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GLOBAL CONSUMERS BEFORE AND DURING THE COVID-19 PANDEMIC: WHAT ASPECTS CHARACTERIZE DIGITAL CONSUMER BEHAVIOR?

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Purpose: Our work assessed patterns of intra and inter-regional e-commerce behavior ex-ante and during the COVID-19 pandemic.

Design/methodology/approach: The research was conducted under a quantitative approach, using a non-experimental longitudinal design focusing on the evolution of groups. Initially, relevant variables were selected from the Passport Euromonitor International Lifestyle survey database for the 2019–2021 period, in a sample of forty countries, for which a cluster analysis and the subsequent parametric and non-parametric tests of comparison between groups were performed, considering socioeconomic, demographic, cultural and e-commerce related variables.

Findings: The patterns of digital consumer behavior in the countries under analysis showed changes during the pandemic, moving from characteristics of greater heterogeneity before COVID-19 to a more homogeneous scenario among consumers in different countries.

Theoretical and methodological implications: This work delve into digital consumer patterns during the COVID-19 pandemic. Additionally, the methodological contribution of the research highlights the use of data clustering techniques for behavioural segmentation, being a replicable example for other researchers.

Originality/value: There is a new term proposed to specific characteristics of the e-commerce consumer where socioeconomic, demographic, and cultural variables are added as a complement to the characterization of the Level of Sophistication by the Digital Consumer.

Keywords: Market situation information. E-commerce. Pandemics.

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1 Introduction

The COVID-19 health crisis generated consequences across diverse sectors of society. In March 2020, the situation was declared a pandemic by the World Health Organization (WHO) and to date, it has counted 514 million confirmed cases (John Hopkins University, 2022; Mahase, 2020).

The spread of the virus had repercussions in most countries generating consequences in terms of increased unemployment, inflationary pressures, disruption of supply chains, impact on education and the deterioration of physical and mental health (Economic Commission for Latin America and the Caribbean [ECLAC], 2020; Garcia et al., 2021; Garcia Perez de Lema et al., 2021; Kumar et al., 2021; Verschuur et al., 2021; World Health Organization [WHO], 2020).

Given that consumption is associated with a particular time, location and context (Sheth, 2020), the health conditions during the pandemic and the short reaction time caused immediate changes in the consumption decisions of individuals and companies. Aspects such as social distancing, general uncertainty and mobility limitations influenced changes in purchasing behaviour (Jílková & Králová, 2021; Sheth, 2020).

During this time consumer hoarding of essential goods and services was evident, with an emphasis on cleanliness, protection, personal hygiene, and food (Di Crosta et al., 2021; Kirk & Rifkin, 2020; Sheth, 2020). In turn, people improvised alternative means to maintain customs and traditions that were part of their lifestyle, such as religious services, commemorative dates, and social events.

In the first stage of the pandemic, the purchase of non-essential goods was postponed, and a smaller share of the household budget was allocated to the purchase of durable goods such as houses, cars, and household appliances. Discretionary services such as concerts, insurance, sports, bars, and restaurants showed the same trend (Jílková & Králová, 2021; Sheth, 2020). However, Di Crosta et al. (2021) identified in parallel that hedonic purchases, in some cases, were a means of escape from the pressure and stress caused by the health crisis.

Changes in consumer habits caused by the pandemic potentiated the digitization of lifestyle, generating that companies and public services reach consumer's homes, with education, health, entertainment, and groceries as a clear example. From this context, electronic commerce or e-commerce (EC) emerged as an immediate response of consumers and small and medium enterprises to offer-purchase goods and services that meet the needs of the market (E-commerce Europe, 2021; Fairlie & Fossen, 2022; Guthrie et al., 2021; Organization for Economic Cooperation and Development [OECD], 2020).

Although important lines of research derived as the effect of the pandemic are envisioned in the future, several authors consider it inevitable that some digital alternatives discovered by consumers may be integrated into their lifestyles permanently (Jílková & Králová, 2021; Kirk & Rifkin, 2020; Sheth, 2020). Therefore, the adaptation of existing habits and the formation of new habits will shape consumer behaviour in the future (Mehta et al., 2020).

According to research referenced by various authors (Blazquez-Resino et al., 2021; Donthu & Gustafsson, 2020; Eger et al., 2021; Jílková & Králová, 2021), there is a knowledge gap that evidences the possible changes in the behaviour of digital consumers because of the reality generated by the pandemic. This could be enriched if a longitudinal approach were to be considered allowing the identification of ex-ante and ex-post effects of the pandemic. Therefore, this study identified patterns of change in e-commerce motivators from a multicultural perspective over a three-year period.

The research is based on data from the Passport Lifestyle Survey (Euromonitor International, 2019-2021) in forty countries around the world. Robust clustering techniques were used to generate profiles of countries with similar behavioural patterns for the 2019–2021 period. Using Hofstede's multidimensional approach and its interpretation complementarily for the results obtained in our analysis.

This research contributes to the literature on e-commerce and consumer behaviour, giving indications of the differences between e-commerce motivators in different regions of the world and their possible-moderating factors. Additionally, the methodological contribution of the research highlights the use of data clustering techniques for behavioural segmentation, being a replicable example for other researchers. Consequently, the research question posed is: What patterns can be identified among different global digital consumer profiles due to COVID? Do social, economic, and cultural factors influence digital consumer behavior?

The article is organized as follows: the second section shows the literature review that supports the proposed hypotheses, in section three, the methodological aspects that were considered are indicated. In the fourth section, the obtained results are described, followed by a discussion of the results in section five. Finally, conclusions and some implications of our work are discussed.

2 Literature review and hypothesis development

The study of similar characteristics in different grouping typologies facilitates the conformation of groups of people or objects (Ward, 1963) where precisely this objective of organizing sets with the greatest possible homogeneity explains the relevance and importance of the issue. Notwithstanding the above, there is little evidence in the literature on EC regarding the establishment of similar characteristics that facilitate the construction of consumer profiles through clustering.

The literature review was conducted to identify the state of the art on clustering in EC, particularly with respect to the types of methodological approaches used and the characteristics that would be convenient to consider for the conformation of consumer groups by this means of purchase. Finally, the theoretical references applicable to the analysis of clusters by EC were analysed and the working hypotheses were proposed.

2.1 Cluster analysis in the study of e-commerce consumer profiles

Ever since commercial internet applications, knowing the common characteristics among people who purchase via EC has become a particularly relevant issue. As part of the changes that the health pandemic has brought globally, the increased penetration of EC to purchase goods and services generates that accurately grouping consumer groups by EC requires further study due to the new interests and objectives that arise from commercial, academic, and public policy perspectives.

The particular convenience of forming clusters of consumers achieves several benefits; to cite one case, the implementation of personalized services in EC is sought, thereby minimizing the overload of irrelevant information according to the characteristics and needs of the consumer (Sari et al., 2016). Another benefit is that different socioeconomic and cultural aspects of societies can be considered to perform grouping of different consumers (Merhi, 2021).This is particularly important to consider for the overall analysis of EC in the wake of disruptive events such as the COVID-19 pandemic. Another important benefit, is the formulation of more efficient business strategies in the context of lack of resources, which is enhanced from the availability of data in virtual environments. (Bodea & Ferguson, 2014; French, 2016; Lee, 2016).

