08, 09, 10 e 11 de novembro de 2022
ISSN 2177-3866

Segmentation of E-Commerce Nonusers: Clustering the Reasons Not to Shop Online

GABRIEL NERY-DA-SILVA
ESCOLA DE ADMINISTRAÇÃO DE EMPRESAS DE SÃO PAULO (FGV-EAESP)

MARCELO HENRIQUE DE ARAUJO
CENTRO UNIVERSITÁRIO ÁLVARES PENTEADO (FECAP)

FERNANDO DE SOUZA MEIRELLES
ESCOLA DE ADMINISTRAÇÃO DE EMPRESAS DE SÃO PAULO (FGV-EAESP)

Agradecimento à orgão de fomento:
We thank J. Figueiredo (ESPM, Escola Superior de Propaganda e Marketing) for comments on the analysis and E. Diniz for initial inspiration. We also thank the Coordination for the Improvement of Higher Education Personnel (CAPES) for the doctoral scholarship awarded to G.N.S., and Getulio Vargas Foundation's São Paulo School of Business Administration (FGV EAESP) for resource support.

SEGMENTATION OF E-COMMERCE NONUSERS: CLUSTERING THE REASONS NOT TO SHOP ONLINE

ABSTRACT

E-commerce plays an important role in the Brazilian economy and has become essential for enterprises and consumers alike. However, many people still do not use e-commerce for several reasons. Here, we questioned whether Brazilian e-commerce nonusers all have the same reasons not to purchase online or whether different behavior patterns might lead them to cluster in different groups. To answer these questions, we conducted cluster analyses on a large sample (N = 9,065) from a national survey on the use of information and communication technology in Brazil. We identified three types of e-commerce nonusers: one consisting predominantly of Generation Xers and Baby Boomers; another characterized by disbelieving postures on e-commerce; and the last cluster suggesting that its members have to see the product to believe it. Overall, nonusers have different reasons not to shop online, but they also share some similarities in this regard. Furthermore, socioeconomic factors do not seem to affect their behavior. Overall, our findings suggest that merchants have failed to attract customers' attention and that tangibility is the major hurdle to be overcome.

Keywords: Consumer behavior, online shopping, nonshopper segmentation, electronic market, retailing, shopping preference.

1. INTRODUCTION

E-commerce giants such as Amazon, Alibaba, MercadoLivre, and eBay have proven how widespread the online market is. Furthermore, the online market is also an option for retailers to expand their market and increase their profitability (G. Li, Zhang, Chiu, Liu, & Sethi, 2019), given the increasing number of online shoppers. Statista (2021a) reported that over two billion people worldwide purchased goods and services online in 2020, representing an increase of 6.7% over the previous year. As a result of this relevance, for more than two decades, research has dedicated considerable effort to profiling online customers (H. Li, Kuo, & Russell, 1999; Nakano & Kondo, 2018; Pawełoszek & Korczak, 2016; Spena, D'Auria, & Bifurco, 2021; Wiedmann, Buxel, & Walsh, 2002; Zhou, Wei, & Xu, 2021).

Studies have thus overemphasized the segmentation of online shoppers at the expense of better understanding the segmentation of online nonshoppers – who in this study are also referred to as e-commerce nonusers. With the exceptions of Swinyard and Smith (2003), Anckar (2003), and Iglesias-Pradas, Pascual-Miguel, Hernández-García, and Chaparro-Peláez (2013), little scientific research has attempted to segment e-commerce nonusers. Scholars have rarely been concerned with classifying them based on their reasons not to shop online. The vast majority of the literature depends on acceptance models (M. K. Chang, Cheung, & Lai, 2005) and concentrates on the factors affecting people's intention to use e-commerce (Hsu, Chang, & Chuang, 2015; Moorthy et al., 2017) or not (Mainardes, Souza, & Correia, 2020), their motivation for using it (Ganesh, Reynolds, Luckett, & Pomirleanu, 2010), trust or lack thereof (Bach, Silva, Souza, Kudlawicz-Franco, & Veiga, 2020; Hsu et al., 2015; Maia, Lunardi, Longaray, & Munhoz, 2018), the perceived risk associated with e-commerce (Bach et al., 2020; Y. Li, Li, Zhang, Zhang, & Gong, 2020), or the perceived benefits (Lestari, 2019). As Iglesias-Pradas et al. (2013) claim, there is too much focus on technology acceptance models (TAMs).

