DIVERSE GROUPS OF SMARTPHONE USERS AND THEIR SHOPPING ACTIVITIES

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Abstract: *The analysis of customers' purchasing activities, their preferences and future potential are the subject of interest of many experts in the field of marketing. Smartphones became the common devices used during purchasing process. By examining purchasing behavior of smartphone owners, the valuable insights useful for modeling new selling strategies could be mined. The main objective of this study is to analyze different behavioral patterns of smartphone users during the pre-purchase stage of the purchase process. To achieve these goal, we analyzed the data from Consumer Barometer containg data for 56 countries and 78,920 respondents. We created 3 new latent variables – factors - while reducing the number of variables (11) entering the cluster analysis by using factor analysis. Subsequently, using the cluster analysis and the method of k-medians, we created four clusters of users. Even though there are more active and less active clusters, the most popular activities involved getting store directions and checking where to buy a certain product. Users from European countries (represented by Cluster 1 and 2) use smartphones in the pre-purchase process very little, showing conservative approach towards smartphones in these countries. On the other hand, users in Cluster 3 and 4 seem to be the most active smartphone users in terms of purchasing process.*

Keywords: *Smartphone User, Mobile Shopping, Mobile-first, k-medians, Cluster Analysis*

JEL Classification: *M31, M15.*

Introduction

Scientific and technological progress in the field of digital media and devices connected to the Internet has changed the nature of the purchasing process and added to its complexity. Thus, the customer can choose from almost endless variety of choices regarding devices and media which may be used in the implementation of various activities associated with the purchase. This growing trend increases the difficulty of management decisions regarding the composition of the communications mix of companies while trying to achieve positive user experience throughout the entire duration of purchase process - from the urge to buy through the actual purchase to the customer service associated with the use of the product (Scott, 2013; Halligan and Shah, 2014; Roberge, 2015). The development in mobile devices also implies that users increasingly abandon desktops/laptops and use smartphones to consume online content. The growth in the number of user devices, as well as the process of linking online and offline environment led to the creation of a new type of user - omnichannel user. The model of omnichannel customer's behavior assumes that the customer will interact with the company using a number of channels and devices before the actual purchase (Dorman, 2013). Deloitte (2015) states that 9% of consumers in the United States own several mobile devices (smartphone, tablets and wearable devices). Juaneda-Ayensa et al. (2016) refers to these users as 3.0 users. He states that these omnichannel users switch devices very often, which causes companies difficulties in controlling customers' purchasing processes. The issue of omnichannel users grabbed attention of companies and academics alike and a number of academics have already researched it, namely Piotrowicz and Cuthbertson (2014), Peltola et al. (2015), Lazaris et al. (2015) and others. Omnichannel users and their behavior is an issue that is beyond the scope of this study. Poushter (2016) in his study states that the amount of users owning a smartphone has increased sharply also in developing economies, but there are still significant differences when the smartphone ownership rate is compared for example with African countries. The author of the study also states a strong positive correlation between the ownership of smartphones with gross domestic product per capita. The study by Research New Zealand (2015) states that between 2013 and 2015 the share of smartphone use in New Zealand increased to 46%. In addition, the study states that daily use of other devices decreases. Deloitte (2015) pointed to the fact that most respondents use a mobile phone while doing other activities such as shopping at the store, talking to family or friends, watching TV, or while eating in a restaurant. It gives companies the opportunity to reach their target customer almost anytime and everywhere. Tossell et al. (2015) using Smartphone Addiction Measurement Instrument studied on a sample of 34 students whether the use of smartphones under the predetermined conditions affects smartphone addiction. At the end of the experiment 21 out of 34 students agreed with the statement that they are addicted to their smartphones. Report Salesforce (2014) also points out that only 85% of respondents see their mobile device as a central part of their everyday life, 90% of respondents aged between 18-24 years agreed. By becoming central part of people's life, smartphones have also become a central part of people's purchasing life. The following review of literature provides an evidence confirming this statement.