Regarding the types of groupings according to the characteristics of interest, it can be said that these particularities should be reviewed according to the specific needs of the work to be conducted. In our research, it was of interest to organize the variables to segment and group the countries in a given cluster according to the database used (Euromonitor International, 2019-2021).

In some previous research with online consumers in Spain and the United Kingdom (Frasquet et al., 2015) the authors analysed characteristics and motivations at different stages of the purchase process for cases where the consumer could use both virtual and face-to-face means to conduct the purchase. In this study, it was found that when using two diverse types of goods (apparel and electronics) in the five defined segments (using the k-means method), there are significant differences when comparing the responses according to the consumer's country of origin.

The grouping by country of origin of the online consumer is a convenient way to form clusters because it is possible to compare changes in the consumer profile where the country of residence can be taken as a grouping variable by virtue of the convergence of other cultural and socioeconomic variables that provide a specific profile according to nationality.

2.2 Grouping characteristics and methods

The review of consumer buying habits by EC is of particular interest because of its direct applicability to the design of segmentation strategies. A work conducted in the early second decade of this century (Wu & Chou, 2011) indicates as an advantage of EC segmentation, the possibility for companies to extract information from online consumer databases, which allows the identification of customers with higher purchase value, predict their future purchase behaviour and make decisions proactively, based on this type of information. In their work, Wu & Chou (2011) employed two methods to propose customer segmentation by EC, one of these methods was k-means, which is indicated as part of the standard segmentation methods for categorical characteristics (Magidson & Vermunt, 2002).

Regarding the methodologies to be used in each sample, different authors have proposed methods to conduct the construction of these groupings. Among the most widely used is Ward's method (Ward, 1963), which consists in grouping people or objects by optimizing an objective function that seeks to minimize the heterogeneity between the elements of the set, or maximize the homogeneity between them hierarchically. This method shares with grouping algorithms such as k-means (MacQueen, 1967) the approach of finding subsets where the amount of information that is lost in the process is minimal, but differs in the particularity regarding the hierarchization of the groups, where it may be possible that there is not enough information to conduct the process of organization.

Also, with the improvement of computational systems made in the past forty years, other methods such as Structural Equation Clustering (SEM) have been proposed more recently. New studies conducted out by different authors (Fordellone & Vichi, 2020; Morisada et al., 2019) show the necessary conditions when employing SEM for cluster analysis, where the main criticism made to hierarchical methods such as Ward (1963) or non-hierarchical methods such as k-means (MacQueen, 1967) is precisely that it does not consider the causal nature of the variables that allows the segmentation to be carried out.

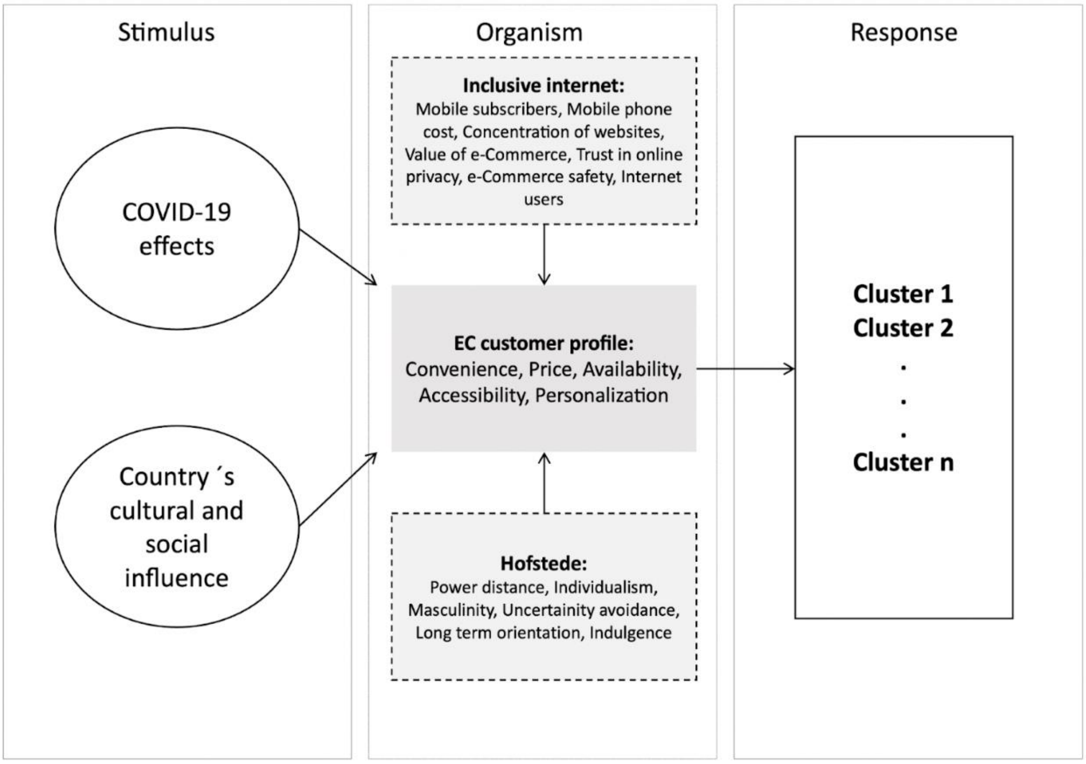
It is of our interest for this first clustering by EC, to consider the more traditional methods, particularly for several reasons: firstly, because of the characteristics of the secondary information that will be used (Euromonitor International, 2019-2021). Secondly, the scale of the data that appears in the database fits well with traditional clustering methods, which remain valid as part of the analysis that can be conducted when analysing profiles and generating segments in a given market.

2.3 Theoretical model used to form the clusters and research hypotheses

The Stimulus-Organism-Response (SOR) theory (Tolman, 1932) was considered in this research to evaluate the grouping variables that form different clusters. This theoretical approach was employed in six out of a total of thirty-four studies on EC evaluation and consumer responses, ranking first in preference by the research teams that developed these studies (Chan et al., 2017). These authors consider that the SOR theory succeeds in effecting the ranking of factors affecting online product purchases. This theory starts from the classical concept employed by the paradigm of environmental psychology, which assumes that individuals receiving a certain stimulus, produce different responses to certain phenomena (Chan et al., op.cit.). Figure 1 shows the theoretical model proposed for cluster research.

Figure 1

Proposed Theoretical Model



From the theoretical basis used, we propose the definition "Level of Sophistication of the Digital Consumer (LSDC)" as the purchase profile of digital media that a person could have when considering the historical behaviour regarding the use of virtual media, the socio-cultural conditions of the country of residence and the economic conditions of the immediate environment. A low LSDC assumes that the person is characterized by inexperience in the use of virtual media to purchase goods and services, and that in their country of origin the socio-cultural and economic environment is unfavourable for developing EC.