The failure to pay due attention to the complaints of e-commerce nonusers leads to the loss of many potential customers, especially in Brazil, which is the largest e-commerce market in Latin America – with 31.2% market share – and which has practically doubled its annual revenue since 2019 (Statista, 2021a). According to the Brazilian Internet Steering Committee (*Comitê Gestor da Internet* [CGI.br], 2020), 84 million individuals in Brazil alone access the Internet but do not shop online. This number represents 66% of Internet users. The respondents of the survey conducted by the CGI.br (2019) reported nine reasons why they opted not to shop online even though they have Internet access. These reasons included a preference for shopping in person (85%), concerns regarding personal data privacy or product/service quality (63%), and lack of Internet skills (30%). As can be seen, the reasons do not affect all respondents proportionally.

Given this disproportion, in addition to the scarce literature on e-commerce nonusers, this study advances the understanding of the topic by addressing the following research questions: do e-commerce nonusers all have the same reasons not to purchase online or are there dissimilar behavior patterns that might lead nonusers to cluster in different groups?

To answer these questions, we used unsupervised machine learning on the answers of a nationwide Brazilian household survey and we identified three clusters of e-commerce nonusers: one consisting predominantly of Generation Xers and Baby Boomers; another characterized by disbelieving postures on e-commerce; and the last one suggesting that its members have to see the product to believe it. Overall, e-commerce nonusers have different reasons not to shop online but they also share some similarities. More importantly, socioeconomic factors do not seem to affect their behavior substantially. Overall, our findings suggest that merchants have failed to attract customers' attention and that tangibility is the major hurdle to overcome.

2. LITERATURE REVIEW

The literature has identified several barriers to and drivers of adopting and using technology-dependent systems such as e-commerce, m-commerce, and mobile banking. These include risk and trust (Faqih, 2016; Laumer & Eckhardt, 2012; Pavlou, 2003), value (Hsu et al., 2015; Laukkanen, 2016), previous experience (Hernandez, Jimenez, & Martín, 2009), perceived cost (Moorthy et al., 2017), perceived usefulness (Faqih, 2016; Lestari, 2019), and lack of Internet skills (Iglesias-Pradas et al., 2013; Scheerder, van Deursen, & van Dijk, 2017; van Deursen, Courtois, & van Dijk, 2014). From a list of twelve inhibitors of online purchasing, Anckar (2003) found four main barriers to e-commerce use: shopping limitations, cost, financial risks, and search problems.

However, in the e-commerce use literature, research generally addresses these barriers and drivers either from the perspective of the e-commerce user (Bach et al., 2020; Lestari, 2019; Y. Li et al., 2020) or by comparing online shoppers and nonshoppers (Faqih, 2016; Sohail, 2014; Swinyard & Smith, 2004). Nonshoppers are seldom addressed alone. The drawback of this general approach is that studies neglect the underlying principles of e-commerce nonusers' behavior (Hernández-García, Iglesias-Pradas, Chaparro-Peláez, & Pascual-Miguel, 2011).

Scholars have argued that e-commerce nonusers are not a homogenous group (Swinyard & Smith, 2003, 2004). Some nonusers may be computer illiterate while others are relatively digitally skilled but nevertheless do not trust e-commerce. Swinyard and Smith (2003) identified four groups of online nonshoppers, namely 'fearful browsers', 'shopping avoiders', 'technology muddlers', and 'fun seekers.' Their characteristics range from distrusting e-commerce to preferring to physically see the product, to being computer illiterate.