1 Statement of a problem

Holmes et al. (2013) pointed out that in addition to the actual shopping smartphones are also used in the process of searching for information and alternatives. Mobile devices are used more often when it comes to buying products that require a higher level of engagement. Our own study carried out by Pollák, Nastišin and Kakalejčík (2015) and the complementing study (Bucko, Kakalejčík and Nastišin, 2015) showed that 96% of respondents combine desktop and mobile devices in various ratios. Moreover, the study showed that approximately 66% of respondents purchased a product using smartphones, while the most smartphones user use their device to search for product information (76%), visit the website of a company (71%), or search for product reviews (69%). In 2015, Google announced that the number of searches on mobile devices surpassed the number of searches on desktop devices (Sterling, 2015). This finding is directly related to the study carried out by DigitasLBi (2015), which discusses the fact that customers have access to information about the product directly in the store which in turn influences their shopping behavior. The survey results showed that 77% of Internet users were influenced by a mobile device, 28% of users made their purchase via a mobile device. 55% of smartphone users think that the combination of the Internet and the smartphone has changed the way their shop at stores. Studies on the use of smartphones in the shopping process were published by the following academics and their collectives: Wang et al. (2015), Einav et al. (2014), Olivier and Treblanche (2016), Thakur (2016), Groß (2015). Based on the review of the above studies show that mobile device users cannot be overlooked when analyzing the user experience and marketing. However, as there is a gap in development of particular countries, we assume this emerging trend doesn't affect users and selling companies in the same way all around the world. By creating the similar groups of countries, companies are able to identify most critical segments of smartphone users and afterwards prioritize the optimization of the buyer journey of the smartphone users. By ignoring mobile device users we would not be able to get a whole picture of the current shopping activities of consumers and predicting their future behavior will be complicated, thus leading to poor user experience and loss of customers. As there is an assumption that mobile-first trend will continue to grow, not adjusting the buyer journey based on this trend can lead to the destruction of the companies' client base.

2 Methods

The main objective of this study is to analyze different behavioral patterns of smartphone users during the pre-purchase stage of the purchase process based on the current knowledge. By decomposing the main objective we have arrived to the following sub-objectives:

- analyze the current state of the issue of smartphones use with a focus on their use in the buying process;
- analyze the interdependencies between the variables included in the database and organizing factors in groups in order to reduce the number of variables;
- divide users by variables into homogeneous groups using the method of cluster analysis;
- define the basic attributes of the previously created clusters of users and compare these clusters.

The behavior of smartphone users from selected countries was analyzed using data obtained from the consumer research carried out by Google - Consumer Barometer (2017). Data from this consumer survey were obtained from two sources. The first was a questionnaire that focuses on online population. The second one was a consumer study that aim was to calculate the total population of adults in order to adjust the results of the first part of the questionnaire. The questionnaire was conducted between January and April 2016. The data file contains data from 56 countries - Europe (29), Asia (18), America (5), Africa (3) and Australia - a total of 78,920 respondents. The analysis posed the following question: "What kind of product research you made via your smartphone?" That question was posed to respondents in the questionnaire survey aimed at pre-purchase product research. The input variables are shown in Tab. 1.

Tab. 1: Description of input variables (in %)

Variable	Min	Lower quartile	Median	Average	Upper quartile	Max
A. Got ideas, inspiration online	11.00	18.00	24.50	25.07	30.00	57.00
B. I found relevant brands online	12.00	17.00	21.00	21.18	23.25	40.00
C. Compared products, their features and price online	22.00	30.00	35.00	34.48	38.00	51.00
D. Sought opinions/ review/ advice online	9.00	18.00	21.50	21.96	25.00	36.00