By virtue of the existing pandemic conditions, it is presumed that COVID-19 defined changes in the previous profiles of the online consumer, therefore the following working hypotheses are proposed:

H1*: Digital consumers had changes in their purchase and consumption profiles due to the COVID-19 pandemic according to the person's country of origin.*

H2*: Social, economic, and cultural factors of digital consumers influence their purchase and consumption profiles.*

H3*: The COVID-19 pandemic influences the trend toward similar or homogeneous patterns among digital consumers according to the person's country of origin.*

3 Methodology

3.1 Data for clustering

For the construction of the clusters, the Passport Euromonitor International Lifestyle survey (Euromonitor International, 2019-2021) was used. We selected the period from 2019 to 2021 to analyze the effects before and during the pandemic conditions. The research team had no involvement in the design, acquisition, and tabulation of the data. This survey was applied to online consumers aged 15 to 65 and older, during the 2019–2021 period. The survey asks about the reasons for purchasing products online. From the variety of purchase stimuli referenced in the database, the following were selected (Table 1).

Table 1

Incentive to Buy Products Online

Stimulus	Description
Convenience	Ability to order at anytime from anywhere
Price	Best price
Availability	Desired model/version of the product was not available in store
Accessibility	Ability to access site on different devices
Personalization	Able to customize products according to my preferences

The survey considered a sample of 39,657 people for 2019, 40,440 people in 2020 and 40,038 people during the 2021 period, distributed in 40 countries.[1]. The variables used are the proportions of people who responded affirmatively to the effect of the stimulus on their online shopping behaviour, according to the country and year evaluated.

3.2 Clustering

The understanding of behavioural patterns in intra and inter-regional, ex ante, and ex post pandemic e-commerce, was met through the application of cluster analysis using the non-hierarchical k-means clustering algorithm, as proposed by MacQueen, (1967), in which each group is represented by its centre (mean of the points assigned to the cluster). The Euclidean distance matrix was used to determine the number of clusters and the following graphical methods were employed: total within-cluster sum of square or WSS known as the elbow method (Syakur et al., 2018; Thorndike, 1953), silhouette method (Rousseeuw, 1987), D-index or

[1] Argentina, Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, Egypt, France, Germany, Hong Kong, India, Indonesia, Italy, Japan, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Nigeria, Peru, Philippines, Poland, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Taiwan, Thailand, Turkey, United Arab Emirates, United Kingdom, USA and Vietnam.

Dindex (Lebart et al., 2000), Hubert index (Hubert & Arabie, 1985) and the R package NbClust (Charrad et al., 2014).

3.3 Supplementary data

Pattern and difference identification between the clusters, was developed using the Hofstede model (Hofstede, 2011) which analysed the cultural behaviour of the countries. We consider this theoretical approach because that is validated in multicultural research.

This method includes six dimensions that are measured from 0 to 100: distance from power, uncertainty avoidance, individualism, masculinity, long-term orientation and finally, indulgence. Each was calculated for all countries in the sample in 2011, the resulting version was used in this study. Out of the sample, only the United Arab Emirates did not have the value of two of the dimensions, long-term orientation, and indulgence.

Another complementary source of the study was the inclusive internet index created by The Economist Group (The Economist Intelligence Unit, 2019-2021), this is calculated yearly, and its fifth edition was updated in 2021, as a result data for the three years of the scope of this research is available. The value of the index ranges from 0 to 100, where 100 represents the maximum value of inclusion. Hong Kong and New Zealand do not have an index estimate for 2019.

Finally, we considered some variables that integrate the inclusive internet index that are relevant to analyse individually because they contribute to understanding and typifying the clusters in terms of their demographic, socioeconomic profiles, and aspects of EC (Table 2).

Table 2

Sociodemographic and E-commerce Variables

Variable	Description	Unit
Mobile subscribers	Mobile subscribers	Per 100 inhabitants
Cost	Mobile phone cost (postpaid tariff)	Percentage of monthly GNI per capita
Concentration	Concentration of websites using country-level domains	Qualitative rating 0-3, 3=best
Value	Value of e-Commerce	Percentage
Trust	Trust in online privacy	Percentage
Safety	e-Commerce safety	Percentage
Users	Internet users (percent of population)	Percentage of population
Population	Population	Millions
Urban population	Urban population	Percentage of total population
GNIpc	GNI per capita	USD per person
GINI	GINI coefficient	Score, 0-100; 0 is perfect equality,

Variable	Description	Unit
		100 is perfect inequality
Poverty	Population under the poverty line	Percentage of population

Analysis of variance (ANOVA) was used to compare the cluster means according to the dimensions of the Hofstede index and the inclusive internet index, as well as for the variables in Table 2. The least significant difference test (LSD) developed by Fisher (1935) was used as a post hoc test. The Shapiro-Wilk test (Shapiro & Wilk, 1965) was used to test the normality of the errors and the Levene test (Levene, 1960) was used to verify the homogeneity of variances, considering 5% significance. In cases of non-compliance with the assumptions, the Kruskal-Wallis test (Kruskal & Wallis, 1952) was used, which corresponds to the non-parametric counterpart of the one-way analysis of variance. Pearson's correlation analysis was used to study relationships between variables. The analysis was performed in the statistical software RStudio version 3.6.1 (R Core Team, 2019).

4 Results

The research findings are organized as follows: initially the results of the verification of the assumptions of the analysis of the variance model for all variables according to the cluster are shown, then the results of the clustering by countries and their ANOVAs are shown, and finally the comparisons between groups for the complementary variables are shown.

For the variables that made up the clusters, the assumptions of the ANOVA model were always completed ($p>0.05$). In the case of the variables of the Hofstede index and the inclusive internet index, this was not always the case, in some cases the assumptions were met at 1% significance, even the individualism dimension presented problems of heteroscedasticity for 2019 and 2021, so for this case the non-parametric counterpart Kruskall-Wallis (KW) was applied. The high non-compliance with the assumptions of the analysis of variance for the demographic, socioeconomic and EC variables, compromises the use of this method, as a result we opted for KW.

4.1 Clusters by countries

Data for two hundred entries in the Passport Lifestyle survey database (Euromonitor International, 2019-2021) were analysed and with the normalized data, graphical tests were performed to estimate the optimal number of clusters. There was great diversity of results between methods when defining this value. The R package NbClust (Charrad et al., 2014) considers 30 indices, of which only those that suggested two or more clusters were considered, for the 2019–2021 period. The resulting clustering proposals range from two to ten clusters. The WSS method presents a smooth curve with a slightly ambiguous break point, as a result it was complemented with the silhouette method to make the decisión. Among all proposals analysed, we observe that the number of clusters decreased year after year. Combining what was observed in these graphs and considering that the general trend is toward fewer clusters over time, it was finally decided to use five clusters in 2019, three for 2020 and two for 2021.

The implementation of the k-means method shows changes for the five online purchase incentives according to the population of the countries considered. Table 3 shows the summary statistics for the period under analysis.