Iglesias-Pradas et al. (2013) conducted an independent study and segmented e-commerce nonusers based on their reasons (barriers) not to shop online. The authors identified four types of online nonshoppers, namely, 'skeptical/distrustful', 'infrastructure-conditioned', 'product-conditioned', and 'others.' They also classified nonshoppers based on six drivers that might engage them in e-commerce, namely, ‘risk-avoiders’, ‘needers’, ‘analog-world shoppers’, ‘e-shopping ignorant’, ‘hesitant’, and ‘others.’ Their typology reaffirmed some characteristics previously found in the literature and extended them by introducing new aspects that further distinguish e-commerce nonusers.

Studies differ in terms of the type of data analysis. In segmenting nonshoppers, Anckar (2003) and Swinyard and Smith (2003) employed factor analysis and obtained classifications based on data variance/covariance. On the other hand, Iglesias-Pradas et al. (2013) used latent class analysis and benefited from the technique’s capability to identify underlying categories and to group observations based on similar responses.

Curiously, we have found no studies that have used unsupervised machine learning such as cluster analysis to **segment e-commerce nonusers**, even though the technique is a classical tool for classifying observations based on their similarities, has strong power to create taxonomy, and has been successfully employed to segment e-commerce **users** (Pawełoszek & Korczak, 2016; Zhou et al., 2021). Moreover, research on characterizing e-commerce nonusers according to their motives for not shopping online has considerably decreased since Iglesias-Pradas et al.'s (2013) study, with the aforementioned general approach prevailing as in Faqih's (2016) study, which, despite addressing online nonshoppers, is heavily concentrated on adopting rather than rejecting online purchasing.

Finally, customer profiles change over time, as does technology; consequently, new influencing factors may emerge, some may be accentuated, and others may become irrelevant. Thus, it is necessary to update e-commerce nonuser segmentation based on more recent surveys and using other quantitative methods to verify what has changed over the years. We therefore decided to address the segmentation of e-commerce nonusers by employing cluster analysis on a list of reasons reported by Internet users that prevent them from purchasing online. In doing so, alternative views of online nonshoppers might emerge and contribute to understanding their dynamic behaviors.

3. MATERIALS AND METHODS

All statistical analyses were performed in RStudio 1.3.959 (©2009-2020 RStudio, PBC). The data used in this study are freely available on the website of the Regional Center for Studies on the Development of the Information Society (*Centro Regional de Estudos para o Desenvolvimento da Sociedade da Informação* - Cetic.br, 2019) and are used aggregately.

3.1. Sample Selection and Description

This study used the information and communication technology (ICT) Households 2018 microdata from the Cetic.br (2019) website, a CGI.br's associated department. The ICT Households survey is a nationwide survey conducted since 2005 with the objective of measuring the availability, possession, and use of ICT by the Brazilian population aged ten years and older. This survey’s data collection occurs through structured questionnaires composed of closed questions with defined answers that are administered in face-to-face interviews with the respondents (CGI.br, 2019). The sample is representative of the country and consisted of 20,544 respondents in the 2018 wave. For this paper, we used the subsample of respondents who reported their motives for not buying goods or services online (9,522 respondents, 46.3% of the total).

In the ICT Households 2018 e-commerce module, indicator H2 contains the reports of respondents who bought online and those who did not. We used the respondents who reported not buying online. A very small number of respondents (<1%) did not answer question H2 or reported not knowing whether they had bought online or not. Because this amount was a negligible number, we considered them as not having bought online. Exploratory analyses led us to find 457 outliers, who were removed to enhance the formation of clusters. Thus, the final sample analyzed contained 9,065 respondents. Of those respondents, 42.8% were male. The average age was 35.9 ± 17.1 (mean ± SD). Levels of education were divided into illiterate/preschool (4%), elementary education (43%), secondary education (43.5%), and tertiary education (9.5%). Family income was distributed among no income (24.6%), up to the minimum wage (MW, 43.7%), more than the MW and up to twice the MW (20.8%), more than twice the MW and up to three times the MW (6.3%), more than three times the MW and up to five times the MW (3.3%), more than five times the MW and up to ten times the MW (1%), and more than ten times the MW (0.3%). For social classes, 14.5% are upper class (classes A and B); 50.5% were middle class (class C), and 35% were lower class (classes D and E). Finally, 91% of respondents lived in urban areas and 9% in rural areas.

