Online shopping determinants of Croatian consumers

Prudky, Ivan; Vretenar, Nenad; Jardas Antonić, Jelena

Source / Izvornik: **INTERDISCIPLINARY MANAGEMENT RESEARCH XIX, 2023, 475 - 491**

Conference paper / Rad u zborniku

Publication status / Verzija rada: **Published version / Objavljena verzija rada (izdavačev PDF)**

Permanent link / Trajna poveznica: https://urn.nsk.hr/urn:nbn:hr:192:674139

ONLINE SHOPPING DETERMINANTS OF CROATIAN CONSUMERS

Ivan PRUDKY, mag.oec.
University of Rijeka, Faculty of Economics and Business

E-mail: ivan.prudky@efri.hr

Nenad VRETENAR, Ph.D.
University of Rijeka, Faculty of Economics and Business

E-mail: nenad.vretenar@efri.hr

Jelena JARDAS ANTONIĆ, Ph.D.
University of Rijeka, Faculty of Economics and Business

E-mail: jelena.jardas.antonic@efri.hr

Abstract

Understanding consumer behavior is one of the focal points of decision theory. Over the past decade, a substantial increase in the popularity of online shopping has been observed worldwide. The significant acceleration of this trend can be attributed to the COVID-19 pandemic, which affected consumers' traditional shopping behavior and forced them to shop without visiting physical stores. The increasing popularity of online shopping necessitated a better understanding of the factors driving behavior. In this research, based on a sample of 394 respondents, we aimed to find influential socio-demographic factors that affect online shopping habits and decision-making. To this end, we constructed a binary logistic regression model to estimate the influence of socioeconomic factors on online purchasing decisions. To support the logistic regression model results, we examined significant differences in views on online shopping among socio-demographic subgroups. Statistically significant influences on online shopping decisions include a person's age, education level, and employment status. Gender and urbanization level of residence showed no influence on online shopping behavior.

Keywords: *decision-making, online shopping, socio-demographic influence, logistic regression*

JEL Classification: *D12, D81*

1. INTRODUCTION

The digital transformation of the economy and society is increasingly prominent. Comparing data from the last ten years, the number of households with Internet access in the EU has increased by 20 percentage points (PP). Internet services are no longer used only for communication or entertainment purposes but also for accessing information, civic and political action, health information, e-learning, and e-commerce services (Eurostat, 2022a). The EU has recognized and plans to take advantage of the development trends of the ICT industry and its impact on all areas of society and the economy. Therefore, the EU has set up a plan for the Digital Decade goals to promote the development of society by improving ICT infrastructure, skills, public services, and business opportunities (Eurostat, 2022b). Companies have recognized the share and frequency of e-commerce use by individuals and, to strengthen their market position, offer them to purchase their products and services through physical and online channels. Over the last decade, an increase in the private purchase of goods and services via the Internet by individuals of all ages is noticeable (over 20 PP of increase when comparing the values in 2012 and 2022). General trends observed within EU member states are a positive correlation between education level and employment status with the use of e-commerce, a significant increase in the use of e-commerce services by specific age groups, a significant increase in the use of e-commerce services when purchasing certain product groups and the service, and a significant difference in the use of the e-commerce service to obtain goods and services (Eurostat, 2023a).

From the perspective of the collaborative economy, Croatia is at a relatively low level of online purchases among the EU-27 member states (Eurostat, 2023b). Although the volume of private online purchases at the level of individuals is lower than the EU-27 average, exponential growth can be observed if we look at the movements of online products and services by individuals in Croatia. In 2012, this was done by 23.08% of private individuals within 12 months. In 2017, this figure was 28.78%, and in 2022 it reached 56.15% of individuals who provided online products or services within 12 months (Eurostat, 2023c;

Eurostat, 2023d). The significant increase in e-commerce services by individuals in the Republic of Croatia to obtain goods and services opens a considerable market potential that companies must exploit. Knowledge of purchasing habits, preferences and behavioral patterns is essential for exploiting the newly created market potential. Identifying the socio-demographic characteristics of consumers who buy products and services online is critical to identifying a market niche. Recognizing and understanding the market niche provides more precise insights into behavioral patterns and the possibility of influencing consumers to choose your company's products and services when shopping online.

As the relative share of the Croatian population with experience in online shopping is growing but still comparably lagging within the EU-27, understanding their preferences and patterns is essential for decision theory and market participants' operations management and marketing efforts. This research aims to understand Croatian customers' decision-making when shopping online. Our main aim is to analyze and give insight into the critical demographic determinants that shape Croatian consumers' online shopping preferences, i.e., the influence of consumers' gender, age, attained education level, employment status, and urbanization level of consumers' residence on their online shopping decision-making.