Table 3

Summary Measures of the Variables Used in the Cluster Analysis by Year

Year 2019					
Summary measure	**Convenience**	**Price**	**Availability**	**Accessibility**	**Personalization**
Average	37.44	43.32	20.42	23.86	15.50
Standard deviation	7.66	8.33	5.86	8.09	5.16
Coef. variation	20.45	19.24	28.71	33.92	33.28
Minimum	18.50	22.60	4.70	9.10	5.60
Maximum	60.30	59.80	31.40	42.50	27.70
Asymmetry	0.38	-0.38	-0.46	0.32	0.09
Kurtosis	1.00	-0.03	0.32	-0.48	-0.70
Year 2020					
Summary measure	**Convenience**	**Price**	**Availability**	**Accessibility**	**Personalization**
Average	34.98	42.46	18.77	20.15	13.74
Standard deviation	7.95	8.51	4.49	7.60	5.50
Coef. variation	22.72	20.04	23.94	37.71	39.99
Minimum	15.60	16.80	8.30	9.10	5.50
Maximum	55.20	56.60	27.90	37.40	24.40
Asymmetry	-0.02	-0.77	-0.29	0.36	0.40
Kurtosis	0.03	0.64	0.05	-0.93	-1.01
Year 2021					
Summary measure	**Convenience**	**Price**	**Availability**	**Accessibility**	**Personalization**
Average	33.63	40.04	18.43	20.05	13.87
Standard deviation	7.31	8.96	4.51	6.96	4.77
Coef. variation	21.75	22.37	24.48	34.73	34.36
Minimum	19.20	15.10	7.50	8.00	6.30
Maximum	49.00	62.90	28.90	33.90	24.30
Asymmetry	0.17	-0.18	-0.01	0.33	0.39
Kurtosis	-0.67	0.89	-0.19	-1.02	-0.74

Generally, price is the most relevant variable for digital consumers globally, followed by convenience. The proportion of consumers decreased year after year for the five main incentives. For 2020, the highest levels of variation were presented for the variables convenience, accessibility and personalization, precisely the year in which the WHO (WHO, 2020) declared the pandemic by COVID-19.

The differences between the proportions of people who responded to each variable according to country of origin, where only price increased its level of variability (CV). While the dispersion of the other variables was lower at the global level, suggesting greater homogeneity among the participants from the different countries represented.

For the three years of analysis, dimension one is mostly represented by the stimulus accessibility, followed by convenience and the second dimension is explained by price and personalization, in that order for the first two years, however, in 2021, personalization had a greater weight than price.

Regarding the ANOVA for purchase incentives, for the period analysed the variables were always highly significant ($p < 0.01$) (Table 4). In 2019 the countries included in cluster 2 presented a profile associated with valuing convenience, where only residents of the United Arab Emirates changed this pattern of behaviour during the 2021 period. The same behaviour can be observed for variables availability, accessibility and personalization.

Similarly, for the incentive obtained from the price of goods and services for digital purchases, of all the consumers in the eight countries that before the pandemic showed greater willingness to the impact of prices on their EC purchase decisions, only half of them (Brazil, Poland, Russia and South Korea) maintained this variable as a greater motivator compared to people in the other countries by 2021.

Table 4

Analysis of the Variables for Clustering

Year 2019												
Variable	**F value**		**Cluster 1 (n=8)**		**Cluster 2 (n=8)**		**Cluster 3 (n=5)**		**Cluster 4 (n=8)**		**Cluster 5 (n=11)**	
Convenience	18.2043	***	41.5625	b	46.7500	a	27.0000	d	35.3500	c	33.9364	c
Price	18.4098	***	51.9250	a	43.8250	b	30.6200	d	48.4125	ab	38.7727	c
Availability	9.0072	***	23.6000	a	26.5375	a	14.0800	b	17.8375	b	18.4000	b
Accessibility	31.0297	***	25.1000	b	35.0750	a	12.7000	c	17.3000	c	24.6455	b
Personalization	30.1872	***	13.8750	c	21.8625	a	10.2600	d	10.1125	d	18.3636	b
			Brazil, New Zealand, Poland, Russia, Singapore, South Korea, Sweden, USA		India, Indonesia, Malaysia, Nigeria, Philippines, South Africa, Thailand, United Arab Emirates		Hong Kong, Japan, Netherlands, Spain, Taiwan		Australia, Belgium, Canada, Denmark, France, Germany, Italy, United Kingdom		Argentina, Chile, China, Colombia, Egypt, México, Morocco, Perú, Saudi Arabia, Turkey, Vietnam	

Year 2020								
Variable	**F value**		**Cluster 1 (n=14)**		**Cluster 2 (n=12)**		**Cluster 3 (n=14)**	
Convenience	25.5481	***	36.6857	b	26.225	c	40.7643	a
Price	20.8143	***	49.2571	a	34.0667	c	42.8643	b
Availability	10.1835	***	19.6143	a	14.8667	b	21.2571	a
Accessibility	36.9798	***	16.3786	b	14.8583	b	28.4571	a
Personalization	35.5616	***	10.0000	b	11.1500	b	19.7071	a
			Australia, Belgium, Brazil, Canada, Denmark, Germany, Italy, New Zealand, Poland, Russia, Singapore, Sweden, United Kingdom, USA		Argentina, Chile, Colombia, France, Hong Kong, Japan, México, Morocco, Netherlands, Perú, Spain, Taiwan		China, Egypt, India, Indonesia, Malaysia, Nigeria, Philippines, Saudi Arabia, South Africa, South Korea, Thailand, Turkey, United Arab Emirates, Vietnam	

Year 2021						
Variable	**F value**		**Cluster 1 (n=13)**		**Cluster 2 (n=27)**	
Convenience	50.4812	***	41.4846	a	29.8407	b
Price	13.3736	***	46.5385	a	36.9037	b
Availability	21.8740	***	22.3077	a	16.5593	b
Accessibility	76.2780	***	28.1462	a	16.1519	b
Personalization	18.2580	***	17.7308	a	12.0074	b
			Brazil, India, Indonesia, Malaysia, Nigeria, Philippines, Poland, Russia, South Africa, South Korea, Thailand, Turkey, Vietnam		Argentina, Australia, Belgium, Canada, Chile, China, Colombia, Denmark, Egypt, France, Germany, Hong Kong, Italy, Japan, México, Morocco, Netherlands, New Zealand, Perú, Saudi Arabia, Singapore, Spain, Sweden, Taiwan, United Arab Emirates, United Kingdom, USA	

Note: 10% of significance (*); 5% of significance (**); 1% of significance (***). Means with the same letter are not significantly different (p>0.05).

The Hofstede model contemplates six cultural dimensions, of which power distance is the only one that showed significant differences among the clusters for the three years of analysis (Table 5). This dimension refers to how society accepts, even expects, unequal distributions of power. For 2019, the extremes were cluster 2 (India, Indonesia, Malaysia, Nigeria, Philippines, South Africa, Thailand, United Arab Emirates) with the highest mean value (79). In this group a hierarchical order in which each person has his or her place is more readily accepted. Alternatively, cluster 4 (Australia, Belgium, Canada, Denmark, France, Germany, Italy, United Kingdom) has the lowest mean value (43.5). In these countries, social forces are in constant pressure to balance the distribution of power. The averages of these two clusters differ from each other, but, in the relationship with the other clusters, overlaps are observed.

