The Effects of Consumer Demographics and Payment Method Preference on Product Return Frequency and Reasons in Online Shopping

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THE EFFECTS OF CONSUMER DEMOGRAPHICS AND PAYMENT METHOD PREFERENCE ON PRODUCT RETURN FREQUENCY AND REASONS IN ONLINE SHOPPING

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Abstract In online shopping, product returns are very common. In order to reduce them, one must first understand who are making them and why are they being made. In this study, we aim to address these questions by examining product return behaviour from a consumer-centric rather than the more traditional product-centric, retailer-centric, and order-centric perspectives. More specifically, we focus on the effects of four demographic characteristics of consumers (i.e., gender, age, education, and income) as well as their payment method preference on their product return frequency and product return reasons. As the data, we use the responses from 560 Finnish online consumers, which were collected with an online survey and are analysed both quantitatively and qualitatively. We find gender, age, payment method preference, and average online shopping frequency to affect average product return frequency, whereas product return reasons were found to be affected by only gender and average product return frequency.

Keywords: product return frequency, product return reasons, online shopping, demographics, payment method preference, logistic regression

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1 Introduction

In online shopping, returning a purchased product back to its seller is very common (Ofek, Katona & Sarvary, 2011). The product return rates in online shopping are about three times as high as in traditional brick-and-mortar shopping, and by 2022, about 13 billion products with a total worth of $573 billion have been forecasted to be returned annually in the United States alone (Deloitte, 2019). These high numbers can be considered problematic for both businesses and society at large. From a business perspective, product returns result in not only loss in sales but typically also in additional costs related to reverse logistics, return handling, and potentially throwing away the returned products if they cannot be resold (Ofek et al., 2011). In turn, from a social perspective, shipping products back and forth between sellers and buyers is far from being environmentally friendly or in line with the principles of sustainable electronic commerce (Oláh et al., 2019). Therefore, it makes sense to both business and society at large to aim at reducing product returns. However, to be able to do this, two fundamental questions must first be asked and answered: who are making the product returns and why are they being made?

In prior research, these questions have traditionally been approached from a very product-centric, retailer-centric, or order-centric perspective, whereas the studies adopting a more consumer-centric perspective have been rare (cf. Section 2). In this study, our objective is to address this gap in prior research by examining exploratively (without any *a priori* hypotheses) the effects of four demographic characteristics of consumers (i.e., gender, age, education, and income) as well as their payment method preference (i.e., how do they typically prefer to pay when shopping online) on their product return frequency (i.e., how often do they make product returns) and product return reasons (i.e., why do they make product returns). As the data for this, we use the responses from 560 Finnish online consumers, which were collected with an online survey in 2019 and are analysed quantitatively by using ordinal and binomial logistic regression as well as qualitatively by using content analysis.

After this introductory section, we will briefly discuss the theoretical foundation of the study in Section 2. This is followed by reporting of the research methodology and the research results in Sections 3 and 4. The results are discussed in more detail in Section 5 before concluding the paper with a brief discussion about the limitations of the study and some potential paths of future research in Section 6.

2 Theoretical Foundation

As already mentioned above, most of the prior studies on the antecedents of product return behaviour in the context of online shopping have focused on a very product-centric, retailer-centric, or order-centric perspective by examining how product return behaviour is affected by the factors related to the ordered product, the retailer from whom it is ordered, or the particular order transaction. Some examples of these factors are inventory availability, order delivery reliability, and expected order delivery timeliness (Rao, Rabinovich & Raju, 2014), assortment size and order size (Yan & Cao, 2017), retailer reputation (Walsh, Albrecht, Kunz & Hofacker, 2016), shipping and return fees (Lantz & Hjort, 2013; Lepthien & Clement, 2019; Shehu, Papies & Neslin, 2020), product reviews (Minnema, Bijmolt, Gensler & Wiesel, 2016; Sahoo, Dellarocas & Srinivasan, 2018; Wang, Ramachandran & Sheng, 2021), as well as package opening process (Zhou, Hinz & Benlian, 2018).