2. LITERATURE REVIEW

The idea that consumer demographic characteristics could help understand and explain their online shopping behavior is not new and has already been tested in scientific research. *Gender* differences are among the most studied. A study by Yahya and Sugiyanto (2020) showed that women were likelier to shop online than men. Similar results and conclusions are found in other work (Moon et al., 2021; Hood et al., 2020), while Truong and Truong (2022) found that the gender difference is reflected in women spending more money online. Recent research by Vretenar et al. (2023) shows that women are more likely to shop online for certain types of products, such as clothing and shoes, which is consistent with the conclusions of Boustany (2022). Kim et al.'s (2020) research point to gender differences in shopping mode choices.

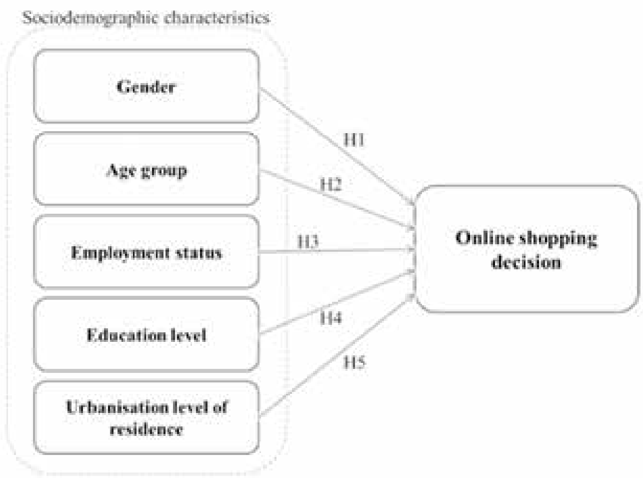
The following demographic difference we expected to influence shopping behavior is *age*. Again, previous research by Moon et al. (2021) and Hood et al. (2020) has shown that age is a relevant factor in understanding shopping decisions, as their research found that younger shoppers are more likely to shop online. Buhaljoti (2022) et al. concluded that consumers are more likely to shop online up to age 30, while the likelihood decreases. Consistent with these conclusions are research findings (Audrain-Pontevia & Vanhuele, 2016; Rummo et al., 2022) showing that older people are more likely to shop in stores. Truong and Truong (2022) concluded that older consumers spend more time shopping online than younger consumers, while Giannakopoulou et al. (2022) found that younger consumers are more likely to purchase groceries online.

Employment status is a variable that could be intuitively associated with purchase decisions, and some research confirms this. Frank and Peschel (2020) found that married people with children are more likely to shop online to save time, which is consistent with the findings of other studies of European working consumers (López Soler et al., 2021; and Smith et al., 2022). However, no connection between shopping patterns and employment status was found in research by Pattanaik, Mishra and Moharana (2017), and education level also had no influence. The influence of a consumer's attained *education level* on shopping behavior was somewhat doubtful. İlhan and İşçioğlu (2015) found that consumers with higher education were more likely to buy groceries online, which was also confirmed in a Belgian sample in a study by Dominici et al. (2021). Van Droogenbroeck et al. (2017) concluded that educated consumers are more likely to prefer online purchases. However, Troung and Troung (2022) found that educated consumers spend less on online purchases. Consumer's *urbanization level of residence* influence was least explored or commonly grouped with other influencing factors while the shopping decision-making process was analyzed. Although it could be argued that people living away from major urban centers are more inclined to shop online, research mainly supports the opposite, with some studies (Abdul Hussein et al., 2020; Hood et al., 2020) associating living in urban areas with a higher likelihood of shopping online. However, the latter study (Hood et al., 2020) indicated that consumers outside urban areas shop more online.

Based on the review of relevant literature on potential influencing socio-demographic factors, we have constructed five hypotheses regarding factors influencing consumers' online shopping behavior (model visualization in Figure 1):
H1: Gender significantly affects a consumer's decision to shop online.
H2: Age significantly affects a consumer's decision to shop online.
H3: Employment status significantly affects a consumer's decision to shop online.
H4: Attained education level significantly affects a consumer's decision to shop online.

H5: Urbanisation level of residence significantly affects a consumer's decision to shop online.

Figure 1. Online shopping decisions' socio-demographic influences



Source: authors' construction

To examine the set hypotheses of our research, we used a logistic regression model since the proposed dependent variable is classified as a binary one, and the independent variables take the form of binary or categorical values (Sreejesh et al., 2013; Harrell, 2015; Wilson & Lorenz, 2015). Logistic regression models have proven to be a helpful analysis method as it has been used in several relevant studies examining consumer shopping behavior (Vohra & Soni, 2015; Serener, 2016; Beckers et al., 2018; Bryła, 2018).

