Salminen, J., Seitz, S., Jansen, B.J. & Salenius, T. (2017) 'Gender effect on e-commerce sales of experience gifts: Preliminary empirical findings', *The 17th International Conference on Electronic Business*, Dubai, December 4-8.

Gender effect on e-commerce sales of experience gifts: Preliminary empirical findings

Joni Salminen, Qatar Computing Research Institute, HBKU; and Turku School of Economics, jsalminen@hbku.edu.qa
Sarem Seitz, Otto-Friedrich University Bamberg, sarem.seitz@gmail.com
Bernard J. Jansen, Qatar Computing Research Institute, HBKU, bjansen@hbku.edu.qa
Tommi Salenius, Parcero, tommi.salenius@parcero.fi

ABSTRACT

We analyze purchase data from 493 customers of an e-commerce store selling experience gifts to find how gender correlates with average purchase value, category of purchased products, and the use of discount codes. We find no significant differences for average purchase value or category of purchased products, but according to the data, women are more likely to use discount codes than are males. Ideas for further research concerning the gender effect on online shopping behavior are discussed.

Keywords: e-commerce; online consumer behavior; online purchase behavior; online shopping behavior; gender

INTRODUCTION

In both e-commerce and online advertising, gender is a typical targeting and segmentation criterion [13]. Products and offers are often tailored according to a customer's gender. As Chiu et al. [2, p. 416] note, "by learning gender differences, e-tailers and advertisers can better target right consumers and consequently foster more positive attitudes and online purchase intentions." Digital marketers use gender targeting for several purposes, including choice of products to promote, linguistic formulation of messages, and image selection. For example, Jansen et al. [12] find that the gender-orientation of search keywords influences advertising performance. In addition to online marketers, e-commerce designers and human-computer interaction (HCI) researchers benefit from information on gender differences [11].

While prior studies have pointed out overall differences between men and women in their purchase behavior [18] [5] [16] [15], the online purchase behavior of the two genders is much less studied, apart from few examples [6] [7]. Slyke et al. [22] observe the same (p. 1529): "Among the many characteristics that impact the use of e-commerce, one that has received relatively little attention is gender." Kim et al. [13] note that the growing importance of the Internet further highlights the need for understanding online users' behaviors from a gender point of view. Because behavioral gender differences have been established in other contexts, it is therefore worthwhile to examine whether they take place in online shopping, and, if so, how. To this end, we are looking for answers to several questions relating to gender and online customer behavior:

1. How do e-commerce purchases of experience gifts split between men and women?
2. Do the products bought differ by gender? If so, how?
3. Which gender is more likely to use discount codes?

Although, as shown in the next section, there are some prior studies researching gender effect on online customer behavior, we could not locate any prior study specifically focusing on the above questions, even though these questions are important to online retailers. To answer these questions, we collect e-commerce data from 493 individual customers of an e-commerce store which sells experience gifts and is based in Finland. Experience gifts are electronic or physical gift-cards that include the right to claim an experience service from a specified service provider that collaborates with the e-commerce company. Examples of experience gifts include tandem jump, rally driving, dinner in the dark (or sky), etc. Experience gifts are part of the trend for immaterial consumption that recently has become widespread across the world [3] [4]. The concept has become popular in many countries, including UK, Australia, Sweden, and Finland, as an alternative to buying tangible goods (things) as a gift.

To answer the first two questions, we compare the genders by a) quantity, b) total sales value, and c) average purchase value. For the third question, we code the use of coupons by comparing the price before discount and final price. In brief, we find no statistically significant differences for average order price and choice of products, but a significant effect in the use of discount codes, finding that males are on average 1.38 times more likely to use them. The implications are that, when specifically target female online shoppers, it may be beneficial for retailers to use coupons as a recruiting tactic.

RELATED LITERATURE

We conduct a literature survey by retrieving related literature with keywords such as ["online purchase behavior" +gender]. We find several research papers, published in journals or conference proceedings, of which 19 are deemed relevant for this study by reading their abstracts. A further investigation into these research papers reveals three themes in prior literature examining gender effect on online shopping: 1) equality and power, 2) adoption of online commerce, and 3) behavioral differences.