In contrast, far fewer studies have adopted a more consumer-centric perspective by focusing on the characteristics of the consumers who are ordering the products. Of them, in this study, we will focus on four demographic characteristics (i.e., gender, age, education, and income) as well as payment method preference. Our reason for selecting gender, age, education, and income as explanatory variables is based on the fact that although the effects of demographic characteristics on online shopping adoption have been examined in numerous prior studies (cf. Cheung, Zhu, Kwong, Chan & Limayem, 2003; Chang, Cheung & Lai, 2005; Cheung, Chan & Limayem, 2005; Zhou, Dai & Zhang, 2007), with the main focus being on the same four variables that we are focusing in this study (i.e., gender, age, education, and income), we are not aware of any prior studies that would have examined their effects on product return behaviour, although similar effects can be assumed to exist also in this context. In turn, our reason for selecting payment method preference as an explanatory variable is based on the fact that although we are not aware of any prior studies that would have examined the effects of payment method preference on product return behaviour, Yan and Cao (2017) have argued that the payment method used in a particular order (which once again is an order-centric rather than a consumer-centric factor) does affect product return behaviour. They also found support for this argument by observing that paying an order with a credit card results in a higher product return rate. Thus, rather than the payment method used in a particular order, also payment method preference more generally can be assumed to have similar effects.

3 Methodology

The data for this study was collected in an online survey between February and March 2019. The respondents were recruited mainly by sharing the survey link through the internal communication channels of our university. In addition, because the respondents who completed the survey were able to take part in a price draw of ten cinema tickets, the survey link was posted to six websites promoting online competitions. The survey questionnaire was in Finnish and consisted of multiple items related to the demographics, personality, values, and online shopping behaviour of the respondents. This study utilises the responses to eight of those items. The first four items measured the gender, age, education, and income (as yearly personal taxable income) of the respondents. The fifth item measured payment method preference by using a closed-ended question with five answer options: a bank payment (a direct payment from a bank account), a card payment (a payment with either a bank or credit card), PayPal or MobilePay (the two most popular online payment services in Finland at the time, which charge the payment from one's linked bank account, bank card, or credit card), invoice (in one or multiple instalments), and cash on delivery (a payment when the order is delivered). In addition, the respondents had the option to state any other payment method if needed, but nobody used this option. The sixth and seventh items measured average online shopping frequency and average product return frequency by using closed-ended questions. The eighth and final item measured the most typical reasons for making product returns by using an open-ended question in which the respondents could state one or multiple reasons.

The collected data was analysed in three phases. In phase one, we used cumulative odds ordinal logistic regression to examine the effects of gender, age, education, income, and payment method preference on average product return frequency by using average online shopping frequency as a control variable. In phase two, we analysed the most typical reasons for making product returns by using content analysis in which we read each response, identified the reasons in them, and then tried to group them into more general categories based on common themes. In phase three, we used binomial logistic regression to examine the effects of gender, age, education, income, and payment method preference on stating a specific reason for making a product return by using average online shopping frequency and average product return frequency as control variables. As the statistical software for conducting the logistic regression analyses, we used IBM SPSS Statistics 27.

4 Results

Table 1: Sample statistics

	N = 560		N = 462		N = 302	
	N	%	N	%	N	%
Gender						
Man	169	30.2	140	30.3	79	26.2
Woman	391	69.8	322	69.7	223	73.8
Age						
Under 30 years	262	46.8	230	49.8	149	49.3
30–49 years	201	35.9	156	33.8	113	37.4
50 years or over	97	17.3	76	16.5	40	13.2
Education						
Lower than tertiary education	222	39.6	185	40.0	109	36.1
Tertiary education or higher	338	60.4	277	60.0	193	63.9
Yearly personal taxable income						
Less than 15,000 €	223	39.8	216	46.8	130	43.0
15,000–29,999 €	102	18.2	101	21.9	67	22.2
30,000 € or more	145	25.9	145	31.4	105	34.8
Do not want to disclose	90	16.1	–	–	–	–
Payment method preference						
Bank payment	275	49.1	227	49.1	138	45.7
Card payment	96	17.1	83	18.0	54	17.9
PayPal or MobilePay	106	18.9	94	20.3	67	22.2
Invoice	74	13.2	58	12.6	43	14.2
Cash on delivery	9	1.6	–	–	–	–
Average online shopping frequency						
Yearly or less frequently	136	24.3	109	23.6	59	19.5
Monthly	361	64.5	299	64.7	205	67.9
Weekly	63	11.3	54	11.7	38	12.6
Average product return frequency						
Less frequently than yearly	338	60.4	277	60.0	143	47.4
Yearly	167	29.8	140	30.3	122	40.4
Monthly	55	9.8	45	9.7	37	12.3