E. Watched relevant videos online	4.00	8.75	10.50	10.29	12.00	16.00
F. Searched for a relevant offer online	2.00	4.00	6.00	6.96	8.00	18.00
G. Found where to buy/ product availability online	6.00	10.00	12.50	12.79	15.00	24.00
H. Get store direction/ location online	3.00	9.00	12.50	12.54	15.00	26.00
I. Made contact/ requested contact (with brands/ retailers)	3.00	4.00	6.00	5.95	7.00	12.00
J. I was looking for online financial options	0.00	1.00	2.00	2.43	3.00	7.00
K. Other information looked for online	3.00	7.00	10.00	10.52	14.00	20.00

Source: own elaboration by the authors

As can be seen in Tab. 1, the variables contained in the data files contain outliers. For this reason we also adapted the methods used. In order to analyze the data file we used the following statistical methods:

- descriptive statistics tools (tables, bar charts, line charts, box plot, mean, median, quartiles);
- factor analysis;
- cluster analysis using k-medoids. Instead of the Euclidean distance this method uses Manhattan distance because it is more accurate in respect of outliers (Cardot, 2016). During the analysis we made use of The R Project and MS Excel.

3 Problem solving

In the first step of the analysis we had to confirm that it is appropriate to use the factor analysis. Accordingly, the analysis is linked with the correlation matrix of variables.

Tab. 2: The correlation matrix of variables

	A	B	C	D	E	F	G	H	I	J	K
A	**1.00**	0.12	-0.39	-0.48	0.24	-0.31	-0.05	-0.10	0.20	-0.01	-0.11
B	0.12	**1.00**	0.40	0.00	0.33	0.13	0.33	0.16	0.40	0.46	-0.39
C	-0.39	0.40	**1.00**	0.30	-0.06	0.40	0.20	0.32	0.07	0.10	-0.30
D	-0.48	0.00	0.30	**1.00**	0.19	0.44	0.20	0.28	0.13	0.23	0.08
E	0.24	0.33	-0.06	0.19	**1.00**	0.31	0.41	0.37	**0.51**	0.40	-0.12
F	-0.31	0.13	0.40	0.44	0.31	**1.00**	0.11	0.41	0.15	-0.09	-0.20
G	-0.05	0.33	0.20	0.20	0.41	0.11	**1.00**	**0.71**	**0.64**	**0.51**	-0.13
H	-0.10	0.16	0.32	0.28	0.37	0.41	**0.71**	**1.00**	**0.51**	0.30	-0.20
I	0.20	0.40	0.07	0.13	**0.51**	0.15	**0.64**	**0.51**	**1.00**	0.41	-0.28
J	-0.01	0.46	0.10	0.23	0.40	-0.09	**0.51**	0.30	0.41	**1.00**	0.01
K	-0.11	-0.39	-0.30	0.08	-0.12	-0.20	-0.13	-0.20	-0.28	0.01	**1.00**

Source: own elaboration by the authors

The correlation matrix of variables is shown in Tab. 2. The variables are labeled with letters in accordance with Tab. 3. The correlation matrix shows small, medium and large dependencies between the analyzed variables that are color-coded. Since the correlation matrix showed a dependency between variables, we proceeded with the implementation of further tests in order to determine the appropriateness of using the factor analysis. In order to carry out *Kaiser-Mayer-Olkin* test we standardized the data matrix's scale using *z-scores*. The total value of *Kaiser-Mayer-Olkin* test was 0.66, which according to Kráľ et al. (2009) represents the average adequacy of the sample data. Since, however, this value is greater than 0.50, it is suitable to carry out the factor analysis. All selected variables can be used within the analysis.

In the next step we conducted a *Batlett's sphericity test*. In this test, we tested the following statistical hypotheses:
H0: The correlation matrix is an identity matrix.
HA: The correlation matrix is not an identity matrix.

Since the *p-value* was $8{,}853188.10^{-25}$, and thus was lower than the significance level α = 0.05, the null hypothesis was rejected. Since the correlation matrix of variables was not the identity matrix, we accept the alternative hypothesis HA.