The first stream is concerned with the uneven use of technological media by the two genders, and aims at discovering reasons for this state of affairs. For example, Sherman et al. [21, p. 885] postulate that "the Internet has been a male-dominated technology since its beginnings in the late 1960s", also referring to the "Internet gender gap". Rodgers and Harris [20] argue that women are less satisfied with online shopping than men, because they lack support for e-commerce activity. However, Weiser [23] argued the gender gap is rapidly diminishing, with increasing online shopping technology focused on women shoppers [9]. Often, these studies focus on women, rather than objectively comparing both genders. Overall, this stream of research is somewhat dated, at least in the Western context where both male and female audiences have widely embraced online platforms, especially online social networks [1], and e-commerce.

The second stream focused on motivations for men and women to adopt online shopping, or, in the earlier studies, Internet as a whole. For example, Weiser [23] found men use the Internet for entertainment and leisure, whereas women prefer using it for communication and educational purposes. Besides motivation, another important construct here is risk; for example, Garbarino and Strahilevitz [10] studied how gender influences the perception of risk in online purchasing. They found that women perceive a higher level of risk than men. Moreover, according to their study, peer recommendations (word-of-mouth) decrease the perceived risk more for women, and also leads into a higher willingness to buy than for men. Indeed, trust and risk seem to be closely associated with one another, both relating to adoption of online commerce. As explained by Kolsaker and Payne [14, p. 206], "an essential element of successful e-commerce is building relationships with consumers," which, according to them, requires a degree of trust. Chiu et al. [2] found in their structural equation modeling that men responded more strongly to awareness of security, and this influenced their online purchase intention. However, Cyr and Bonanni [6] did not find security impactful for online shopping experience. Other constructs, used by Chiu et al. [2], include innovativeness, perceived usefulness, and perceived ease of use. The effect of the first two is similar for both genders, while perceived ease of use is more important for women (*ibid*.). Finally, social dynamics in the context of e-commerce adoption have been examined. For example, Hwang [11] found the influence of social norms stronger for women, while the effect of enjoyment was stronger for men. Overall, like the first stream, also this stream is somewhat outdated in the sense that e-commerce purchase behavior is already a routine activity for the majority of website users at this day and age, whether they are male or female, and rapidly catching worldwide, including developing markets, such as India[1]. In fact, many novel e-shops, e.g. in fashion (Nelly[2], Zalando[3]) are of interest to women in online shopping.

The third stream deals with differences in purchase behavior. The research here is the scarcest; as noted by Cyr and Bonanni [6, p. 565], "very little is known about the difference in male and female perceptions of this experience." Even though they made this statement some time ago, our survey reveals this still being the case. However, there is some specific work on this area. Cyr and Bonanni [6] found significant differences in perceptions of website design and website satisfaction between males and females regarding online shopping experience; however, there was no significant difference in loyalty. In contrast, Mukherjee and Jansen [17] find significant variations in consumer behavior the genders, so that women are more likely to use brand keywords than men, indicating greater loyalty. Rodgers and Harris [20] identify trust, along with emotion and convenience, as explaining variables for satisfaction with online shopping experience, while Richard et al. [19] find gender differences in navigation behavior on the Internet, so that men exhibit less exploratory behavior (browsing) and lower website involvement than women.

In summary, we find that there is a strong emphasis in prior research on technology adoption and acceptance. Other key constructs include trust and word-of-mouth, online shopping experience, and gender gap. Most of the surveyed research is old, considering the rapidly developing landscape of online shopping; e.g., some studies are postulating women exhibit anxiety over e-commerce use, or the use of computers [24]. With the large proliferation of fashion e.g. e-commerce store, it is not likely these studies represent the current state-of-the-art of gender effects on online purchase behavior. As most studies we found are a decade old, there is a need for refreshed data that represents the current situation in the marketplace. As such, a refreshed look, such as undertaken in this study, is needed to evaluate the current situation of gender effects on online purchase behavior.

