First, it is important to make sure to implement a tool that is accepted by the customers since Figure 3 shows that there are clear differences in acceptance among different tools. Furthermore, they should consider that the acceptance of some tools might deviate across different target groups. While Indian customers will e.g. accept a renting system for online products, German customers would refuse it. But this is not the case for all tools, some are more uncritical regarding cultural differences like a 360-degree-view tool. Nevertheless, online retailers should check on the acceptance prior to implementing new systems or tools by conducting a survey or market analysis or testing it for few products. In case an online retailer operates in different countries he should analyse the acceptance separately by countries or regions, like Europe and Asia for example.

Looking at the next aspect, there are tools that are poorly accepted by customers. But if such a tool has the potential to decrease return rates, online retailers can set incentives to encourage their customers to use it. That is what this study shows on the example of product reviews: According to literature, product reviews lead to a reduction in return rates ([2, p. 171]), but customers won't write them voluntarily. By giving out discounts for a written review the customers' acceptance increases and addition-ally, might cause a repurchase.

Furthermore, this study shows that stricter policies would cause a reduction in return rates. If an online retailer faces high costs due to returns it is a potential option to implement stricter return policies. Here, it is important to consider that this might result in a lower number of purchases by customers [8, p. 148]. To have a profit improvement online retailers should figure out a return policy that balances a reduction in the return rate while not having a significant decline in purchases.

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