In the next step we calculated the appropriate number of common factors. Firstly, we analyzed the principal components. The results are shown in Tab. 3. Since the value of own numbers is in the case of four components higher than 1, and the selection of these four components explains 74% of variation, the factor analysis will focus only on these 4 factors.

Tab. 3: Principal components analysis

	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	K11
Standard deviation (Eigenvalues)	1.90	1.43	1.18	1.04	0.93	0.73	0.63	0.62	0.53	0.50	0.40
Cumulative variability	0.33	0.51	0.64	0.74	0.82	0.87	0.90	0.94	0.96	0.99	1.00

Source: own elaboration by the authors

Since saturation of several factors under one indicator was high, we had to implement different types of rotation - orthogonal (varimax, quartimax, equamax) and oblique (oblimin, promax). The best results were obtained when using equamax rotation. With three variables the saturation was relatively high, and therefore it is impossible to assign a particular variable to a factor. Therefore, three variables with high saturation were excluded from the analysis.

After removing these variables, it is necessary to repeat the whole process again. The value of *Kaiser-Mayer-Olkin* statistics was again at the level of 0.66, which represents an average adequacy of sample data. In addition, *Bartlett's sphericity test* again rejected the null hypothesis that the correlation matrix was not the identity matrix. The achieved *p-value* is in fact equal to $3.729983.10^{-16}$, which is below the level of statistical significance of α = 0.05. We thus proceeded to the analysis of the principal components in order to choose the appropriate number of factors for the factor analysis. Based on Tab. 4, we chose three factors for further analysis. Since the three components are greater than 1, and the proportion of cumulative variability is 71%, we consider this selection to be correct.

Tab. 4: Principal components analysis

	K1	K2	K3	K4	K5	K6	K7	K8
Standard deviation (Eigenvalues)	1.73	1.29	1.01	0.89	0.77	0.64	0.58	0.47
Cumulative variability	0.37	0.58	0.71	0.80	0.88	0.93	0.97	1.00

Source: own elaboration by the authors

After selecting factors (3), we proceeded to the factor analysis. To avoid an uncertain outcome, we performed a rotation of factors. Since it was our intention to work with uncorrelated factors, we made use only of orthogonal rotation. Using the quartimax and equamax methods we achieved excellent results - factor saturation of individual factors was really high. Although we did not arrive at the same high saturation of factors using the varimax method, we were able to eliminate the influence of a single indicator on several factors. Therefore, the varimax method was preferred. Factor saturation is shown in Tab. 5.

Tab. 5: Saturation matrix (varimax rotation)

Variables (indicators)	F1	F2	F3	h^2	u^2
A. Got ideas, inspiration online	0.18	**-0.90**	0.03	0.84	0.16
B. I found relevant brands online	0.31	-0.09	**0.72**	0.63	0.37
D. Sought opinions/ review/ advice online	0.27	**0.77**	-0.1	0.67	0.33
E. Watched relevant videos online	**0.74**	-0.17	0.05	0.59	0.41
G. Found where to buy/ product availability online	**0.83**	0.19	0.14	0.74	0.26
H. Get store direction/ location online	**0.76**	0.30	0.11	0.68	0.32
I. Request contact details/ contacted company	**0.8**	-0.1	0.28	0.72	0.28
K. Sought other information	-0.05	0.03	**-0.88**	0.79	0.21

Source: own elaboration by the authors

Based on the factor analysis we arrived at the following three factors:

1. Factor 1: watching relevant videos, verifying product availability, getting store directions, contacting the brand/ store;
2. Factor 2: looking for ideas/ inspiration, reviews and opinions;
3. Factor 3: searching for brands, looking for information.