METHOD

Data Collection

The data was collected by randomly sampling e-commerce orders taking place during August, 2017. The e-commerce store in question sells experience gifts, i.e. electronic or physical gift-cards that include the right to claim an experience service, e.g. tandem jump, rally driving, dinner in the dark, etc. The e-commerce store includes over 1,200 products at the time of writing,

[1]https://www.ecommerce-europe.eu/app/uploads/2016/10/India-B2C-E-commerce-Light-Country-Report.pdf
[2] http://www.nelly.se
[3] http://www.zalando.de

divided under dozens of categories. For this study, each order in the sample was categorized under one of the following categories: 1) flight, 2) driving, 3) wellness, 4) food, 5) water, 6) shooting, 7) escape room, 8) value gift card, 9) courses, and 10) other. The categorization was chosen by looking at the sample as well as the visible categories of the e-commerce store. Table 1 shows the distribution of products into these categories.

Table 1: Distribution of sample orders into product categories.

Category	**Description**	**Frequency**
Courses	Short courses and workshops, e.g. raw chocolate workshop.	16
Driving	Driving experiences, e.g. “Ferrari vs. Lamborghini”.	35
Escape room	Experiences where the participants try to escape a room by solving problems based on hints.	30
Flight	Flight experiences, e.g. hot air balloon ride.	49
Food	Experiences relating to restaurants, food and eating, e.g. “dinner in the dark”.	129
Shooting	Shooting experiences, e.g. “Shooting for two”.	15
Value gift card	Generic gift card of specific value, e.g 100 EUR.	40
Water	Water-related experiences, e.g. flyboarding and diving.	23
Wellness	Wellness experiences, e.g. spa treatments, hot yoga, and similar.	76
Other	Other experiences not matching the previous categories.	80

In sum, the data consists of 493 rows, in which gender and product category are labelled, along with other information required for the analysis. Overall, we included the following variables, retrieved from the e-commerce store’s SQL database: 1) customer ID, 2) price before discount, 3) price, 4) discount (calculated if the previous two differed), 5) product title, 6) product category (manually labelled), and 7) gender (manually labelled).

Data Analysis

We applied statistical analyses, including ANOVA, Kruskal-Wallis, and log-linear models, according to the nature of the data. All tests were performed with p-values below 0.05 being statistically significant. The following sections explain in greater detail the applied procedures and the yielded results.

FINDINGS

Question 1: How Do Purchases Split between Men and Women?

To answer this question, we looked into the general distribution of sales orders. Figure 1 shows total sales quantity by gender.

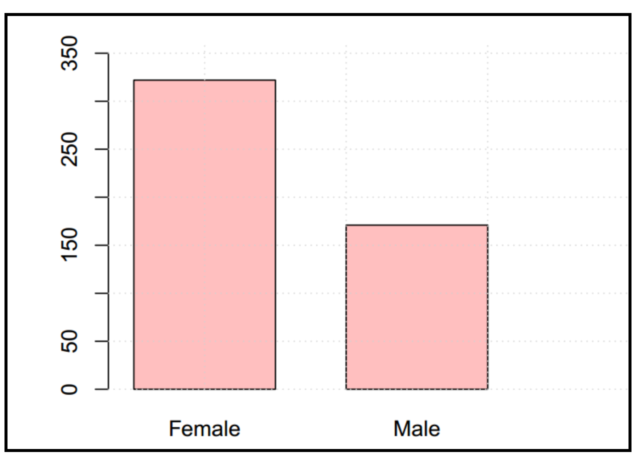

Figure 1: Total sales quantity by gender. Female account for 65% and male 35% of purchases.

As can be seen, based on this sample, women form the majority of the clientele of this particular e-commerce store. The sales value also follows the same pattern so that 63% is attributed to female customers. Although the website is not particularly targeting male or female customers, females tend to frequent it more, as shown also by Google Analytics data (women = 73% of visits, men 27%, in the whole 2016). This pattern of females purchasing more experience gifts is not surprising, but commonly known in the company. In a sister company based in Estonia, for example, the pattern is similar. Next, we looked at the order values by using the "price" metric. Figure 2 shows mean and median order values.

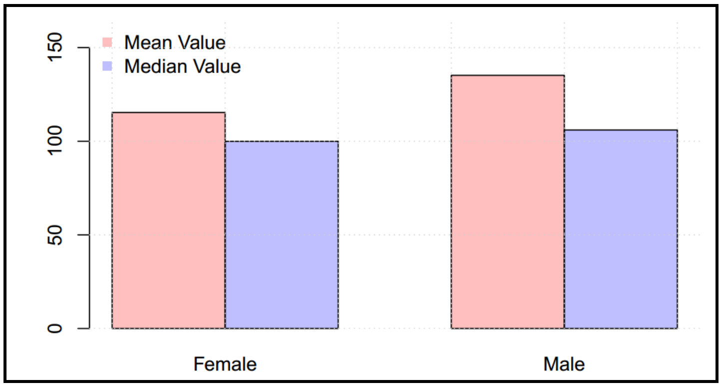

Figure 2: Men tend to buy slightly more expensive experience gifts, but the difference is not statistically significant.