3. SAMPLE, DATA AND METHODOLOGY

Survey questionnaires regarding in-store and online shopping habits and decision-making were constructed using Google Forms and distributed online from May to September 2022. The socio-demographic characteristics of the respondents, together with the model variable operationalization, are presented in Table 1. Most respondents were female (72.3%), with almost half of the respondents falling within the 31-50 age range. One-quarter of the respondents are not employed (unemployed or retired), and the rest are employed pupils and students, private or public sector employees or self-employed. The lowest share of respondents has a lower education level (7.1%), while most have attained a high school level (44.4%). 64.7% of respondents reside in cities with over 20000 residents. A total of 394 respondents represent the sample of research. Descriptive statistics of the sample are given in Table 2. More than 90% of respondents in the sample have previous experience in online shopping (OS: 0 = no, 1 = yes).

Table 1. Socio-demographic characteristics of respondents and model variables operationalization

Socio-demographic characteristic	Model variable operationalization	Frequency	(%)
Gender	GEN		
Male	0	109	(27.7)
Female	1	285	(72.3)
Age group	AG		
<31 years	1	137	(34.8)
31-50 years	2	196	(49.7)
>50 years	3	61	(15.5)
Employment status	ES		
Not employed	1	98	(24.9)
Employed	2	296	(75.1)
Education level	EDU		
Lower education	1	28	(7.1)
High school education	2	175	(44.4)
Bachelor education	3	59	(15.0)
University master education or higher	4	132	(33.5)
Urbanization level of the residence	URB		
Municipality with 0-10000 residents	1	77	(19.6)
Municipality/city with 10001-20000 residents	2	62	(15.7)
The city with 20001+ residents	3	255	(64.7)

Source: authors' calculation

Table 2. Sample descriptive statistics

Variable	Mean	Std. dev.	Min.	Max.
OS	0.9010	0.2990	0	1
GEN	0.7234	0.4479	0	1
AG	1.8071	0.6830	1	3
ES	1.7513	0.4328	1	2
EDU	2.7487	1.0014	1	4
URB	2.4518	0.8001	1	3
N = 394				

Source: authors' calculation

Aiming to find evidence of socio-demographic factors influencing one's decision to shop online, a binary logistic regression model (Sreejesh et al., 2013; Harrell, 2015; Wilson & Lorenz, 2015) with the dependent variable previous online shopping experience (OS) was constructed:

$$OS = log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 GEN + \beta_2 AG + \beta_3 EDU + \beta_4 ES + \beta_5 URB + e\,. \quad (1)$$

The unstandardized beta coefficients determine the movement of the value of the dependent variable. Exponentiated coefficients will show the odds ratios of change of the dependent variable:

$$Odds(OS) = \frac{p}{1-p} = e^{\beta_0 + \beta_1 GEN + \beta_2 AG + \beta_3 EDU + \beta_4 ES + \beta_5 URB}\,. \quad (2)$$

Furthermore, respondents were to evaluate online shopping characteristics and their reasoning for online purchases with the help of a Likert scale measurement. Mann-Whitney U and Kruskal Wallis H tests, followed by Dunn's post hoc pairwise comparison tests (adjusted using Bonferroni's error correction), were conducted to prove significant differences in online shopping determinant evaluation regarding the socio-demographic subgroups (Conroy, 2012; Dinno, 2015; Harris & Hardin, 2013). The differences were used to explain the reason behind established socio-demographic influences on online purchase decisions based on the logistic regression model. To conduct the analysis, STATA 17.0 MP-Parallel Edition was used.

4. EMPIRICAL RESULTS

Based on the log-likelihood ratio test statistics, the five-predictor model provides a better fit than the null hypothesis, where only the model's constant was included. Post-estimation Hosmer–Lemeshow ($\chi2(8) = 7.64$, $p > \chi2 = 0.4695$) and Pearson ($\chi2(77) = 40.28$, $p > \chi2 = 0.9998$) test values are non-significant, indicating a good logistic regression model fit (Hosmer & Lemeshow, 2000; Tabachnick & Fidell, 2019). The value of McFadden's pseudo R2 (R2 = 0.412), as well as Cragg & Uhler's (Nagelkerke) (R2 = 0.491), indicate an excellent model fit (Hensher & Stopher, 1979; Cragg & Uhler, 1970). The results of the binary logistic regression model are presented in Table 3.