3.2. Exploratory Analysis and Cluster Formation

First, we sought to cluster the data by using the CGI.br's (2019) original indicators (N = 9,522). However, the variety of variables led to a low degree of discrimination between respondents. We suspected that this issue was due to collinearity caused by correlations between a few variables. After clustering, we checked for nonsignificant variables with which to discriminate clusters by employing chi-square tests, but all variables were found to be significant, perhaps because of the sample size. Therefore, to overcome this challenge, we adopted an alternative strategy: creating indicators to represent the correlated variables. Consequently, we found 457 outliers (~5% of the total) that were so dissimilar that they only clustered in the final stages and therefore prevented the rest of the data from clustering earlier. We subsequently removed these outliers, and the final sample consisted of 9,065 respondents.

We then relied on the literature to create indicators that could group the variables properly into broader dimensions. Initially, nine dichotomous variables (Table 1) addressed a few reasons why respondents decided not to purchase on the Internet. A preference for shopping in person and concerns regarding personal data privacy or product/service quality stood out. In other words, tangibility, risk, and lack of trust were the most frequent factors people indicate as motives for not shopping online.

Table 1

Variables in the analysis

variable code	Reasons why the respondent did not buy or order products and services on the Internet	Quantity	%
H3_A1	Lack of need	4377	48
H3_B1	Lack of interest	5359	59
H3_C1	Preference for shopping in person and seeing the product	7679	85
H3_D1	Lack of Internet skills	2742	30
H3_E1	Delivery takes too long or it is difficult to receive products at home	4394	48
H3_F1	Concerns about security and privacy, or about providing personal information	5738	63
H3_G1	Impossibility of making online payments	3585	40
H3_H1	Lack of trust in the product that will be received	5933	65
H3_I1	Impossibility of making complaints or returning the product	4811	53

Note: N = 9,065 in every row. The quantity and percentage of 'yes' for each variable are reported.

The variables 'lack of need', 'lack of interest', and 'preference for shopping in person' were grouped and labeled the 'disinterest' dimension. The variable 'lack of Internet skills' was not grouped and labeled the 'inability' dimension. The variables 'delivery takes too long', 'impossibility of making online payments', and 'impossibility of making complaints' were grouped and labeled the 'operational difficulty' dimension. Finally, the variables 'concerns about security' and 'lack of trust' were grouped and labeled the 'distrust' dimension. Table 2 summarizes the indicators. Each dimension is explained next.

Table 2
Summary of the indicators

Code	Item	Description	Indicator	Theoretical support
H3_A1 H3_B1 H3_C1	Lack of need Lack of interest Preference for shopping in person and seeing the product	Lack of interest, need, and/or preference	Disinterest (0–3)	Zepeda and Deal (2009), Iglesias-Pradas et al. (2013), Mainardes et al. (2020)
H3_D1	Lack of Internet skills	Lack of Internet skills (original preserved)	Inability (0–1)	Pavlou (2003), van Deursen et al. (2014), Scheerder et al. (2017)
H3_E1 H3_G1 H3_I1	Delivery takes too long or it is difficult to receive products at home Impossibility of making online payments Impossibility of making complaints or returning the product	Troubles with receiving, paying for, and/or returning the product	Operational difficulty (0–3)	Laukkanen (2016), Zhu and Chen (2013), Nery-da-Silva, Barbosa, and Figueiredo (2021)
H3_F1 H3_H1	Concerns about security and privacy or about providing personal information Lack of trust in the product that will be received	Afraid of providing information or concerns about product/service quality	Distrust (0–2)	Liu and Wei (2003), Pavlou (2003), Li et al. (2020)