Question 2: Do the Bought Products Differ by Gender?

Differences by Price

To answer the first part of this question, we first visualize the data. Figure 3 shows price before discount by gender.

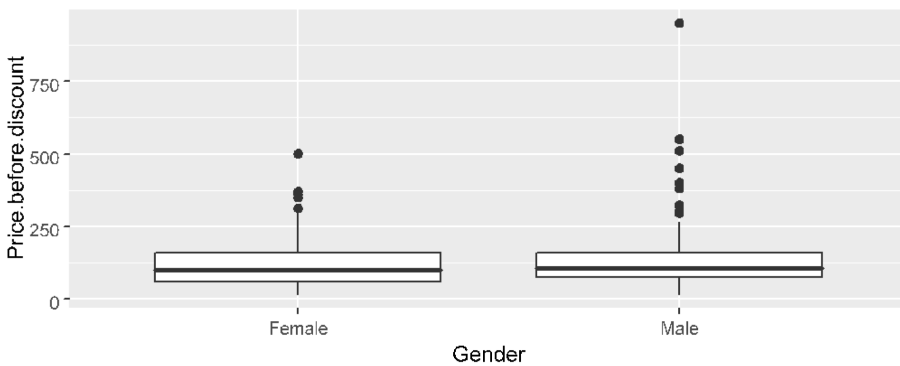

Figure 3: Price before discount by gender (with outlier).

As can be seen, price before discount appears similar for both genders, apart from one high outlier for Male. The outlier, although being a valid realization of the "random" buying process (i.e., occasionally, a customer buys a particularly expensive product), could bias the result if we want to test for overall buying behaviour between genders. Thus, the tests will be conducted for data with and without the outlier. Figure 4 shows the price without the outlier.

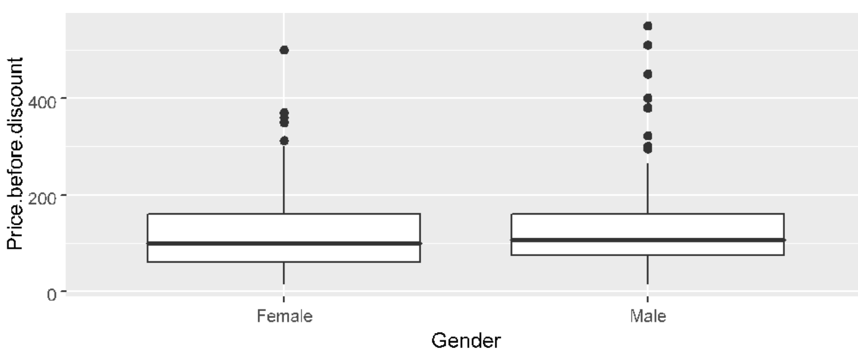

Figure 4: Price before discount by gender (without outlier).

The two groups now seem to differ slightly with a little higher median spending by males. The question is now, whether this difference is statistically significant or if we can assume that the difference is caused by random chance. To find out, we first conducted an ANOVA test, but observed that the ANOVA assumption of normally distributed residuals is violated in the data, so ANOVA is most likely not reliable here. The distribution of residuals is illustrated in Figure 5.

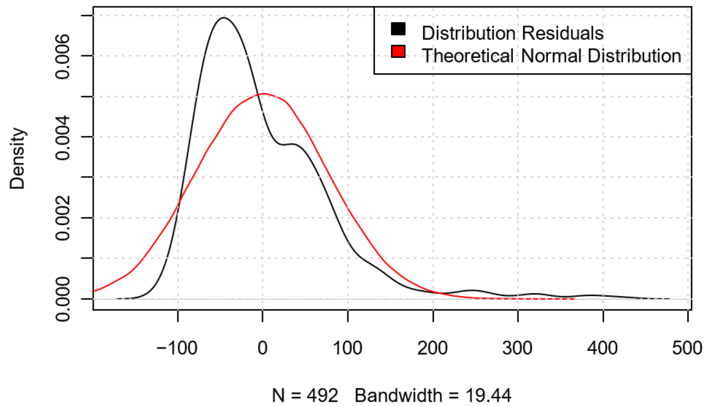

Figure 5: Distribution of residuals.