The analysis of the results failed to interpret the meaning of the newly established factors. Since, however, we had to reduce the number of variables due to the cluster analysis, failure to interpret factors is for us insignificant. The resulting factor saturation helped us create 3 new latent variables containing the factor scores that will be used as input data for the cluster analysis. Before we proceeded to the actual cluster analysis we had to check the presumption that there already are some dependencies between the variables.

Tab. 6: Correlation matrix of factors

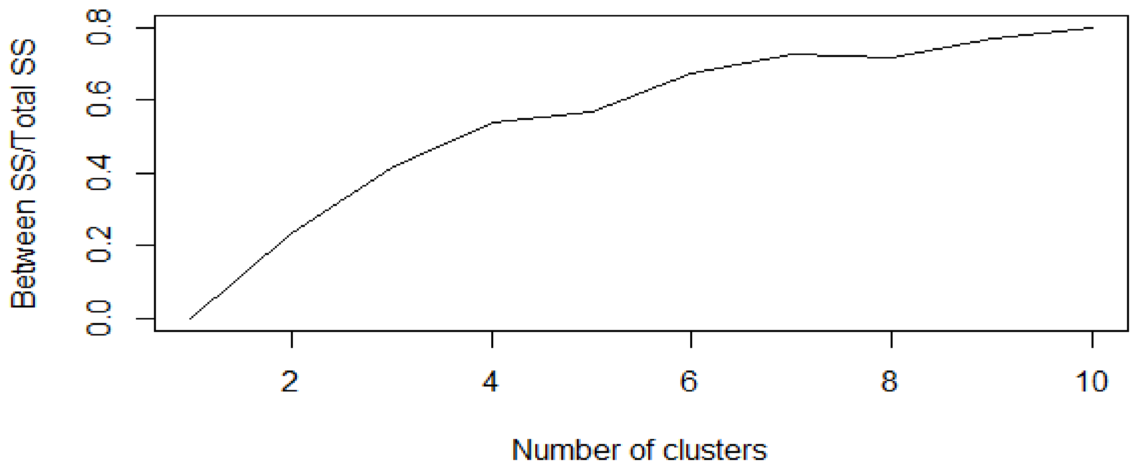
	Factor 1	Factor 2	Factor 3
Factor 1	1.00	$2.830630.10^{-16}$	$-4.214035.10^{-16}$
Factor 2	$2.830630.10^{-16}$	1.00	$1.165143.10e^{-15}$
Factor 3	$-4.214035.10^{-16}$	$1.165143.10^{-15}$	1.00

Source: own elaboration by the authors

Correlation matrix shown in Tab. 6 shows that the correlation coefficients for individual factors pairs are close to zero, which confirms that the results of orthogonal rotation are indeed uncorrelated factors. We then proceeded to the cluster analysis.

Cluster analysis offers a suitable way how to investigate relations between the explored objects. It introduces a method to combine the objects with the similar characteristics. There are the several approaches how to find out the relations between the entities. Firstly, we had to determine the appropriate number of clusters. It is determined by *k-means* method, whilst distance between the objects is quantified by the Euclidean distance. Y-axis in the Chart 1 represents the ratio of the sum of squares between the clusters and the total sum of squares. When choosing the number of clusters, this ratio should be, however, as high as possible. To choose the right number of clusters it is necessary to take into account the curvature of the displayed line. When choosing an appropriate number of clusters it is advisable to choose such a point at which the line breaks significantly. In Fig. 1, this condition can be monitored especially at value of 4 and 7. Due to the size of the data file and possible problems with cluster defining this study will employ *k-medians* method using four clusters.