3.2.1. Indicator 1: Disinterest Dimension

Consumer behavior and attitudes toward a given product or service are complex matters. Several factors have been indicated as influencing people's behavior, such as external conditions (Guagnano, Stern, & Dietz, 1995); values, beliefs, and norms (Zepeda & Deal, 2009); and knowledge (Feldmann & Hamm, 2015). In the information systems (IS) field, Lestari (2019) confirmed that perceived usefulness affects people's intention to adopt e-commerce. Hernández-García et al. (2011) found that perceived compatibility, i.e., whether the technology is seen by an individual as compatible with him/her or not, is the strongest factor influencing nonshoppers' attitudes toward e-commerce. In addition, Laukkanen (2016) focused on consumer rejection of a given technology, Faqih (2016) investigated what slows Jordanian Internet users' adoption of online purchases, and Mainardes et al. (2020) recently investigated why people show disinterest in e-commerce.

From those studies and others in the literature, we know that previous experiences (Hernandez et al., 2009), tangibility (Iglesias-Pradas et al., 2013; Liu & Wei, 2003; Swinyard & Smith, 2003), and value (Hsu et al., 2015; Laukkanen, 2016), among others, account for why some people are not interested in purchasing online. Put simply, they do not see value in e-commerce. As we have seen, three of the CGI.br's (2019) variables measured these factors (H3_A1, B1, and C1). Given their similarity, we grouped them into the same indicator. This indicator was labeled 'disinterest' and consisted of the sum of the variables (range: 0–3).

3.2.2. Indicator 2: Inability Dimension

The variable H3_D1 measures whether the lack of Internet skills is a motive for not purchasing online. Even though one's inability to use ICT tools or access the Internet may lead to operational difficulties when shopping online, it does not necessarily mean that it *is* an operational difficulty; rather, it reflects one's digital skills. Indeed, there is a specific body of literature concentrated on digital skills alone (Araujo & Reinhard, 2018; Scheerder et al., 2017; van Deursen et al., 2014; van Deursen, Helsper, & Eynon, 2016), and treating digital skills as an operational limitation would be a mistake. Therefore, to avoid improper mixing, this variable represented its own dimension and was labeled ‘inability’; its dichotomous characteristic was retained in the calculations.

3.2.3. Indicator 3: Operational Difficulty Dimension

The items that constitute this indicator measured difficulties concerning paying for, receiving, or complaining about products/services (Table 2). These factors are related to operational issues – i.e., given the logistical or bureaucratic requirements or one’s insecurity, an individual would prefer to avoid purchasing online rather than risk doing so and regretting it afterward. Previous experiences (Hernandez et al., 2009), social influence (Mainardes et al., 2020), brand image (Laukkanen, 2016), computer literacy (Swinyard & Smith, 2003), and area of residence (Nery-da-Silva et al., 2021; Zhu & Chen, 2013) are examples of restrictions that lead people to avoid shopping online or adopt some technologies. Thus, the variables H3_E1, G1, and I1 were grouped to form the indicator ‘operational difficulty’, which consisted of the sum of the variables (range: 0–3).

3.2.4. Indicator 4: Distrust Dimension

Pavlou (2003) extensively addressed trust and risk in e-commerce. He proposed the e-commerce acceptance model by integrating trust and risk into the TAM. According to his findings, trust positively affects people’s intentions to transact online and actual online transactions, and negatively affects perceived risk. In turn, the latter negatively affects users’ intentions to transact online. Other studies have also found that perceived risk negatively affects people’s intentions to adopt e-commerce (Bach et al., 2020; Y. Li et al., 2020; Liu & Wei, 2003). These studies confirm that people are wary about providing their data to web retailers, which is confirmed by the CGI.br’s surveys, and such wariness may generate a lack of trust in websites or the system itself. Given that the variables H3_F1 and H3_H1 address this subject matter, they were grouped to form an indicator. This indicator was labeled ‘distrust’ and consisted of the sum of the variables (range: 0–2).