Table 3. Results of the logistic regression

	ß	exp(ß)	se exp(ß)	P>z	95% C.i. for exp(ß)	
					lower	upper
Gender						
Female	-0.4087	0.6645	0.3304	0.441	0.2508	1.7607
Age group						
31-50 years	-3.0605	0.0469	0.0502	0.004***	0.0057	0.3832
>50 years	-4.5531	0.0105	0.0116	0.000***	0.0012	0.0907
Education level						
High school education	1.8259	6.2085	3.7584	0.003***	1.8954	20.3364
Bachelor education	3.1639	23.6638	22.0289	0.001***	3.8168	146.7154
University master education or higher	3.7099	40.8502	31.3720	0.000***	9.0676	184.0336
Employment status						
Employed	1.0907	2.9763	1.4564	0.026**	1.1407	7.7657
Urbanization level of the residence						
Municipality/city with 10001-20000 residents	-0.1062	0.8993	0.7838	0.933	0.1604	5.3686
The city with 20001+ residents	-0.3122	0.7319	0.4543	0.861	0.2507	3.1772
Constant	2.9901	19.8868	23.8785	0.013	1.8902	209.2279
LR $\chi^2(9)$	104.91					
Prob > χ^2	0.0000					
Pseudo R2	0.4124					
* p<0.1. ** p<0.05. *** p<0.01						

Source: authors' calculation

Our results show that consumers' gender and urbanization level of residence does not influence online shopping decision. At the same time, the age group attained education level and employment status were significantly influenced. An increase in age negatively affects the likelihood of shopping online. The odds of people aged 31-50 shopping online are 0.047 times higher than those aged 30 years or under. The odds of someone over 50 shopping online are 0.011 times higher than those aged 30 years or under. The increase in attained education level positively impacts the likelihood of shopping online. The odds of a person with a high school education shopping online are 6.209 times higher than those with lower education. The odds of someone with a bachelor's education shopping online are 23.664 times higher than those with lower education. The odds of a person with a university master's or higher education shopping online are 40.850 times higher than those with a lower education level. Some conclusions of employment status influence on the likelihood of online shopping can be deduced. Employment status positively affects the probability of shopping online, as an employed person's odds of shopping online are 2.976 times higher than those of an unemployed person.

The constructed logistic regression model gave an overall correct classification rate of 93.15%, with a sensitivity of 97.75% and a specificity of 51.28%. A detailed classification matrix is presented in Table 4, with the correctly classified "yes" and "no" answers regarding prior online shopping experience being higher than the incorrectly classified values.

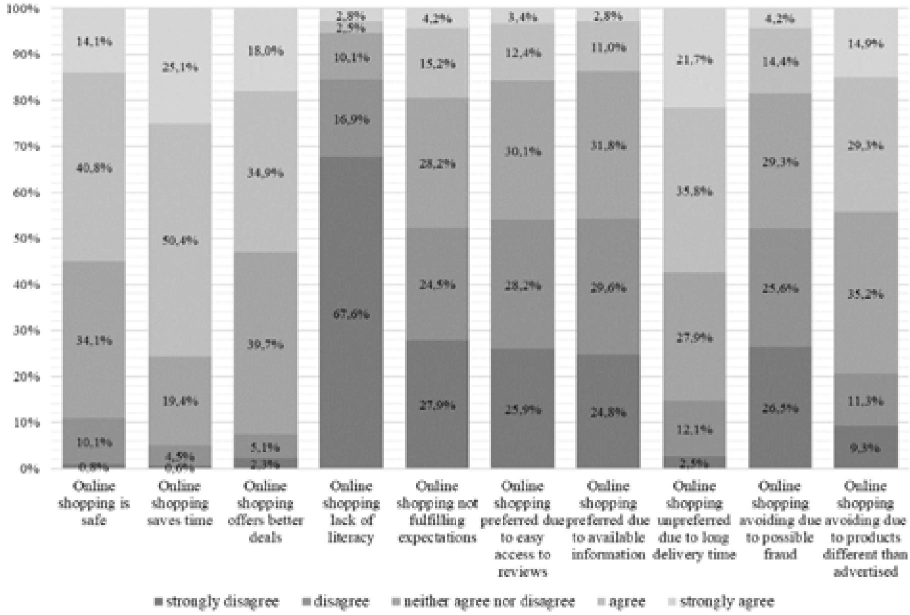
Table 4. Classification matrix

Classified	Yes	No	Total
Yes	347	19	366
No	8	20	28
Total	355	39	394

Source: authors' calculation

Respondents who shopped online (N = 355) evaluated, using a Likert scale measurement (1 = strongly disagree – 5 = strongly agree), statements regarding online shopping decision-making determinants (Figure 2). Respondents agreed that online shopping is safe, saves time and that it offers better deals. Further, they agree that online shopping is preferable due to the available information and somewhat lesser because of the ease of access to reviews. Respondents disagree that online shopping does not meet their expectations and that they lack the literacy to engage in online shopping. Long delivery time makes it not unpreferred to shop online, and slightly deeper concerns are differences in a product compared to what is advertised and other possibilities of fraud.