In total, we received 580 responses to our survey. However, of them, we had to drop 20 responses due to missing or invalid data, thus resulting in a sample size of 560 responses to be used in this study. The descriptive statistics of this sample in terms of gender, age, education, income, payment method preference, average online shopping frequency, and average product return frequency are reported in Table 1. In addition, for the analyses of phase one, we had to drop an additional 98 respondents who had not wanted to disclose their income or had preferred cash on delivery as a payment method, which was too small a category, thus resulting in a sample size of 462 respondents. In turn, for the analyses of phases two and three, we had to drop an additional 160 respondents who had not stated any reasons for making product returns, thus resulting in a sample size of 302 respondents. As can be seen from Table 1, these drops did not considerably change the sample profile.

4.1 Effects on Product Return Frequency

Before examining more closely the effects on product return frequency, we first checked the non-multicollinearity and proportional odds assumptions of cumulative odds ordinal logistic regression. The non-multicollinearity assumption was checked by using the variance inflation factor (VIF) values from basic multiple linear regression. These were all below two, thus suggesting no multicollinearity (Hair, Black, Babin & Anderson, 2018). In turn, the proportional odds assumption was checked by comparing the fit of a model with the proportional odds constrain to a model without the proportional odds constrain with a likelihood-ratio test. Its result ($\chi^2(10) = 17.417$, $p = 0.066$) supported the proportional odds assumption.

The estimated effects are reported in Table 2. All in all, the model was able to explain from 9.6% to 19.0% (McFadden (1973) $R^2 = 0.096$, Cox-Snell (1989) $R^2 = 0.158$, Nagelkerke (1991) $R^2 = 0.190$) of the variance in average product return frequency, fitted the data better than the baseline model with no explanatory variables (as suggested by the likelihood-ratio test), and had an overall good fit with the data (as suggested by the deviance goodness-of-fit test). The statistical significance of the effects was tested with the Wald (1943) χ^2 test, whereas the effect sizes are reported as odds ratios (OR) and their 95% confidence intervals (CI). For categorical variables, the effects are reported for a specific category in comparison to a reference category (in parenthesis). Additionally, if a variable has more than two categories, the result of an omnibus test is reported (on the same row as the name of the variable). As can be seen, gender, age, payment method preference, and average online shopping frequency were all found to have a statistically significant effect on average product return frequency, whereas the effects of education and income were found to be statistically not significant. More specifically, women had 2.134 times greater odds than men of being more frequent returners, whereas the odds of being a more frequent returner decreased with age by an odds ratio of 0.975 per year. In terms of payment method preference, those who preferred paying by invoice had 2.999 times greater odds of being more frequent returners than those who preferred bank payments. Finally, as expected, in terms of average online shopping frequency, more frequent shoppers also seemed to be more frequent returners. That is, those who shopped monthly had 3.743 times greater odds of being more frequent returners than those who shopped yearly or less frequently, whereas those who shopped weekly had 5.932 times greater odds of being more frequent returners than those who shopped yearly or less frequently.

Table 2: Effects on average product return frequency

	Wald χ^2			**Odds ratio**	
	χ^2	**df**	**p**	**OR**	**95% CI**
Gender	–	–	–	–	–
Woman (vs. man)	10.972	1	< 0.001	2.134	[1.363, 3.341]
Age	7.033	1	0.008	0.975	[0.957, 0.993]
Education	–	–	–	–	–
Tertiary or higher (vs. lower than tertiary)	1.917	1	0.166	1.365	[0.879, 2.120]
Yearly personal taxable income	2.778	2	0.249	–	–
15,000–29,999 € (vs. less than 15,000 €)	2.070	1	0.150	1.477	[0.868, 2.513]
30,000 € or more (vs. less than 15,000 €)	2.033	1	0.154	1.485	[0.862, 2.557]
Payment method preference	13.579	3	0.004	–	–
Card payment (vs. bank payment)	0.911	1	0.340	1.303	[0.756, 2.246]
PayPal or MobilePay (vs. bank payment)	2.339	1	0.126	1.487	[0.894, 2.474]
Invoice (vs. bank payment)	13.179	1	< 0.001	2.999	[1.657, 5.425]
Average online shopping frequency	23.559	2	< 0.001	–	–
Monthly (vs. yearly or less frequently)	19.462	1	< 0.001	3.743	[2.082, 6.728]
Weekly (vs. yearly or less frequently)	19.913	1	< 0.001	5.932	[2.714, 12.967]