3.3. Cluster Analysis

As our interest was exploratory, we first employed a hierarchical clustering analysis (HCA) to examine all possible solutions. In this procedure, we employed Gower's (1971) association metric – available in the cluster package of RStudio – because the metric can handle different types of variables simultaneously.

Next, the average linkage algorithm was applied to cluster the data. We chose this algorithm rather than Ward’s method because the latter tends to create clusters with approximately the same number of observations (Hair, Black, Babin, & Anderson, 2019), and variations in cluster sizes are a characteristic we were interested in identifying. The cophenetic correlation coefficient (Sokal & Rohlf, 1962) also influenced our choice of the average linkage algorithm. The cut tree was determined by studying the dendrogram and heights and considering silhouette method estimates (Kaufman & Rousseeuw, 1990).

To optimize the results, we followed Hair et al.'s (2019) suggestion of combining hierarchical and nonhierarchical cluster analyses. Thus, the partitioning around medoids (PAM) algorithm was employed in the nonhierarchical clustering analysis because this algorithm is less sensitive to noise and outliers than other methods are (Kassambara, 2017; Kaufman & Rousseeuw, 1990).

3.4. Cluster Validation Statistics

To assess cluster validation, we verified the cophenetic correlation coefficient; within-cluster sum of squares (WSS); average within, between, and silhouette widths; Dunn index; and Pearson-gamma (Halkidi, Batistakis, & Vazirgiannis, 2001). Additionally, we employed one-way analyses of variance (ANOVA) with post hoc analyses and chi-square tests to assess the discriminating power of the clusters.

4. RESULTS

A cluster analysis was conducted on the microdata of the ICT Households 2018 survey (N = 9,065) to investigate whether there are natural clusters of Brazilian e-commerce nonusers grouped by their reasons not to purchase online. To conduct the analysis, we created the four indicators as described in Table 2. The disinterest dimension had a mean of 1.92 ± 0.9, suggesting that people usually have close to two reasons for their lack of interest in e-commerce. A preference for shopping in person predominated (28%), followed by lack of interest (20%) and lack of need (16%). None accounted for 36% of the total. The operational difficulty dimension had a mean of 1.41 ± 1.14, suggesting that people usually have more than one operational difficulty when shopping online; however, this dimension also featured the largest variability. Its distribution was more balanced: impossibility of making complaints (18%), delivery takes too long (16%), and impossibility of making online payments (13%). None accounted for 53% of the total. The distrust dimension had a mean of 1.29 ± 0.82, consisting of lack of trust (33%) and concerns about security (32%), suggesting a nearly either-or condition in this dimension. None accounted for 35% of the total. Finally, the mode was zero (70%) in the inability dimension, as was previously known (Table 1). In creating these indicators, we were able to identify clusters and determine the characteristics of each cluster.

4.1. Outcome of the Hierarchical Cluster Analysis

HCA was performed with 9,065 respondents. By examining the dendrogram, we noted three clear clusters, which was also confirmed by the silhouette method. Cluster 1 (C1) had 2,742 members (30%); cluster 2 (C2) had 2,623 members (29%); and cluster 3 (C3) had 3,700 members (41%). Cophenetic correlation suggested that clustering showed strong fidelity to the original data (c = 0.76). HCA was conducted mainly to guide us through PAM analysis.

4.2. Outcome of the Partitioning Around Medoids Analysis

PAM analysis was also performed with 9,065 respondents, and its results were highly consistent with the HCA results (see Fig. 2A). The coincidence rates were 98%, 76%, and 96% for C1, C2, and C3, respectively. The average distance within clusters was 0.24, suggesting relatively satisfactory cluster compactness, and the average distance between clusters was 0.55, which is over twice that of the within-cluster distance and suggests that there are relatively large distances between the clusters. There was low variability in the observations within clusters, with WSS = 344.08, which is a very small number considering the sample size. The cluster average silhouette widths also indicated relatively good clustering (0.57 for C1, 0.33 for C2, and 0.55 for C3), with an overall average of 0.47. Finally, the Pearson-gamma indicated a strong association among cluster members ($\Gamma = 0.67$), but the Dunn index indicated that the clusters are not as compact and well-separated (Dunn index = 0.08) as they could be.