We then conduct a Shapiro Test for Normality, and indeed find that the assumption of normally distributed errors is clearly violated (p-value=2.2e-16). Thus, we need to use a different test to test the difference between the groups. We choose the Kruskall-Wallis test, which is a non-parametric equivalent of ANOVA and has much lighter assumptions, particularly not requiring normal distribution. Unlike ANOVA, the Kruskall-Wallis test revealed no significant difference (chi-squared = 3.13, df = 1, p-value = 0.076). However, as the p-value is not very far away from being significant, there could be some gender effect on price before discount. However, we have no statistically significant evidence that this is not caused by random noise.

In summary, we looked at the effect of gender on price before discount. We found that the classic ANOVA cannot be used, since the data is highly non-normal. As an alternative, we turned to the non-parametric Kruskall-Wallis test. Testing the price before discount did not reject the null hypothesis of ‘No difference between genders’ (p-value with outlier: 0.076, p-value without outlier: 0.094). The p-values were close to significance, but not significant based on the defined threshold. For price, again, ANOVA could not be used. Kruskall-Wallis p-values were 0.88 (with outlier), 0.96 (without outlier), clearly indicating no significance. Therefore, we find that there is no significant effect of gender on price.

Differences by Product Category

Next, we evaluate the impact of gender on product category purchased. Figure 6 includes order frequency by category and gender.

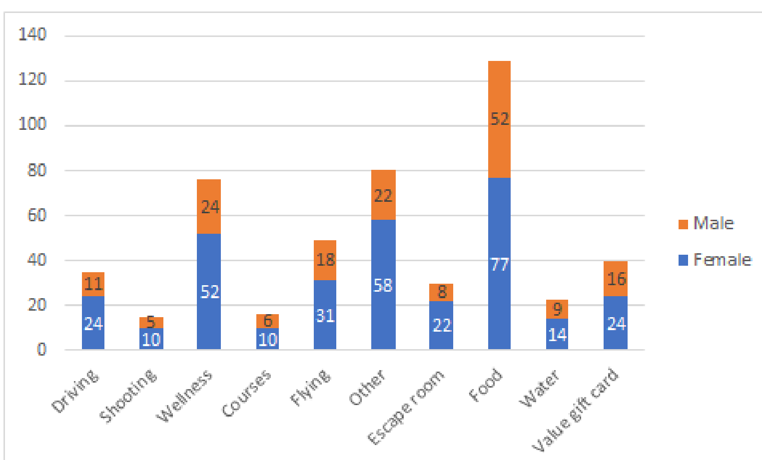

Figure 6: Frequency of purchases by category and gender.

To answer the question of differences, the interaction effects have to be evaluated, not only the single effects of gender and category. To approach the question from a statistical point of view, we model cell frequencies with a (Poisson) log-linear model. In this model, the absolute frequencies in each cell of the contingency table is modelled as a endogenous variables in a linear model with Poisson distribution. The effects are modelled as exogenous, effect coded dummy variables. In the saturated model we use, all possible effects (2 gender effects, 10 category effects, and 2 x 10 interaction effects) are considered. Table 2 shows the results. Note that using effect coding reduces the number of effects in gender and category by one each.

Table 2: Saturated log-linear model (gender and product category).