Likelihood-ratio $\chi^2(10) = 79.527$, $p < 0.001$, deviance goodness-of-fit $\chi^2(760) = 618.853$, $p = 0.814$
McFadden $R^2 = 0.096$, Cox-Snell $R^2 = 0.158$, Nagelkerke $R^2 = 0.190$

4.2 Product Return Reasons

When analysing the stated reasons for typically making product returns, we were able to identify four main reasons. These are listed and described in more detail below. The list also includes the number and the proportion of the 302 respondents who stated a specific reason. Note that one respondent could state multiple reasons.

- **Wrong size or bad fit** (stated by 193 or 63.9%): The most frequently stated reason was the wrong size or bad fit of the ordered product. This typically concerned products that are worn, such as clothes or shoes.
- **Mismatch with product information** (stated by 71 or 23.5%): The second most frequently stated reason was the mismatch of the ordered product with the product information provided by the retailer. For example, the product did not match the product description or product pictures in terms of colour, material, and quality, had some other deviances, or was an entirely wrong product.
- **Faulty or damaged product** (stated by 70 or 23.2%): The third most frequently stated reason was that the ordered product was faulty or damaged during delivery. In other words, there was some extreme quality issue in the product, which went well beyond the product not merely matching the product information.
- **Mismatch with needs, wants, or expectations** (stated by 58 or 19.2%): The most infrequently stated reason was the mismatch of the ordered product with one's needs, wants, or expectations. In other words, there was no obvious mismatch with the product information or other issues in the product, but one just did not like it, found it useless, or experienced buyer's remorse.
- **Other reasons** (stated by 6 or 2.0%): Finally, there were also a few respondents who stated some other reasons, such as suspicion of fraud, ordering the product just to meet some order limit, or returning the product just to spend time.

4.3 Effects on Product Return Reasons

Before examining more closely the effects on product return reasons, we once again first checked the non-multicollinearity assumption of binomial logistic regression by using the VIF values from basic multiple linear regression. These were all below two, thus suggesting no multicollinearity (Hair et al., 2018). When examining the estimated effects, only two of them were found to be statistically significant. First, gender was found to have a statistically significant effect on stating wrong size or bad fit as a reason ($\chi^2(1) = 21.573$, $p < 0.001$) as well as stating a faulty or damaged product as a reason ($\chi^2(1) = 29.228$, $p < 0.001$), whereas average product return frequency was found to have a statistically significant effect on stating a faulty or damaged product as a reason ($\chi^2(2) = 21.872$, $p < 0.001$) as well as stating a mismatch with needs, wants, or expectations as a reason ($\chi^2(2) = 18.285$, $p < 0.001$). More specifically, women had 3.939 times greater odds than men of stating wrong size or bad fit as a reason, whereas men had 6.173 times greater odds than women of stating a faulty or damaged product as a reason. In turn, those who returned less frequently than yearly had 4.202 times greater odds than those who returned yearly and 12.987 times greater odds than those who returned monthly of stating a faulty or damaged product as a reason. In contrast, those who returned yearly had 2.086 times greater odds than those who returned less frequently than yearly of stating a mismatch with needs, wants, or expectations as a reason, whereas those who returned monthly had 8.034 times greater odds than those who returned less frequently than yearly of stating a mismatch with needs, wants, or expectations as a reason.