The discriminating power of the clusters was verified for each dimension (see Table 3 for the central tendency measures and variability). The differences in the variances of the disinterest frequencies were statistically significant between clusters ($H(2) = 1434.75$, $p < 0.001$, Kruskal-Wallis rank-sum test; $\alpha = 0.05$ for Dunn's multiple comparison). Similarly, the differences in the variances of the operational difficulty frequencies were statistically significant between clusters ($H(2) = 4232.29$, $p < 0.001$, Kruskal-Wallis rank-sum test; $\alpha = 0.05$ for Dunn's multiple comparison). The variance of the frequencies in the distrust dimension was significantly different between C1 and C3 ($H(2) = 5984.03$, $p < 0.001$, Kruskal-Wallis rank-sum test and $\alpha = 0.05$ for Dunn's multiple comparison) and between C2 and C3 ($p < 0.001$) but not between C1 and C2 ($p > 0.05$). Finally, differences in frequencies in the inability dimension were also significantly different between clusters (χ^2 (2, N = 9065) = 9065, $p < 0.001$). Altogether, the results suggest that the clusters identify the members well, confirming the existence of heterogeneous groups of nonusers in the Brazilian e-commerce context.

4.3. Overview of the Clusters

Table 3 shows the cluster means and medoids for each indicator. C1 is the cluster in which nearly every reason on the list accounts for its members not to purchase goods and services on the Internet. In contrast, C3 is represented by respondents who scored zero in all but one dimension, suggesting that one factor in the disinterest dimension is the main reason why the members of this cluster reject e-commerce.

Table 3

Cluster means and medoids

Dimension	**Cluster 1**		**Cluster 2**		**Cluster 3**	
	Mean (SD)	*Medoid*	*Mean (SD)*	*Medoid*	*Mean (SD)*	*Medoid*
Disinterest	2.29 (0.82)	**3**	2.05 (0.80)	2	1.40 (0.86)	**1**
Inability	-	**1**	-	0	-	0
Operational difficulties	2.12 (0.99)	2	1.77 (0.92)	2	0.28 (0.52)	0
Distrust	1.75 (0.43)	2	1.74 (0.47)	2	0.27 (0.45)	0
Size (%)	2742 (30%)		3507 (39%)		2816 (31%)	

Note: N = 9,065.

Regarding frequencies, C1 is mostly characterized by respondents affirming that all variables in the disinterest dimension led them to reject e-commerce (Table 3 and Fig. 1A) and it is the only cluster indicating inability as a reason not to buy online (Table 3 and Fig. 1B). It also scored the highest in both the operational difficulty dimension (Fig. 1C) and distrust dimension (Fig. 1D).C2 shares many similarities with C1 in three out of the four dimensions (Fig. 1A, C, D; also see the medoids in Table 3). It tends to represent two motives in both the disinterest dimension (Fig. 1A) and distrust dimension (Fig. 1D) and oscillates between one and two operational difficulties as motives for rejecting e-commerce (Fig. 1C).

C3 is considerably different from the other clusters. It can be easily noticed in Fig. 1A–D that it stands out in scoring at the bottom of the scales in all but one dimension.