Fig. 1: Selecting suitable number of clusters according to k-means method



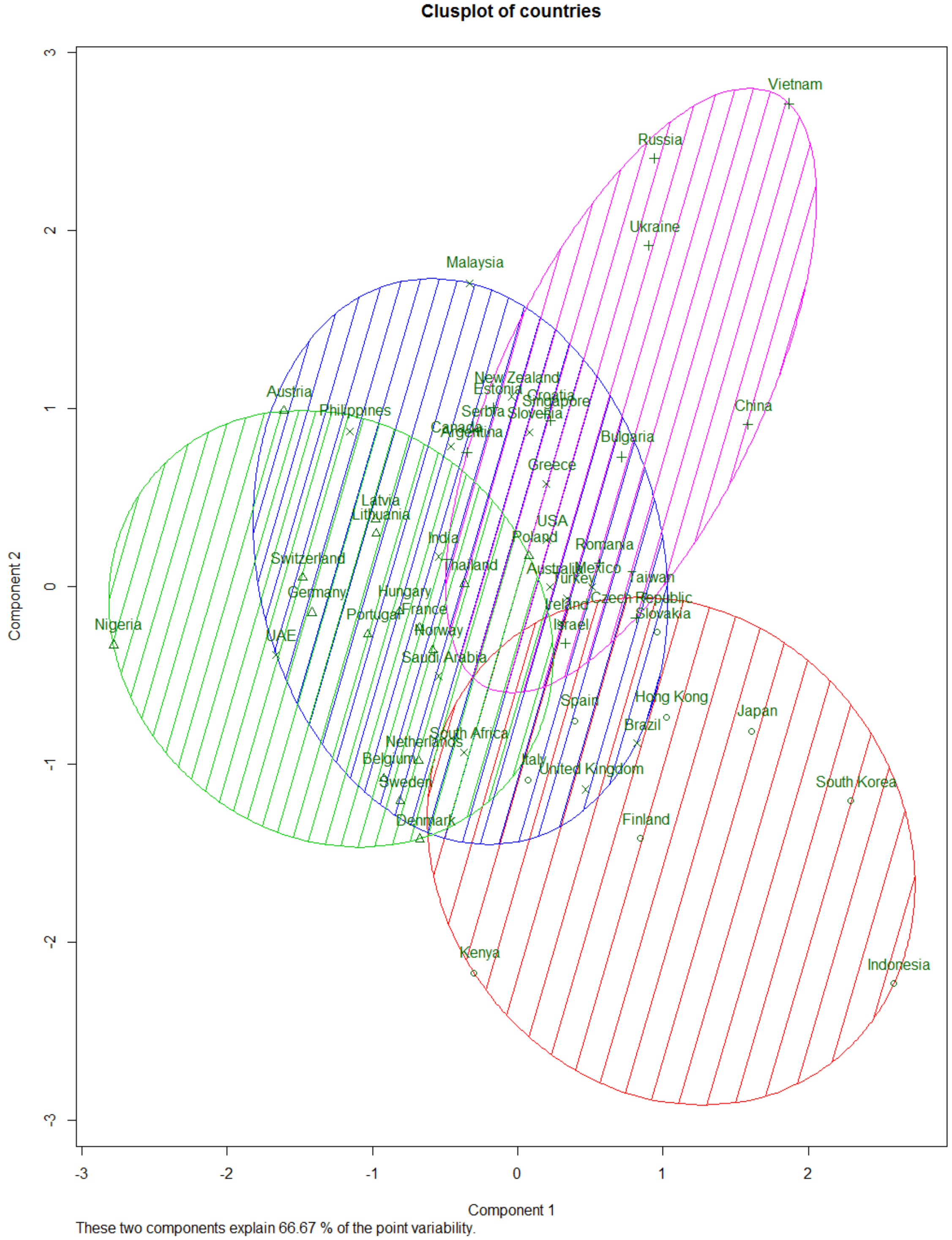
Source: own elaboration by the authors

After selecting the appropriate number of clusters we were able to proceed with the actual cluster analysis.