In 2020, the number of clusters is reduced, however, we observe that extremes remain remarkably similar to the previous year. The countries that previously had the highest average are now in cluster three, which includes China, Egypt, Saudi Arabia, South Korea, Turkiye and Vietnam. Cluster 1 is made up of the countries with the lowest average, with Brazil, New Zealand, Poland, Russia, Singapore, Sweden, and the United States joining this cluster. Additionally, France leaves this extreme to place itself in the intermediate level.

Finally, in 2021, with only two groups, those countries that were previously in intermediate ranges, are now located in an extreme. Some countries changed their tendency, for example, China, Egypt, Saudi Arabia, and the United Arab Emirates, which were in the group with the highest average value in power distance, now move to the lowest. The same case was replicated with Brazil, Poland, and Russia, which moved from the lowest to the highest power distance mean group. Additionally, it is worth mentioning how India, Indonesia, Malaysia, Nigeria, Philippines remained constant in the highest mean group. In the cases of Australia, Belgium, Canada, Denmark, Germany, Italy, and the United Kingdom these were also always present among the countries with the lowest means.

Using Pearson's correlation coefficient, a direct and statistically significant relationship was identified between the power distance variable and the personalization stimulus for the whole period of analysis.

The individualism variable presented problems with the assumptions, mainly with the homogeneity of variances, so in this case the ANOVA results are not considered, and the KW contrast was performed, obtaining statistically significant differences for the first two years of the study, but not for the third

The higher the value of this dimension, the more individualistic the society and the weaker the connections among individuals. At the other extreme, when the value is low, we are dealing with a collectivist society, where people are usually integrated into strong and cohesive groups. This dimension shows an inverse relationship with the previous one, since the clusters that present high value, are also those that have less tendency to inequality in power, for 2019, the lowest mean of individualism was that of cluster 5, however, it is statistically equal to that of cluster 2.

The other index that was considered to contrast was the inclusive internet index, which seeks to measure the extent to which the internet is accessible, affordable, and relevant. This showed differences between the clusters for all years ($p < 0.01$). Table 5 presents societies with lower power distance and higher individualism; these coincide with a higher value in the inclusiveness index.

Table 5

ANOVAs for the Hofstede and Inclusive Internet Index

Year 2019												
Variable	**F value**		**Cluster 1 (n=8)**		**Cluster 2 (n=8)**		**Cluster 3 (n=5)**		**Cluster 4 (n=8)**		**Cluster 5 (n=11)**	
Power distance	5.80	***	57.13	bc	79.00	a	55.00	bc	42.50	c	70.45	ab
Individualism	10.57	***	52.00	b	32.50	c	43.80	bc	77.75	a	27.36	c
Masculinity	0.30		45.13	a	52.88	a	50.60	a	53.50	a	51.64	a
Uncertainity avoidance	0.90		60.13	a	52.00	a	65.80	a	59.63	a	72.18	a
Long term orientation	3.53	**	55.88	ab	37.14	bc	71.40	a	54.00	ab	32.73	c
Indulgence	0.27		50.50	a	50.71	a	44.00	a	56.63	a	49.55	a
Inclusive internet	19.55	***	77.20	a	63.90	b	75.20	a	76.49	a	66.15	b

Year 2020								
Variable	**F value**		**Cluster 1 (n=14)**		**Cluster 2 (n=12)**		**Cluster 3 (n=14)**	
Power distance	10.12	***	47.79	c	61.42	b	76.64	a
Individualism	15.47	***	67.79	a	38.67	b	28.93	b
Masculinity	0.01		50.50	a	50.67	a	51.29	a
Uncertainity avoidance	2.74	*	56.21	b	75.33	a	57.57	ab
Long term orientation	0.21		51.14	a	45.58	a	45.62	a
Indulgence	1.69		55.71	a	54.08	a	42.15	a
Inclusive internet	15.93	***	82.51	a	77.42	b	71.75	c

Year 2021						
Variable	**F value**		**Cluster 1 (n=13)**		**Cluster 2 (n=27)**	
Power distance	8.45	***	74.46	a	55.96	b
Individualism	3.97	*	34.38	a	50.78	a
Masculinity	0.09		49.69	a	51.37	a
Uncertainity avoidance	0.03		61.54	a	62.85	a
Long term orientation	0.01		48.15	a	47.31	a
Indulgence	1.84		44.31	a	53.88	a
Inclusive internet	7.95	***	74.15	b	80.10	a

Note: 10% of significance (*); 5% of significance (**); 1% of significance (***). Means with the same letter are not significantly different (p>0.05).

To further typify the clusters, some variables directly or indirectly related to EC were analysed, in addition to different demographic and socioeconomic indicators. This analysis was performed with the KW test due to the lack of normality and homoscedasticity in most of the variables.

As shown in Table 6, by 2019, four of the EC variables showed differences in at least 10 % significance, in 2020 there were three and by 2021 only two. In this analysis, three indicators stand out, the first one is the number of internet users, measured as a percentage of the population (users), where two groupings stand out, cluster 2 (India, Indonesia, Malaysia, Nigeria, Philippines, South Africa, Thailand, and United Arab Emirates) presents the lowest mean (52 %), statistically equal to cluster 5. Alternatively, cluster 3 (Hong Kong, Japan, Netherlands, Spain, and Taiwan) has the highest mean (87.7 %), which is statistically equal to clusters 1 and 4.

By 2020, the eight countries that had the lowest average continue this trend and are now in cluster 3, with China's addition, Egypt, Saudi Arabia, South Korea, Turkiye and Vietnam. In this year, cluster 1 is the one that presented the highest average number of internet users, and the countries that in the previous year presented the highest average, are now in an intermediate position, however, since 2019, the difference between them was not so clear.

For this variable, significant differences were also found in 2021, the countries that initially presented the lowest averages remained in this category, except the United Arab Emirates, which in the last year moved to the group with the highest average. Some countries such as Brazil, Poland, and Russia, were in the groups with high averages in the first years, however, in the last year, they were part of the opposite group.

The second indicator that stands out in this group of variables is the cost of mobile communications (post-paid tariff), measured as the percentage of monthly GNI per capita (cost), this variable presents a significant and inverse correlation to the previous one (users), even in magnitude, the strength of this association grows with the years Therefore, groups with higher internet user averages have lower mobile communications cost averages and vice versa.

The last indicator that stands out is trust in online privacy, quantified as a percentage (trust), which showed some differences between clusters for the first two years. Cluster 2 also stands out, here as the group with the highest mean, and at the other extreme, cluster 1 has the lowest mean. The trend is similar for the following year, and in the last year, the means did not differ for this variable.

This analysis considered two demographic variables (population and urban population) and three socioeconomic variables (GNI per capita, Gini coefficient and population below the poverty line). In the case of the population variable, measured in millions of people for 2019, the averages differ from each other (Table 6) however, there is so much variability within each group that for that year the difference is not significant. In the following two years, a greater grouping is observed, in 2020 cluster 3 has the highest population mean (276.1 million) and cluster 2 the lowest (49.8 million), although statistically equal to cluster 1.