5 Discussion and Conclusions

In this study, we examined the effects of gender, age, education, income, and payment method preference on product return frequency and product return reasons. In terms of the effects on product return frequency, we found women to have greater odds than men of being more frequent returners and the odds of being a more frequent returner to also decrease with age. In addition, those who preferred paying by invoice were found to have greater odds of being more frequent returners than those who preferred a bank payment. Of these, the finding concerning the effect of payment method preference is largely in line with the study by Yan and Cao (2017), who found that paying an order with a credit card results in a higher product return rate. They explain this finding with the "buy-now-pay-later" mentality associated with credit cards, which is likely to result in more impulsive consumption behaviour and lower the threshold of making a product return because no exchange of money has yet occurred. A similar mentality is likely to also explain why preferring to pay by invoice results in a higher product return rate. In turn, the findings concerning the effects of gender and age are most likely explained by the different online shopping habits of men versus women and younger versus older consumers. For example, women and younger consumers may be more likely to order products with higher return rates, such as clothes and shoes (Deloitte, 2019), whereas men and older consumers may be more likely to order products with lower return rates, such as consumer electronics (Deloitte, 2019). In addition, women may be more likely than men to order products for not just themselves but also others in their family, such as their children. In terms of age, there may also exist a generational gap. That is, older consumers, who are typically less experienced in shopping online, may make product returns more conservatively, resorting to them only when there is something severely wrong with the ordered product. In contrast, younger consumers, who are typically more experienced in shopping online, may make product returns more liberally, sometimes returning the ordered product even when there is actually nothing wrong with it. Or they may even practice bracketing, which means ordering multiple similar products with the intention of keeping only some of them and returning the rest. There were 12 respondents in our sample who explicitly mentioned doing this, and most of them were young consumers in their 20s.

In terms of the effects on product return reasons, we first identified four reasons why consumers typically make product returns: (1) wrong size or bad fit, (2) a mismatch with product information, (3) a faulty or damaged product, and (4) a mismatch with needs, wants, or expectations. These are largely in line with the reasons that have been identified in prior studies. For example, a study by Deloitte (2019) found the top five reasons to be (1) a too small or large size, (2) changing one's mind, (3) style not as expected, (4) not as described, and (5) a defective product. After this, we examined the effects on stating each of the four reasons, finding that women had greater odds than men of stating wrong size or bad fit as a reason, whereas men had greater odds than women of stating a faulty or damaged product as a reason. In addition, we also found that those who made product returns more frequently had greater odds of stating a mismatch with needs, wants, or preferences as a reason, whereas those who made product returns less frequently had greater odds of stating a faulty or damaged product as a reason. One explanation for the finding concerning the gender effect may be the fact that women more often shop online for products like clothes and shoes, in which wrong size or bad fit is likely to be an issue, whereas men more often shop online for products like consumer electronics, which are more prone to faults and more likely damaged during delivery. In turn, one explanation for the findings concerning the effects of product return frequency may be the fact that if one has the tendency of making returns very rarely, then the reasons for those rare returns are likely to relate to some severe issue in the ordered product, such as it being faulty or damaged during delivery. In contrast, if one has the tendency of making returns relatively often, then it becomes less likely that the reasons for them only relate to actual issues in the product and more likely that they relate to things like the mismatch of the product with one's needs, wants, or expectations.

From a theoretical perspective, the main contribution of the study is the finding that consumer-centric factors like gender, age, and payment method preference – in addition to the product-centric, retailer-centric, and order-centric factors that have been more traditionally examined in prior research – can act as antecedents of product return behaviour by being able to explain a considerable amount of the variance in both product return frequency and product return reasons. In turn, from a practical perspective, the main contribution of the study is the implication that if the aforementioned factors indeed affect product return frequency and product return reasons, then online retailers can try to utilise these factors and effects in lowering their product return rates. For example, as those who prefer to pay by invoice were found to have greater odds of making product returns more frequently, some retailers may see it preferable not to offer invoicing as a payment method. Similarly, some retailers may see it preferable to target only the gender and age segments in which the product return frequencies are known to be relatively low.

6 Limitations and Future Research

This study can be seen to have three main limitations. First, because we focused only on Finnish online consumers, we cannot make claims on the generalisability of our findings to other countries. Second, because our sample was not entirely representative of the Finnish online consumer population especially in terms of gender and age, we also cannot make claims on how common or rare the identified product return reasons actually are. For example, wrong size or bad fit may have been found to be the most common reason simply because of the gender and age biases in our sample. However, we do not see these biases affecting our other findings concerning the effects on product return frequency and product return reasons because, by examining the effects simultaneously in one model, we essentially controlled the effects of the other variables when examining the effect of a specific variable. Third, because most of the identified product return reasons are related to the root cause of there being something wrong with the ordered product, there is some conceptual overlap between them. However, we still consider them to give a good overview of the motivational aspects for why consumers make product returns. In future research, some interesting and important paths to follow would be to examine more closely the underlying mechanisms that cause the effects that we observed in this study as well as how the ongoing COVID-19 pandemic has potentially affected our findings.

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