	Estimate	**Std. Error**	**z value**	**Pr(>|z|)**
(Intercept)	2.92200	0.05916	49.390	< 2e-16 ***
Gender1	0.32609	0.05916	5.512	3.55e-08 ***
Driving	-0.13402	0.17325	-0.774	0.439182
Shooting	-0.96598	0.25199	-3.833	0.000126 ***
Wellness	0.64265	0.12522	5.132	2.86e-07 ***
Courses	-0.87482	0.23840	-3.670	0.000243 ***
Flying	0.24018	0.14513	1.655	0.097934 .
Other	0.65375	0.12665	5.162	2.44e-07 ***
Escape room	-0.33675	0.19388	-1.737	0.082408 .
Food	1.22553	0.09972	12.290	< 2e-16 ***
Water	-0.50385	0.20002	-2.519	0.011768 *
Gender1:Driving	0.06399	0.17325	0.369	0.711867
Gender1:Shooting	0.02048	0.25199	0.081	0.935214
Gender1:Wellness	0.06051	0.12522	0.483	0.628955
Gender1:Courses	-0.07068	0.23840	-0.296	0.766873
Gender1:Flying	-0.05428	0.14513	-0.374	0.708387
Gender1:Other	0.15861	0.12665	1.252	0.210428
Gender1:Escape room	0.17971	0.19388	0.927	0.353980
Gender1:Food	-0.12981	0.09972	-1.302	0.192997
Gender1:Water	-0.10517	0.20002	-0.526	0.599017

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

As can be seen, none of the interaction effects is statistically significant in the saturated model. In addition, the saturated model will always perfectly predict cell frequencies, but is likely to include non-relevant variables. Therefore, we use only the significant category variables (p-value below 0.05) and the two largest interaction effects to build a reduced model (removing irrelevant effects) to see if the significance of the interaction changes. Table 3 shows the results from the reduced model.

Table 3: Reduced log-linear model (gender and product category).

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	2.92843	0.05778	50.686	< 2e-16 ***
Driving	0.32481	0.05020	6.470	9.78e-11 ***
Shooting	-1.00580	0.22922	-4.388	1.14e-05 ***
Wellness	0.64945	0.11695	5.553	2.81e-08 ***
Courses	-0.93869	0.22312	-4.207	2.59e-05 ***
Other	0.62589	0.12418	5.040	4.65e-07 ***
Food	1.21165	0.09909	12.227	< 2e-16 ***
Water	-0.56411	0.19126	-2.950	0.00318 **
Gender1:Other	0.19011	0.10536	1.804	0.07117 .
Gender1:Food	-0.11445	0.08684	-1.318	0.18751

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The chi-squared test for lack of fit shows no significance (chi-squared = 0.725), so the reduced model is likely to correctly fit the data. However, the interaction terms are still not significant unlike the leftover single effects, which are highly significant. In addition, the effects of Driving, Flying and Escape room are not significantly different from Value gift card, which is the reference category in this effect coding scheme.

In sum, we examined the effect of gender on product category, and found no evidence that gender has a significant interaction effect with product category. Every deviance from the expected effects of gender and category on their own is likely to be caused by random noise.

Differences by Product

Next, we look at the effect of gender on product purchased. Because the distribution of quantity of sold products follows the typical power law distribution observed in e-commerce industry [8] (see Figure 7), and because decreasing the number of products improves modeling accuracy, we only consider products with seven or more sales.

Figure 7: Distribution of sold product quantities. The x-axis describes individual products, and the y-axis the quantity sold.

As in the case of product categories, we run two log-linear models with Poisson distribution: a saturated and a reduced model. There are no significant interaction effects in the saturated model, but there are a number of significant single effects. We only include single effects with p-value equal to or below 0.1 and their corresponding category-gender interactions into the reduced model. The Chi-Squared test for lack of fit shows no significance, so the model is likely to correctly fit the data. The value of the test statistic for lack of fit (chi-squared = 0.36) is much smaller than for categories, which is due to the much stronger reduction in effects modelled relative to the total number of effects in the saturated model. The results of the reduced model can be seen in

Table 4.

Table 4: Reduced log-linear model (gender and product). Individual product names are omitted.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.56637	0.09142	17.133	< 2e-16 ***
Gender1	0.40881	0.09142	4.472	7.77e-06 ***
Product6	0.28691	0.26741	1.073	0.283
Product7	0.28691	0.26741	1.073	0.283
Product11	0.01288	0.28483	0.045	0.964
Gender1:Product11	-0.28691	0.28483	-1.007	0.314
Gender1:Product6	-0.01288	0.26741	-0.048	0.962
Gender1:Product7	-0.01288	0.26741	-0.048	0.962

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The statistical significance for all effects except the gender effect drops below significance. To see if it is justifiable to assume that Product 6 and Product 7 have any effect on overall buying behaviour, the model is again reduced to only the gender effect and the two mentioned products. The Chi-Squared score (0.52) gets better with a smaller model, thus the data fit here is much better. However, the category effect of Product 6 and Product 7 stays irrelevant, so it is likely that there is no significant Product effect.