Figure 2. Online shopping decision-making determinants



Source: authors' construction

Observing values describing online shopping activities according to the defined age groups, the Kruskal Wallis H test provided evidence of significant differences between the groups in several statements. Separate age groups shared different views regarding online shopping's offering of better deals ($\chi2(2) = 6.592$, $p = 0.037$), availability of information ($\chi2(2) = 6.056$, $p = 0.048$), ease of access to reviews ($\chi2(2) = 15.923$, $p = 0.000$), level of fulfillment of expectations ($\chi2(2) = 10.154$, $p = 0.006$), the possibility of fraud ($\chi2(2) = 10.926$, $p = 0.004$) and the lack of literacy in online shopping ($\chi2(2) = 27.066$, $p = 0.000$). The subgroup's specifics substantiate the reasoning behind the decrease in the likelihood of shopping online with the increase in age. The older shoppers disagree that online shopping offers better deals (M = 2.13), gives better information (M = 2.11) or access to reviews (M = 1.80). Although they disagree with the lack of literacy in online shopping (M = 1.48), other age groups disagree more with that statement. They are the least keen to avoid online shopping because of possible fraud (M = 1.87). Surprisingly, this group disagrees the most about online shopping not fulfilling their expectations (M = 1.80). The youngest group agrees most with getting better deals while shopping online (M = 3.72), better information (M = 3.67) and easier access to reviews (M =

3.53). People aged 31-50 have avoided online shopping due to possible fraud the most (M = 2.70) and state the slightest lack of literacy in online shopping (M = 1.39).

Differences in online shopping perceptions were evident regarding respondents' employment status, as determined using the Mann-Whitney U tests. Groups showed significant differences in their assessment of online shopping's level of fulfillment of expectations ($z = -2.782$, $p = 0.005$), delivery time ($z = -3.404$, $p = 0.001$), product difference to advertising ($z = -2.837$, $p = 0.005$), the possibility of fraud ($z = -3.129$, $p = 0.002$) and their lack of online shopping literacy ($z = -3.829$, $p = 0.000$). A higher level of distrust, noted among not employed subsample, in online shopping differentiates the behavior of the two compared groups. Respondents from the not employed subsample group showed a higher perception of the lack of online shopping literacy (M = 1.97) than those employed (M = 1.45). They said to agree more to not preferring online shopping because of extended delivery times (M = 2.76), products being different than advertised (M = 2.78), and fear of other possibilities of fraud (M = 2.84), compared to the employed respondents (M = 2.27, M = 2.35 and M = 2.33 respectively). Expectedly, because of the previously stated, unemployed respondents stated a higher level of agreement of online shopping not fulfilling their expectations (M = 2.71) compared to the employed (M = 2.31).

Participants with different levels of education have different opinions about several aspects of online shopping, as evident from the Kruskal Wallis H test results. Significant differences were found in their of online shopping's safety ($\chi2(3) = 12.583$, $p = 0.005$), offering of better deals ($\chi2(3) = 8.197$, $p = 0.042$), product difference to advertising ($\chi2(3) = 18.452$, $p = 0.000$), level of fulfillment of expectations ($\chi2(3) = 14.908$, $p = 0.002$), the possibility of fraud ($\chi2(3) = 14.764$, $p = 0.002$) and their lack of online shopping literacy as well ($\chi2(3) = 12.597$, $p = 0.006$). The reasons why the likelihood of online shopping increases with an increase in the acquired level of education can be seen. The lower educated strongly disagree that they lack online shopping literacy (M = 1.11). They do not think online shopping is safe (M = 1.36) and offer better deals (M = 1.50). They disagree with not preferring and avoiding online shopping due to long delivery time (M = 1.42), the possibility of fraught (M = 1.43) and differences in products to the advertisement (M = 1.54). Still, their other views on online shopping can explain such behavior. Bachelor's education level respondents agree the most about catching better deals while shopping online (M = 3.54). Still, they are the most likely to avoid online shopping due to products differing from advertisements (M = 2.39) and due to possible fraud (M = 2.27). The highest education level respondents see online shopping as the safest (M = 3.65).