The urban population variable was measured as a percentage of the total population and was significant for all three years. The clusters with the highest population are those with the lowest percentage of urban population. For 2019 cluster 2 has 57.6 % which generates the lowest mean, and cluster 3 with 88.5 % has the highest urbanization of its population.

Within the socioeconomic factors, GNI per capita showed differences between clusters for all years. For 2019, two groups are differentiated, those with higher median incomes (Clusters 4, 3 and 1) and those with lower median incomes (Clusters 5 and 2). In the following years, the trend is similar. In 2020, Cluster 1 is differentiated with the highest average income and is made up of the countries that previously formed Clusters 1 and 4 except France and South Korea. In 2021 there were some changes, among which we can highlight that Latin America, mostly represented in cluster 5 for 2019, was in the lower middle-income group and in the last year it is more like the countries with higher middle-income.

Finally, the Gini coefficient showed significant differences at 10 % for 2019, cluster 2 presented the highest mean with 42.1, as a result, these countries present a greater inequality in income distribution. At the other extreme, with 32.3, cluster 4 has the lowest mean. Between clusters and in the period of analysis, this value oscillated between 30 and 40, considering that this coefficient oscillates between 0 and 100, and the higher the value, inequality becomes greater.

Table 6

Kruskal-Wallis Test for the Sociodemographic and E-Commerce Variables

Year 2019												
Variable	**H value**		**Cluster 1 (n=8)**		**Cluster 2 (n=8)**		**Cluster 3 (n=5)**		**Cluster 4 (n=8)**		**Cluster 5 (n=11)**	
Mobile subscribers	5.0		131.6	a	139.7	a	148.4	a	114.3	a	116.9	a
Cost	17.9	***	1.0	a	1.8	b	0.9	ab	0.5	a	1.7	b
Concentration	10.1	**	2.7	b	1.4	a	1.8	ab	2.3	ab	1.8	ab
Value	3.3		61.2	a	56.6	a	67.2	a	58.4	a	55.2	a
Trust	12.5	**	41.3	a	60.4	c	46.1	ab	50.6	abc	54.0	bc

Safety	5.7		56.5	ab	57.0	ab	50.0	a	61.0	ab	62.4	b
Users	16.2	***	83.8	b	52.0	a	87.7	b	85.3	b	64.7	a
Population	3.9		99.3	a	260.8	a	44.4	a	44.4	a	181.9	a
Urban population	13.3	**	82.3	bc	57.6	a	88.5	c	83.0	bc	70.3	ab
GNIpc	23.4	***	33183.8	b	8948.8	a	36473.4	b	43537.5	b	8634.5	a
GINI	12.0	**	38.1	ab	42.1	b	36.7	ab	32.3	a	41.6	b
Poverty	2.1		0.5	a	4.3	a	0.4	a	0.3	a	0.4	a

Year 2020

Variable	H value		Cluster 1(n=14)		Cluster 2(n=12)		Cluster 3 (n=14)	
Mobile subscribers	0.2		123.9	a	135.9	a	129.4	a
Cost	10.5	***	0.8	a	1.3	b	1.5	b
Concentration	2.6		2.4	a	2.0	a	1.6	a
Value	3.8		63.0	a	62.0	a	71.1	a
Trust	5.9	*	51.6	a	50.0	a	63.3	b
Safety	2.7		61.7	a	54.8	a	63.6	a
Users	7.9	**	86.2	b	77.9	ab	60.8	a
Population	5.4	*	74.1	a	49.8	a	276.1	b
Urban population	13.7	***	83.0	b	83.7	b	60.3	a
GNIpc	16.5	***	41361.4	b	24018.1	a	11097.1	a
GINI	3.2		35.7	a	39.9	a	40.2	a
Poverty	0.8		0.4	a	0.4	a	2.6	a

Year 2021

Variable	H value		Cluster 1(n=13)		Cluster 2 (n=27)	
Mobile subscribers	0.5		131.4	a	131.8	a
Cost	4.1	**	1.8	b	0.9	a
Concentration	1.4		1.8	a	2.2	a
Value	2.1		72.9	a	66.3	a
Trust	0.3		50.7	a	54.4	a
Safety	0.9		55.2	a	59.5	a
Users	8.8	***	61.7	a	83.6	b
Population	8.4	***	212.0	b	103.2	a
Urban population	13.4	***	61.4	a	82.3	b
GNIpc	12.8	***	9078.5	a	34726.4	b
GINI	1.8		41.1	a	37.3	a
Poverty	0.5		2.8	a	0.4	a

Note: 10% of significance (*); 5% of significance (**); 1% of significance (***). Means with the same letter are not significantly different (p>0.05).

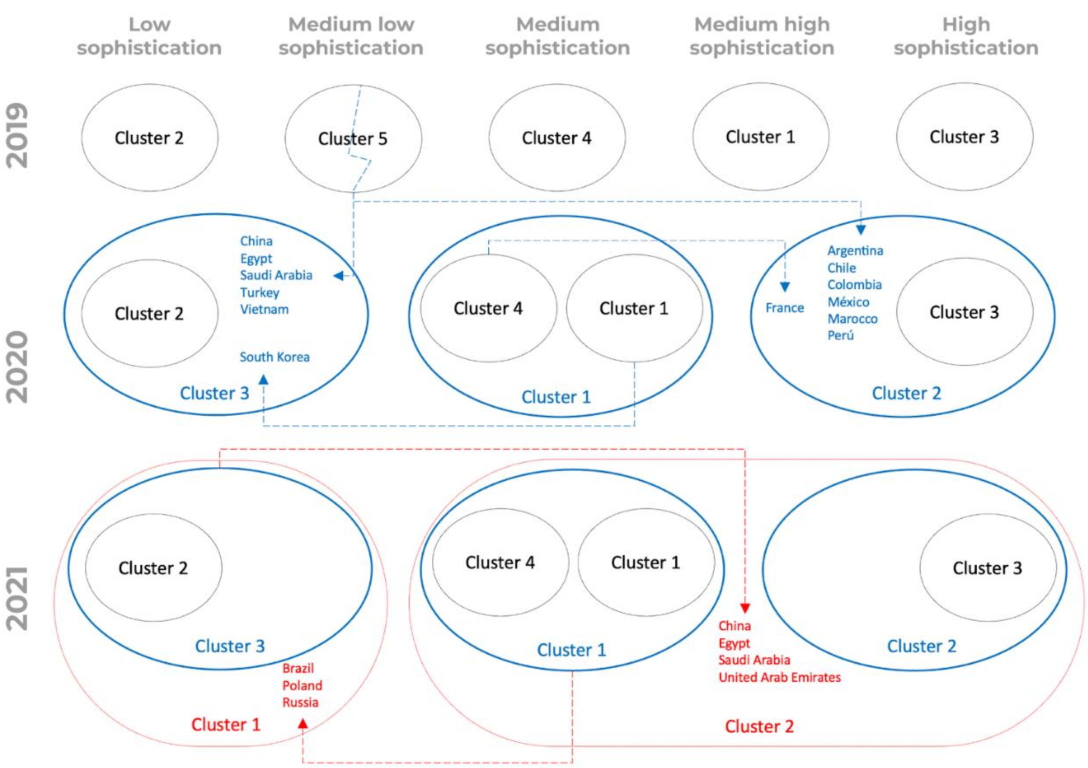
Finally, by jointly analysing the purchase stimuli, demographic, and socio-cultural variables, and EC indicators, the clusters were categorized on an ordinal scale of sophistication (Figure 2). During the 2019 period, cluster 2 was the group with the lowest level of sophistication, in contrast to cluster 3, which had the highest sophistication profile. This would imply that before the pandemic, digital consumers in countries such as India and the United Arab Emirates exhibited less sophisticated digital consumption behaviour compared with consumers in countries such as Japan or Spain.