In sum, we find no evidence of gender having a significant interaction effect with product. However, gender as a single effect does have a significant effect on product. This means that women are on average more likely to buy overall, leading to a higher chance of buying any product, but there is no statistically significant category/product that women or men are more likely to buy. A major impediment with this analysis, however, is the low number of sales for many products. Although a general tendency is apparent, the statistical tests conserve many hypotheses (i.e., give not enough confidence in the existence of actual interaction). If more evidence on interaction is available in the form of other data or fundamental knowledge, it could be included as a priori knowledge in a Bayesian framework. If not, more data should be collected over time to get clearer results, especially for tests that are currently on the edge of showing significance.

Question 3: Which Gender Is More Likely to Use Discount Codes?

To answer this question, we first tabularize the data (see Table 5) in order to get an overview.

Table 5: Discount code use by gender.

Discount	Female	Male
Yes	68	50
No	254	121

At first look, the table looks like there is a gender effect on discount. However, this could also be caused by the fact that women are more likely to buy than men in our sample, and due to the difference in discount code usage frequency versus non-usage frequency (i.e., the single effects of gender and discount). Thus, we have to test if the interaction effects of gender and discount are statistically significant. We model cell frequencies with a (Poisson) log-linear model, and find the following results (Table 6).

Table 6: Regression analysis of gender and discount code use.

	Estimate	Std. error	Z value	Pr(>|z|)
(Intercept)	4.61616	0.05415	85.255	< 2e-16 ***
Gender	0.26226	0.05415	4.844	1.28e-06 ***
Discount	-0.55040	0.05415	-10.165	< 2e-16 ***
Gender:Discount	-0.10851	0.05415	-2.004	0.0451 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The interaction effect of gender on discount is statistically significant. There is evidence that men are more likely than women to use a discount code. A regression model shows that a male customer is, on average, around 1.38 times more likely to use a discount coupon than a female customer.

CONCLUSION AND DISCUSSION

Based on our literature review, we observed that it is time to shift from the general adoption of e-commerce by genders into analysis of actual behavioral differences. We concluded, by surveying the literature, that this shift has not yet taken place, and therefore more studies are needed to understand gender effects on online shopping behavior.

Based on the empirical findings, it seems that the online purchase behavior of experience gifts between males and females is not drastically different, apart from their use of discount codes, in which we found that men are significantly more likely to use discount codes (about 1.38 times more than women on average). This overall conclusion is somewhat in line with Kolsaker and Payne [14], who also found no significant differences between the genders in the online shopping context. In many aspects, there clearly is common explanatory variables between online shoppers, regardless of them being male or female. Moreover, our sample was fairly small, both in terms of time and number of observations. It also focused on a single store which poses a limitation.

Based on the limitations, our proposals for future studies are two: first, two examine the gender effects with a bigger dataset, ranging over several years, and including more product-level data to learn more about the observed general difference. A larger dataset could reveal, in addition to gender differences such as customer loyalty, also interesting evolutionary aspects in terms of general purchase behavior of online customers. In addition, for comparative purposes, we could also examine another country's dataset as well. Second, to examine latent effects, such as attitudes, lifestyles, and the like, to understand more deeply what drives online purchase behavior. As shown by the literature review, many social constructs have been applied in association with gender to better understand individuals' online shopping behavior. For example, in Weiser's [23] study the gender differences were mediated by age and Internet experience; there are likely to be other, equally or more important constructs that explain consumers' online shopping behavior.

REFERENCES

[1] Centola, D. (2010). The Spread of Behavior in an Online Social Network Experiment. *Science*, 329(5996), 1194–1197.

[2] Chiu, Y.-B., Lin, C.-P., & Tang, L.-L. (2005). Gender differs: assessing a model of online purchase intentions in e-tail service. *International Journal of Service Industry Management*, 16(5), 416–435.

[3] Clarke, J. R. (2006). Different to 'dust collectors'? The giving and receiving of experience gifts. *Journal of Consumer Behaviour*, 5(6), 533–549.