5. DISCUSSION

Even though gender is considered one of the most influential demographic characteristics in explaining decision-making, the influence of gender on the online shopping decision of Croatian consumers' was not confirmed in this research. Therefore, in our model, gender did not influence the decision to shop online, and hypothesis H1 is rejected. However, age, the second variable we expected to make a difference, proved to do so. The influence of age is in a direction supported by previous literature: with an increase in age, the likelihood of shopping online decreases, and therefore, hypothesis H2 is confirmed. Moreover, the differences in views on online shopping between different age groups can partially explain such a movement. Although online shopping fulfills their expectations the most out of the group, the oldest generation does not recognize online deals as much better. The oldest age group does not grade the greater availability of information and utility of product reviews as the youngest group of participants does. The middle age group shows the highest online shopping literacy and is the wariest of possible fraud. Although additional research is needed to verify this thoroughly, the results may suggest that the middle-aged group of online consumers who matured alongside the rise of the Internet are more aware of peculiarities and adept at online shopping than younger consumers who grew up with the Internet as an everyday experience and older consumers who started to embrace it only at a more mature age.

Employed consumers are likelier to shop online than unemployed ones, confirming hypothesis H3. One might think that respondents from the subgroup "not-employed" are less keen to buy online because they have fewer funds. However, besides unemployed people, this group comprises all respondents who were not in a working relationship when they filled in the questionnaire, which includes students, retired people, homemakers, etc. Nevertheless, as today the employed consumers of most occupations have some exposure to online transactions, it might be speculated that they have more online experience and, therefore, less fear and resistance to buying online.

According to our results, the lower educated participants feel the most knowledgeable about online shopping. Such results seem counterintuitive and might be seen as a confirmation of Goethe's quote that doubt grows with knowledge. The evaluations of this subgroup on further online shopping statements showed they are less bothered with longer delivery time, the dangers of products not being true to what is advertised, or other possibilities of fraud. This might be because they see online shopping as unsafe and not offering better deals than in-store shopping. Although people with higher education levels are much more concerned about the differences in products and fraud, they tend to see online shopping as safe and an opportunity to get better deals. Such difference in perspective of respondents with higher levels of education helps to explain the higher likelihood of purchasing products online with the increase of attained education level of a consumer. The stated result leads to the confirmation of hypothesis H4. The level of urbanization of residence also showed no significance in our model; therefore, hypothesis H5 is rejected. Such results can be explained by the relatively equal spread of ICT infrastructure, which enabled similar opportunities for online shopping, i.e., the availability of the Internet does not differ significantly across the country, nor does its use in online shopping.

6. LIMITATIONS AND FUTURE RESEARCH

Although this sample allowed us to run the logistic regression, analyze online purchase preferences, and obtain statistically significant results, a larger sample might allow us to draw more telling conclusions, as such conclusions would allow for better generalization of consumer behavior while shopping online. In addition to a larger sample, we seek a better balance among respondents regarding gender and educational groups for future research. Finally, in our future research, we intend to collect data on respondents' place of residence and try to balance the number of respondents in the central regions of Croatia. Such an enriched research sample should allow for more representative conclusions about Croatian consumers and provide an opportunity to analyze possible regional differences among Croatian consumers.

7. CONCLUSION

This study confirmed most of our hypotheses and the expected behavioral differences between subgroups of consumers but also led to some unexpected conclusions. Although it should always be expected that some of the previously made assumptions will not be confirmed, as was the case for most of our assumptions, we still did not expect the rejection of our first hypothesis, i.e., that our logistic regression model would not confirm behavioral differences in online shopping between consumers of a different gender. This study's scientific importance is primarily the contribution of additional insights into factors impacting consumer online shopping behavior. The paper provides a stimulus for further investigating consumer decision-making factors. Decision-making is the keystone of decision theory and a significant part of microeconomics. The essence of consumer choice is their preferences. However, preferences are not autonomous, as numerous studies show that various socio-demographics and other factors influence preferences. In this research, preferences were influenced by age, education level, and employment status among the variables studied. At the same time, place of residence, apart from gender, did not play a role when considering its size. In the management field, particularly operations management and marketing, these findings could prove helpful in better understanding the effectiveness of sales efforts and channels. For business people, this research could help develop strategies for online sales and adjust inventory management. Researching consumer behavior, therefore, allows businesses to tailor their actions to meet the needs of their customers.

This paper is supported through project ZIP-UNIRI-2023-14 by the University of Rijeka.

REFERENCES

AbdulHussein, A., Cozzarin, B. & Dimitrov, S. (2022). Changes in consumer spending behaviour during the COVID-19 pandemic across product categories. *Electron Commerce Research*. https://doi.org/10.1007/s10660-022-09618-9.

Audrain-Pontevia, A.-F. & Vanhuele, M. (2016). Where do customer loyalties really lie, and why? Gender differences in store loyalty. *International Journal of Retail & Distribution Management*, 44(8), p. 799-813. https://doi.org/10.1108/ijrdm-01-2016-0002.