The extreme clusters maintained their pre-pandemic trend. However, among the clusters with intermediate levels, cluster 5 experienced more changes: during the 2020 period, this group split in half, one part joined cluster 2 to form a new group with low levels of sophistication, and the other half, which corresponds mostly to Latin American countries, went from being in a medium-low level to a high level of sophistication, with cluster 3.

In the last year of analysis, some countries that were initially in cluster 5 moved to the group with higher sophistication and the countries that showed a decrease in their level of sophistication were Brazil, Poland, and Russia.

Figure 2

Cluster Sophistication Level (2019-2021)



By comparing the results obtained from the analysis of the variables under study, it is highly likely that the stimuli received by the digital consumer reported in the Passport Lifestyle survey (Euromonitor International, 2019-2021) are consistent with the proposed theoretical model. This is a result of the influence generated by the COVID-19 pandemic and the socioeconomic and cultural conditions, for the period considered, the responses of consumers in their digital consumption habits and consequently, in the conformation of the different clusters.

The working hypotheses are confirmed regarding the change in digital consumer profiles. According to the country of origin of the individuals, the results suggest the existence of a change in the profile of the digital consumer when compared to the pre-pandemic scenario, mainly the sophistication patterns and such H1 is validated.

Our results also validated the influence that social, economic, and societal factors represented in the changes of their buying and consumption patterns. And such H2 is validated.

Finally, our results suggested the COVID-19 pandemic influences the trend toward similar or homogeneous patterns among digital consumers according to the person's country of origin and such H3 is validated.

5 Discussion

5.1 Clustering

The optimal number of clusters is recognized as one of the major challenges presented using the cluster analysis method (Sugar & James, 2003). To date there are several proposals to estimate it, from the WSS (Syakur et al., 2018; Thorndike, 1953) which is considered one of the first to be developed, to proposals such as those of Shi et al. (2021) where adjustments to the algorithm that defines the optimal number of clusters for the elbow method are proposed. When evaluating several of these methods, it was observed that there is no unanimous decision regarding the existence of a methodologically superior alternative; in contrast, there are several studies and results as well as points of view.

In reference to this, Charradet al. (2014) suggest two alternatives, the first is to rely on the majority rule, and as a second option they recommend considering only the indices that perform best in simulation studies. In our research, the first option was not feasible, given that for a sample of forty countries considering ten or nine clusters (suggestion of most tests for the 2019 and 2020 period respectively) we would have few countries per cluster and a fuzzy analysis due to the large disaggregation. As a result, the choice of clusters is mainly supported by the silhouette method (Rousseeuw, 1987), whose efficiency has been tested and subjected to evaluation in simulated and real data in which it has shown good performance (Starczewski & Krzyżak, 2015).

The issue of methods and the definition of the optimal number of clusters in EC work considers some important challenges. A first consideration would be the method chosen to obtain a reasonable *k* value as part of the intended clustering of the digital consumer. Several authors have proposed alternative approaches, such as search engines by-product similarities

(Peng et al., 2004) as well as the definition of heuristics to achieve precisely a clustering where k is not generated *a priori* by guessing through researchers opinion but using probabilistic methods (Carlis & Bruso, 2012). In our work, although that has not been a relevant issue an exhaustive analysis of the different methods available to approximate the "optimal k" referred to by different authors was considered.

A second consideration is the variable types to make a convenient grouping of the digital consumer. As we have shown, the choice of variables on the responses of digital consumption habits in terms of convenience, accessibility, personalization, price, and availability, achieved a satisfactory grouping by country of origin of the consumer. It is important to highlight that in our work, it was impossible to discriminate by type of product or service consumed due to the information that was used for the analysis. To illustrate this consideration with a case, the global automotive industry has modified the variables used to make the groupings of its customers, moving from aspects of identity and geographical location of the consumer, to other aspects associated with the logistics of manufacturing and movement of inventories to the dealers that serve different markets globally (Sturgeon et al., 2008). For the case of the general EC industry, defining variables associated with the logistics of goods distribution could allow a better approximation of the "ideal cluster."

In our research, we have reviewed that for the case of countries like Russia, the research of Kaminskiy (2014), highlights how the role of the actors associated with the logistics of parcel distribution could more profoundly impact the profile of the digital consumer than variables such as those we have employed in this analysis. This will be an idea that we will seek to verify in our future work.

5.2 Sophistication in the EC

From the results obtained, the lowest levels of incentive in the variables convenience, availability, price, and accessibility are associated with countries of medium-high and high sophistication.

Aligned to the previous argument, the research by Garín-Muñoz et al. (2019) identified that countries such as the Netherlands, the United Kingdom, France, Denmark and Germany, have high internet penetration and high rates of EC penetration. These results partially explain the low valuation of digital consumers on the incentives of accessibility and availability in these types of societies, where greater familiarity is assumed by that digital consumer. This is a factor that has been previously reviewed for EC environments (Gefen, 2000) and it is recognized that the greater the familiarity with a EC space, the greater the influence on purchase intention in this way. As part of the results of our work, we have the presumption that societies more familiar with virtual ecosystems will have low valuations of incentives such as accessibility and availability of products, due to the recognition of both incentives as normal aspects of the economic conditions of these societies. The type of societies we identify in our research are populations with higher levels of sophistication of their digital consumers.

This is a critical issue since this level of sophistication could be explained in terms of the perceived usefulness that, over time, the use of virtual media has managed to establish in societies such as those indicated. A particular case of application of EC would be the possible adoption of new business models in these societies, such as the so-called *Fintech*; there are studies that have analysed how the "new normality" post COVID-19 would generate a favourable impact for the emergence and growth of this type of industry (Le, 2021) and it could be thought that societies with greater LSDC will include this type of change in their respective economies sooner.

In relation to complementary variables, Garín-Muñoz et al. (2019), validated the positive correlation between socioeconomic characteristics and the likelihood of e-commerce adoption. According to the results of these authors, the profile of people with more than 17 years of study and a net monthly income above 3000 euros presented higher probabilities of EC adoption. These characteristics are linked to users in upper-middle and high-income countries, such as countries in clusters 1, 3, and 4.

Complementing the previous argument, when reviewing the number of internet users, we find an evident direct relationship with LSDC. Pre-pandemic conditions showed that countries with fewer "internet users" could be associated with lower LSDC. In contrast, the onset of the health pandemic breaks this relationship, which could challenge the idea that providing greater connectivity conditions will produce a more sophisticated digital consumer in post pandemic conditions, cases such as South Korea and India are a sample of countries with extreme values in terms of the level of users and yet share several relevant traits in their respective digital consumers. Such considerations open space for future lines of work.