[4] Clarke, J. (2008). Experiences as gifts: from process to model. *European Journal of Marketing*, 42(3/4), 365–389.

[5] Coley, A., & Burgess, B. (2003). Gender differences in cognitive and affective impulse buying. *Journal of Fashion Marketing and Management: An International Journal*, 7(3), 282–295.

[6] Cyr, D., & Bonanni, C. (2005). Gender and website design in e-business. *International Journal of Electronic Business*, 3(6), 565–582.

[7] Fan, Yi-Wen, & Miao, Yi-Feng. (2012). Effect of electronic word-of-mouth on consumer purchase intention: The perspective of gender differences. *International Journal of Electronic Business Management*, 10(2), 175–181.

[8] Fenner, T., Levene, M., & Loizou, G. (2010). Predicting the long tail of book sales: Unearthing the power-law exponent. *Physica A: Statistical Mechanics and Its Applications*, 389(12), 2416–2421.

[9] Gao, Y., Reddy, M., and Jansen, B. J. (2017) ShopWithMe!: Collaborative Information Searching and Shopping for Online Retail. *Proceedings of the 50th Hawaii International Conference on System Sciences (HICSS-50).* Waikoloa, Hawaii. p. 505-514. 4-7 January.

[10] Garbarino, E., & Strahilevitz, M. (2004). Gender differences in the perceived risk of buying online and the effects of receiving a site recommendation. *Journal of Business Research*, 57(7), 768–775.

[11] Hwang, Y. (2010). The moderating effects of gender on e-commerce systems adoption factors: An empirical investigation.

Computers in Human Behavior, 26(6), 1753–1760.

[12] Jansen, B. J., Moore, K., & Carman, S. (2013). Evaluating the Performance of Demographic Targeting Using Gender in Sponsored Search. *Information Processing Management*, 49(1), 286–302.

[13] Kim, D.-Y., Lehto, X. Y., & Morrison, A. M. (2007). Gender differences in online travel information search: Implications for marketing communications on the internet. *Tourism Management*, 28(2), 423–433.

[14] Kolsaker, A., & Payne, C. (2002). Engendering trust in e-commerce: a study of gender-based concerns. *Marketing Intelligence & Planning*, 20(4), 206–214.

[15] Kolyesnikova, N., Dodd, T., & Wilcox, J. (2009). Gender as a moderator of reciprocal consumer behavior. *Journal of Consumer Marketing*, 26(3), 200–213.

[16] Mostafa, M. M. (2007). Gender differences in Egyptian consumers' green purchase behaviour: the effects of environmental knowledge, concern and attitude. *International Journal of Consumer Studies*, 31(3), 220–229.

[17] Mukherjee, P., & Jansen, B. J. (2014). Performance analysis of keyword advertising campaign using gender-brand effect of search queries. *Electronic Commerce Research and Applications*, 13(2), 139–149.

[18] Peters, J. (1989). Youth Clothes-Shopping Behavior: An Analysis by Gender. *Adolescence*, 24(95), 575.

[19] Richard, M.-O., Chebat, J.-C., Yang, Z., & Putrevu, S. (2010). A proposed model of online consumer behavior: Assessing the role of gender. *Journal of Business Research*, 63(9), 926–934.

[20] Rodgers, S., & Harris, M. A. (2003). Gender and E-Commerce: An Exploratory Study. *Journal of Advertising Research*, 43(3), 322–329.

[21] Sherman, R. C., End, C., Kraan, E., Cole, A., Campbell, J., Birchmeier, Z., & Klausner, J. (2000). The Internet Gender Gap Among College Students: Forgotten But Not Gone? *CyberPsychology & Behavior*, 3(5), 885–894.

[22] Slyke, C., Bélanger, F., Johnson, R., & Hightower, R. (2010). Gender-Based Differences in Consumer E-Commerce Adoption. *Communications of the Association for Information Systems*, 26(1).

[23] Weiser, E. B. (2000). Gender Differences in Internet Use Patterns and Internet Application Preferences: A Two-Sample Comparison. *CyberPsychology & Behavior*, 3(2), 167–178.

[24] Yang, B., & Lester, D. (2005). Gender differences in e-commerce. *Applied Economics*, 37(18), 2077–2089.