Beckers, J., Cárdenas, I. & Verhetsel, A. (2018). Identifying the geography of online shopping adoption in Belgium. *Journal of Retailing and Consumer Services*, 45, p. 33-41. https://doi.org/10.1016/j.jretconser.2018.08.006.

Boustani, N.M., Sayegh, M.M. & Boustany, Z. (2022). Attitude towards Online Shopping during Pandemics: Do Gender, Social Factors and Platform Quality Matter? *Journal of Risk and Financial Management,* 15(10). https://doi.org/10.3390/jrfm15100474.

Bryła, P. (2018). Organic food online shopping in Poland. *British Food Journal,* 120(5). p. 1015-1027. https://doi.org/10.1108/bfj-09-2017-0517.

Buhaljoti, A., Habili, M. & Abazi, A. (2022). The impact of knowing the profile of online shoppers on online shopping: Evidence from city of Berat, Albania. *WSEAS Transactions on Business and Economics,* 19, p. 1265-1270. https://doi.org/10.37394/23207.2022.19.112.

Conroy, R.M. (2012). What hypotheses do "nonparametric" two-group Tests actually test? *The Stata Journal: Promoting Communications on Statistics and Stata,* 12(2), p. 182-190. https://doi.org/10.1177/1536867x1201200202.

Cragg, S.G. & Uhler, R. (1970.) *The demand for automobiles, Canadian Journal of Economics,* 3(3), p. 386-406. https://doi.org/10.2307/133656.

Dinno, A. (2015). Nonparametric pairwise multiple comparisons in independent groups using Dunn's test. *The Stata Journal: Promoting Communications on Statistics and Stata,* 15(1), p. 292-300. https://doi.org/10.1177/1536867x1501500117.

Dominici, A., Boncinelli, F., Gerini, F. & Marone E. (2021). Determinants of online food purchasing: The impact of socio-demographic and situational factors. *Journal of Retailing and Consumer Services,* 60. https://doi.org/10.1016/j.jretconser.2021.102473.

Eurostat (2022a). Digital economy and society statistics - households and individuals. [available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Digital_economy_and_society_statistics_-_households_and_individuals, access May 12, 2023]

Eurostat (2022b). Towards Digital Decade targets for Europe. [available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Towards_Digital_Decade_targets_for_Europe, access May 12, 2023]

Eurostat (2023a). E-commerce statistics for individuals. [available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=E-commerce_statistics_for_individuals, access May 12, 2023]

Eurostat (2023b). Internet purchases - collaborative economy (2020 onwards). [available at: https://ec.europa.eu/eurostat/databrowser/view/isoc_ec_ce_i/default/table?lang=en, access May 12, 2023]

Eurostat (2023c). Internet purchases by individuals (until 2019). [available at: https://ec.europa.eu/eurostat/databrowser/view/isoc_ec_ibuy/default/table?lang=en, access May 12, 2023]

Eurostat (2023d). Internet purchases by individuals (2020 onwards). [available at: https://ec.europa.eu/eurostat/databrowser/view/isoc_ec_ib20/default/table?lang=en, access May 12, 2023]

Frank, D.A. & Peschel, A.O. (2020). Sweetening the Deal: The Ingredients that Drive Consumer Adoption of Online Grocery Shopping. *Journal of Food Products Marketing,* 26(8), p. 535-544. https://doi.org/10.1080/10454446.2020.1829523.

Giannakopoulou, M., Adamides, G. & Stylianou, A. (2022). Consumer Adoption of Online Grocery Shopping: Findings from a Case Study in Cyprus. *Proceedings of HAI-*

CTA 2022, Theodoridis, A., Koutsou, S. (Ed.), Hellenic Association on Information & Communication Technologies in Agriculture, Food and Environment (HAICTA), Athens, 22-25 September 2022, p. 164-171.

Harrell, F.E. (2015). *Binary Logistic Regression*. In *Regression Modeling Strategies. With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis (Springer Series in Statistics)*, Cham: Springer, p. 219-274. https://doi.org/10.1007/978-3-319-19425-7_10.

Harris, T. & Hardin, J.W. (2013). Exact Wilcoxon signed-rank and Wilcoxon Mann–Whitney ranksum tests. *The Stata Journal: Promoting Communications on Statistics and Stata*, 13(2), p. 337-343. https://doi.org/10.1177/1536867x1301300208.

Hensher, D.A. & Stopher, P.R. (1979). *Behavioural Travel Modelling*, 1st ed., New York: Routledge. https://doi.org/10.4324/9781003156055.

Hood, N., Urquhart, R., Newing, A. & Heppenstall, A. (2020). Socio-demographic and spatial disaggregation of e-commerce channel use in the grocery market in Great Britain. *Journal of Retailing and Consumer Services*, 55. https://doi.org/10.1016/j.jretconser.2020.102076.