Using the k-means method we defined 4 clusters consisting of the following countries:

- **Cluster 1** (10 countries): Finland, Italy, Slovakia, Spain, Hong Kong, Indonesia, Japan, South Korea, Taiwan, Kenya;
- **Cluster 2** (16 countries): Austria, Belgium, Denmark, France, Germany, Hungary, Latvia, Lithuania, Netherlands, Norway, Poland, Portugal, Sweden, Switzerland, Thailand, Nigeria;
- **Cluster 3** (13 countries): Bulgaria, Croatia, Czech Republic, Estonia, Romania, Russia, Serbia, Ukraine, China, Singapore, Vietnam, Argentina, Israel;
- **Cluster 4** (17 countries): Greece, Ireland, Slovenia, United Kingdom, Australia, India, Malaysia, New Zealand, Philippines, Brazil, Canada, Mexico, USA, Saudi Arabia, Turkey, United Arab Emirates, South Africa.

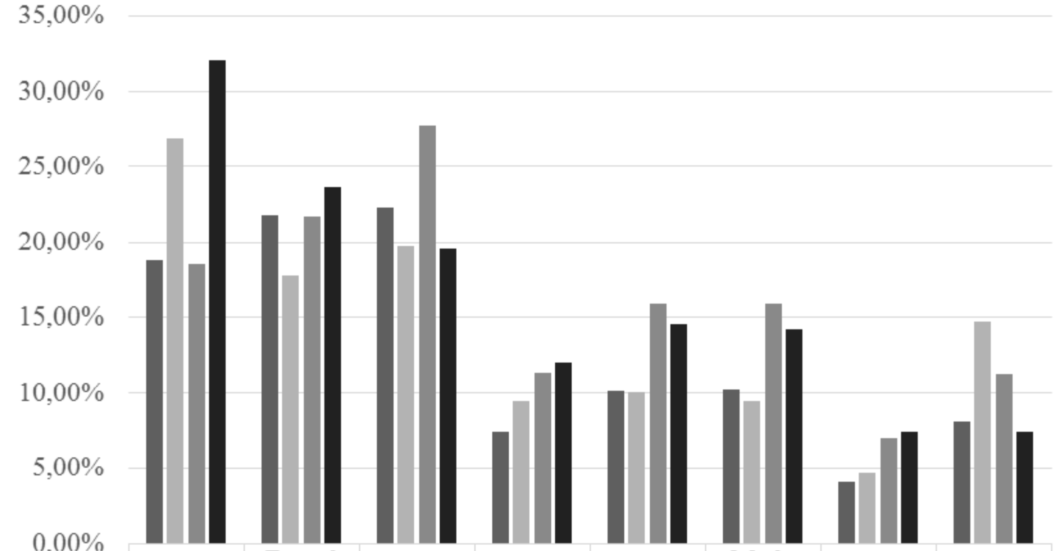
Fig. 2: Clusplot (k-medians method, 4 clusters)



Source: own elaboration by the authors

Clusplot in Fig. 2 shows the division of countries into the clusters with respect to the components obtained in the factor analysis. Looking at the clusters, we can observe a kind of spatial correlation. For example, *Cluster 2* contains the countries that are the neighboring European countries. *Cluster 3* consists of the countries of the Eastern Europe plus China. *Cluster 4* consists of the American countries, along with the English-speaking countries. Only *Cluster 1* involves countries that can be considered outliers. More than a geographical representation of countries across clusters, the objective of this study is to define the differences between users who use smartphones in these clusters. For this purpose, the average values of individual variables were calculated, and their comparison can be seen in the Fig. 3.