5.3 Relationships between sophistication in EC and culture

Hofstede's cultural dimensions have recently been employed for the analysis of the effects of COVID-19, with a focus on the area of health and its policies. Duarte et al. (2022) through a correlation analysis propose that the cultural background of each country is also responsible for the differences observed in the results of the pandemic. For their part, He et al.

(2022) focused on exposing how cultural traits can explain the international discrepancy in pandemic outcomes, and how the interaction of these traits with state action affects the fulfilment of health policies.

The applications to the study of EC have been seen in works such as Mohammed & Tejay (2017) who focused on the impact of information privacy as an inhibiting factor, and found that culture affects e-commerce adoption. A year earlier, Kidane & Sharma (2016) hypothesized, that the effect of power distance and individualism on EC decreases with experience, furthermore, they posit that EC leads to centralization of commerce. This impact generated by usage experience, could be visualized from the familiarity perspective discussed in the previous section.

Recently, Faqih (2022) published his research on the adoption dynamics of online shopping during the pandemic era, focusing on developing countries, in which he analysed the moderating impact of cultural differences in the trust-intention relationship in online shopping and demonstrated that the differences identified among digital shopper behaviour can be partially explained by cultural differences. Recently, Kao et al. (2021) validated the cultural effect on the cognitive processes associated with the perception of discounts and promotional information in e-commerce between Australia and Taiwan. In the same vein, it is interesting to note that the change in LSDC that occurred in Middle Eastern countries identified with the highest internet usage by their population (Ramadan & Nsouli, 2022). By moving from low LSDC before the pandemic to higher levels of digital sophistication by 2021, it could be thought that the level of adoption of digital technology, particularly social networks, allowed consumers to modify in a short time their ways of purchasing and consuming goods and services, which has been the subject of study by other researchers in these countries (Ramadan & Nsouli, 2022; Sharma et al., 2022).

The findings of Weber & See (1998) in the context of Hofstede's (2011) cultural dimensions identified the dichotomy between individualism and collectivism as the duality with the greatest significance in studies associated with consumer behaviour. Consistent with this finding, the results obtained in our research validate this argument, given that the duality of these dimensions was evident in the groupings obtained and countries with more collectivist societies could be associated with a lower LSDC.

The findings of Kao et al. (2021) and Malhotra et al. (2005) point to a negative perception of discounting in societies with individualistic tendencies. This behaviour is associated with the consumer's expectation of additional features and value, which is negatively associated with price reduction. Additionally, the individualistic consumer values the personalization of products and services as a means of emotional self-satisfaction (Park et al., 2013).

The relationship between individualism, personalization and price insensitivity was not clearly reflected in the results of our work, where we obtained diverse results. For example, countries such as the United States and New Zealand, which are highly individualistic, significantly value price and moderately value personalization, refuting the theoretical argument. In contrast, countries such as Japan, Taiwan, and Hong Kong, all with elevated levels of collectivism, are associated with low levels of importance in personalization, the latter result being congruent with the theory.

However, a direct and statistically significant relationship was identified between power distance and the degree of importance of personalization, which may be associated with the material needs of personalization to demonstrate a particular hierarchical level within society.

Among the results obtained, the atypical behaviour of China and Russia with respect to the average profile of the EC consumer is evident. In relation to the Russian market, Kaminskiy (2014) concludes that several particularities are associated with e-commerce that influence the consumer profile, among which are long times in the delivery of packages, deficiencies in the user experience on local sites, distrust in electronic means of payment and prioritization of purchases in local businesses. In addition to the above factors, the language and cultural barriers complement the context of the EC consumer in Russia and China, partially validating the atypical behaviour found in the research results.

6 Conclusions

According to the information considered and the analysis conducted, some relevant considerations can be concluded.

First, the number of clusters decreased as the pandemic evolved, implying greater homogeneity in digital consumer profiles around the world. This can be explained as a response to increased exposure to virtual environments globally, where previous characteristics such as convenience, accessibility, availability, price, and personalization of the digital consumer changed and grouped consumers from different countries according to the degree of what we have called the Level of Sophistication of the Digital Consumer (LSDC).

These levels of sophistication are influenced by the socio-cultural and economic conditions to which the consumer is exposed depending on the country of residence. In cases of countries where their inhabitants have been more familiar with virtual ecosystems in the pre-pandemic era, a higher LSDC is presumed, where aspects such as accessibility to virtual resources, as well as the availability of goods and services that can be purchased by EC, do not represent a *sine qua non-condition* to evaluate the level of employment or the quality of the virtual media used, precisely due to this higher level of familiarity with digital media.

From the results, it could be seen that consumers in some countries saw a meaningful change in their LSDC during the analysed period. This was the case for Saudi Arabia, United Arab Emirates, and countries in the Latin American region. In an opposite scenario, other countries maintained low levels of LSDC, as was the case particularly in African countries such as Nigeria and South Africa as well as in Southeast Asia (India, Malaysia, Indonesia, Philippines, Vietnam, and Thailand). Cases apart, countries such as Brazil, Russia, Poland, and South Korea show a decline in sophistication.

Secondly, the main variables that were considered in the digital consumer clusters were maintained and evolved during the pandemic. During the 2019–2021 period the variables price, convenience and accessibility explained most strongly the conformation of each cluster, which allows us to establish that the utilitarian type variables represent the greatest weight in the characterization of the digital consumer. Complementarily, it can be said that there is no clear relationship with other variables such as personalization, where in new versions of the Passport Lifestyle survey could dispense with the use of that variable and consider the inclusion of another that fits better to the post COVID characteristics of the digital consumer.

Thirdly, it was found that in addition to the central variables, there is a relationship with the contextual elements (demographic, social, cultural, and economic) of each country. Therefore, they can be used as segmentation variables via behavior for future studies focused on people who consume goods and services digitally.

Among the limitations found by the authors, the use of secondary sources of information stands out, which did not allow the validity of the variables with the units of study to be rectified, the rigor of the data collection to be verified, or the validity of the instrument used.

Simultaneously, the answers obtained are based on the perception of e-commerce users in the countries analysed, and there is a certain level of subjectivity that cannot be verified. In the same way, it is important to mention the existence of some missing data in the databases, as well as the absence of information in regions such as Central America.

Finally, it is considered that the research enables us to generate relevant inputs to public policy makers who promote the agenda of digitization and implementation of electronic commerce in micro, small and medium enterprises. For example, the convenience of the EC environment could benefit local production and logistics of transportation for different perishable food items, in this case, that can be promoted for an agricultural policy that use EC with that intention.

Authors' contribution

Contribution	Rivera, L. R. S	Aguilar, L. E. B	Monge, A. V.
Conceptualization	X	-----	X
Methodology	X	X	X
Formal analysis	X	X	X
Investigation	X	X	X
Resources	X	X	X
Data Curation	-----	X	-----
Writing - Original Draft	X	X	X
Writing - Review & Editing	X	X	X
Visualization	X	X	X
Supervision	X	X	X
Funding acquisition	----	-----	X

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