Hosmer, D. W. & Lemeshow, S. (2000). *Applied Logistic Regression*, 2nd ed., New York: John Wiley & Sons. https://doi.org/10.1002/0471722146.

İlhan, B.J. & İşçioğlu, T.E. (2015). Effect of women's labor market status on online grocery shopping, the case of Turkey. *Eurasian Business Review*, 5(2), p. 371-396. https://doi.org/10.1007/s40821-015-0029-x.

Kim, J.-H., Kim, M., Yoo, J. & Park, M. (2020). Consumer decision-making in a retail store: the role of mental imagery and gender difference. *International Journal of Retail & Distribution Management*, 49(3), p. 421-445. https://doi.org/10.1108/ijrdm-10-2019-0353.

López Soler, J.R., Christidis, P. & Vassallo, J.M. (2021). Teleworking and Online Shopping: Socioeconomic Factors Affecting Their Impact on Transport Demand. *Sustainability*, 13. https://doi.org/10.3390/su13137211.

Moon, J.H., Yunseon C. & HakJun S. (2021). Determinants of Consumers' Online/Offline Shopping Behaviours during the COVID-19 Pandemic. *International Journal of Environmental Research and Public Health*, 18(4). https://doi.org/10.3390/ijerph18041593.

Pattanaik, S., Mishra, B.B. & Moharana, T.R. (2017). How Consumer Demographics is Associated with Shopping Behaviour? A Study on Indian Consumers. *Siddhant - A Journal of Decision Making*, 17(2), p. 195-206. https://doi.org/10.5958/2231-0657.2017.00022.2.

Rummo, P.E., Roberto, C.A., Thorpe, L.E., Troxel, A.B. & Elbel, B. (2022). Age-Specific Differences in Online Grocery Shopping Behaviors and Attitudes among Adults with Low Income in the United States in 2021. *Nutrients*, 14(20). https://doi.org/10.3390/nu14204427.

Serener, B. (2016). Statistical Analysis of Internet Banking Usage with Logistic Regression. *Procedia Computer Science*, 102, p. 648-653. https://doi.org/10.1016/j.procs.2016.09.456.

Smith, L.G., Widener, M.J., Liu, B., Farber, S., Minaker, L.M., Patterson, Z., Larsen K. & Gilliland, J. (2022). Comparing Household and Individual Measures of Access through a Food Environment Lens: What Household Food Opportunities Are Missed When

Measuring Access to Food Retail at the Individual Level? *Annals of the American Association of Geographers,* 112(2), p. 542-562. https://doi.org/10.1080/24694452.2021.1930513.
Sreejesh, S., Mohapatra, S. & Anusree, M.R. (2013). *Binary Logistic Regression.* In Sreejesh, S., Mohapatra, S. & Anusree, M.R. (Ed.). *Business Research Methods.* Cham: Springer, p. 245–258. https://doi.org/10.1007/978-3-319-00539-3_11.
Tabachnick. B.G. & Fidell. L.S. (2019). *Using Multivariate Statistics*, 7th ed., U.S.: Pearson Education
Truong, D. & Truong, M.D. (2019). How do customers change their purchasing behaviors during the COVID-19 pandemic? *Journal of Retailing and Consumer Services,* 67. https://doi.org/10.1016/j.jretconser.2022.102963
Vohra, J. & Soni, P. (2015). Logit modelling of food shopping behaviour of children in retail stores. *Management Research Review,* 38(8), p. 840-854. https://doi.org/10.1108/mrr-03-2014-0061.
Vretenar, N., Prudky, I. & Kruljac Stanojević, S. (2023). Purchase Preferences in Croatian Stores Framed by Shoppers' Demographic Characteristics. *12th International Scientific Symposium Region, Entrepreneurship, Development,* Leko Šimić, M. (ed.) Josip Juraj Strossmayer University of Osijek, Faculty of Economics and Business in Osijek, Osijek, 15-16 June 2023, p. 807-824
Wilson, J.R. & Lorenz, K.A. (2015). *Standard Binary Logistic Regression Model.* In Chen, S., Chen, D.-G. (Series Ed.). *Modeling Binary Correlated Responses Using SAS, SPSS and R (ICSA Book Series in Statistics 9).* Cham: Springer, p. 25-54. https://doi.org/10.1007/978-3-319-23805-0_3.
Yahya, S. & Sugiyanto, C. (2020). Indonesian Demand for Online Shopping: Revisited. *Journal of Indonesian Economy and Business,* 35(3), p. 188-203. https://doi.org/10.22146/jieb.55358.