Fig. 3: Comparison of average values of the variables in the analyzed clusters (k-median)



	Got ideas, inspiration online	Found where to buy/product availability online	Get store direction /location online	Discovered relevant brands online	Watched relevant videos online	Made contact/requested contact (with brands/retailers)	Sought opinions /review/ advice online	Other information looked for online
Cluster 1	18,80%	21,80%	22,30%	7,40%	10,10%	10,20%	4,10%	8,10%
Cluster 2	26,88%	17,75%	19,69%	9,44%	10,00%	9,50%	4,69%	14,75%
Cluster 3	18,54%	21,69%	27,69%	11,31%	15,92%	15,92%	7,00%	11,23%
Cluster 4	32,06%	23,65%	19,53%	12,00%	14,59%	14,18%	7,41%	7,41%

Source: own elaboration by the authors

Based on Fig. 3, it can be seen that the users belonging to *Cluster 1* use their smartphone to find stores nearby, where to buy the product and to find inspiration for the potential purchase. When compared with other clusters, *Cluster 1* users are way ahead when it comes to the above-mentioned activities. When it comes to other activities, *Cluster 1* users are among those less active smartphone users in the buying process. *Cluster 2* users use their smartphones to find inspiration, store location or check product availability. Along with Cluster 1 users they are among those less active smartphone users in the buying process. However, it should be mentioned that *Cluster 2* users sought information not covered by the options of the questionnaire. *Cluster 3* users use their smartphones to get store directions, check the availability of the product and for inspiration. Among all groups of users *Cluster 3* users use their smartphones to get store directions, watch relevant videos and get contact details the most frequently. For those users it is the most important to have mobile-optimized videos, a contact form that is smartphone-friendly, and other smartphone-friendly features (e.g. dial phone numbers by clicking). Much like in other cases, also *Cluster 4* users use their smartphones mainly to search for inspiration online, check product availability and get store directions. The first two activities are being dominated by *Cluster 4* users. They are also more likely to search for relevant brands online and seek views and recommendations in relation to products. Together with a *Cluster 3* users they are the most active users of smartphones. We recommend companies to adjust their websites to be more smartphone-friendly just because of these users.

Generally, we can summarize the above as follows:

- It is possible to create latent variables that group serveral purchasing activities into fewer factors without missing the significant portion of the information carried by data;
- Even though there are more active and less active clusters, the most popular activities include pre-purchase activities – getting store directions and checking where to buy a certain product. Other activities are not carried out on such a large scale;
- Users in *Clusters 3* and *4* use their smartphones to the largest extent possible, therefore it makes most sense to optimize websites for smartphone users mainly in these countries;
- European countries in *Clusters 1* and *2* use smartphones in the pre-purchase process very little, showing conservative approach towards smartphones in these countries.

Due to uniqueness of the study, it is not possible to compare clusters of countries from our results to the clusters analyzed by other authors. However, it can be seen, that when focusing on more representative structure of respondents (juxtaposed to study by Pollák, Nastišin and Kakalejčík (2015)) it can be spotted that more general sample of users doesn't prefer the use of smartphones in the purchasing process in the same way as more granular sample of respondents (20-28 years old). Moreover, as the execution of observed acitivities is not done solely on smartphones, we agree on existence of omnichannel users mentioned by Dorman (2013). Even though studies by Tossell et al. (2015) and Salesforce (2014) proved that smartphones are a central part of people lives, the results of our study didn't provide clear evidence that smartphones are also major in terms of purchasing process. The areas of the future research should definitely include the analysis of the increase/decrease of this trend. In order to create more precise segmentation of smartphone users, we suggest to conduct the similar study on the individual-level data instead of country-aggregated data.

Conclusion

The use of smartphones in the buying process is becoming an increasing trend which increases the complexity of the customer journey, and makes it harder for companies to optimize it. The main objective of this study was based on the established theoretical background to analyze different behavioral patterns of smartphone users during pre-purchase stage of the purchase process. The first part of the analysis reduced the number of variables entering the subsequent cluster analysis using the factor analysis. Using *k-medians* we were able to create 4 clusters of countries. Users in *Clusters 1* and *2* use their smartphones in the shopping process to a lesser extent than users in *Cluster 3* and *4*. Despite the limitations resulting from the analysis (the sample consisting of aggregated data, ambiguity of the factor analysis and uncertainty of its results, the appropriateness of the clustering methods), the results of this study are useful for companies operating in the analyzed markets.

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