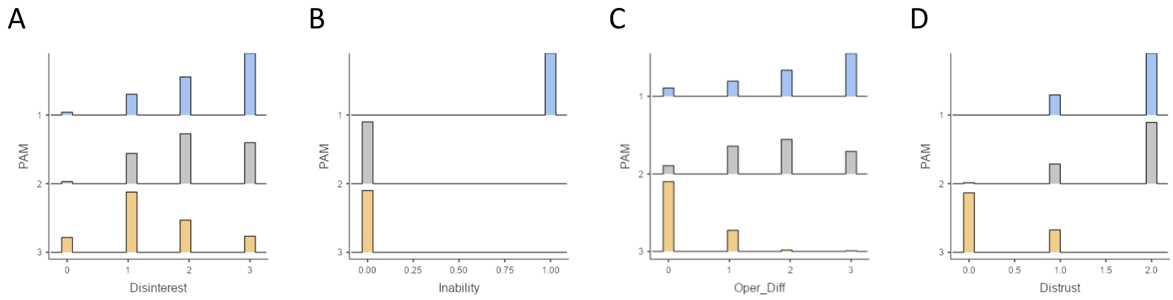

Fig. 1. Visual distribution of frequencies of the clusters in each indicator. Bar chart of frequencies of each cluster in (**A**) disinterest dimension, (**B**) inability dimension, (**C**) operational difficulty dimension, (**D**) distrust dimension.

We also explored the descriptive characteristics of each cluster after they were formed. There was a balanced distribution of members across the clusters, with C2 being the largest (Fig. 2A). C1 differs from the others in terms of age. It consists of older people (average age = 43.3; Fig. 2B), whereas the others present an average age of approximately 30 (Fig. 2B). C3 has a modal age of eleven, which is likely associated with the cluster characteristics.

Fig. 2C depicts the social class distribution in each cluster. We can see little participation among the upper class (A-B) in C1 and some equilibrium between the other classes in the same cluster. The upper class is represented similarly in C2 and C3 (~50%), and the middle class (class C) is proportionally distributed equally throughout the clusters. The lower class (D-E) tends to belong to C1 rather than to C2 and C3. Regarding the distribution of areas of residence, no relevant differences among the clusters were found (Fig. 2D). The proportion of urban residents across clusters was 91 ± 0.02%.

On the other hand, socioeconomic factors varied more across clusters. The charts in Fig. 2C, E and F show that one's socioeconomic attributes may be associated with the cluster to which one belongs. Based on the medoid values in Table 3, C1 is the cluster in which almost every reason forms members' decisions not to purchase online. In Fig. 2E (left), C1 consists more of illiterate members (7%) than the others do, and most of the members have elementary education (54%); in addition, it is the only cluster affected by inability issues. This result is consistent with previous studies that suggest that a lack of digital skills is more expected from less educated people (Araujo & Reinhard, 2018; CGI.br, 2019).

In C2, we see greater participation among people with a secondary or tertiary education (Fig. 2E, center). Compared to C1, the proportion of elementary-educated individuals falls by 20%, whereas that of secondary-educated individuals rises by 18%, which is practically an inversion of the proportions from C1 to C2. Additionally, people with tertiary education are more common in C2 than in C1.

C3 has a balanced distribution of proportions between elementary- and secondary-educated people (43% and 41%, respectively; Fig. 2E, right). Tertiary-educated individuals comprise 12% of the total, just as in C2. Illiterate individuals are slightly more present in C3 than in C2, perhaps because of the large presence of younger people in C3. Therefore, most of illiterate individuals, when considering their social position and not their age, are in C1.

Taken together, these results suggest that education is a factor slightly associated with one's decision to use e-commerce. It is reasonable to assume that the lower one's educational level is, the more one tends to overestimate the process of purchasing online, leading him/her to affirm exaggeratedly that each reason on a given list accounts for why he/she prefers to reject e-commerce over benefiting from it.

Finally, in Fig. 2F, we plotted the distribution of family income in each cluster. Irrespective of the proportion, earning from zero up to twice the MW is always the three most frequent income strata in all clusters, meaning that the distribution remained like that of the original sample. However, there is a slightly higher presence of high-income earners in C2 (Fig. 2F, center), suggesting that high-income earners tend to belong more to C2. C3 has a higher proportion of incomeless members (31%; Fig. 2F, right) than C1 and C2, which is most likely explained by the high presence of young members in that cluster (see Fig. 2B).

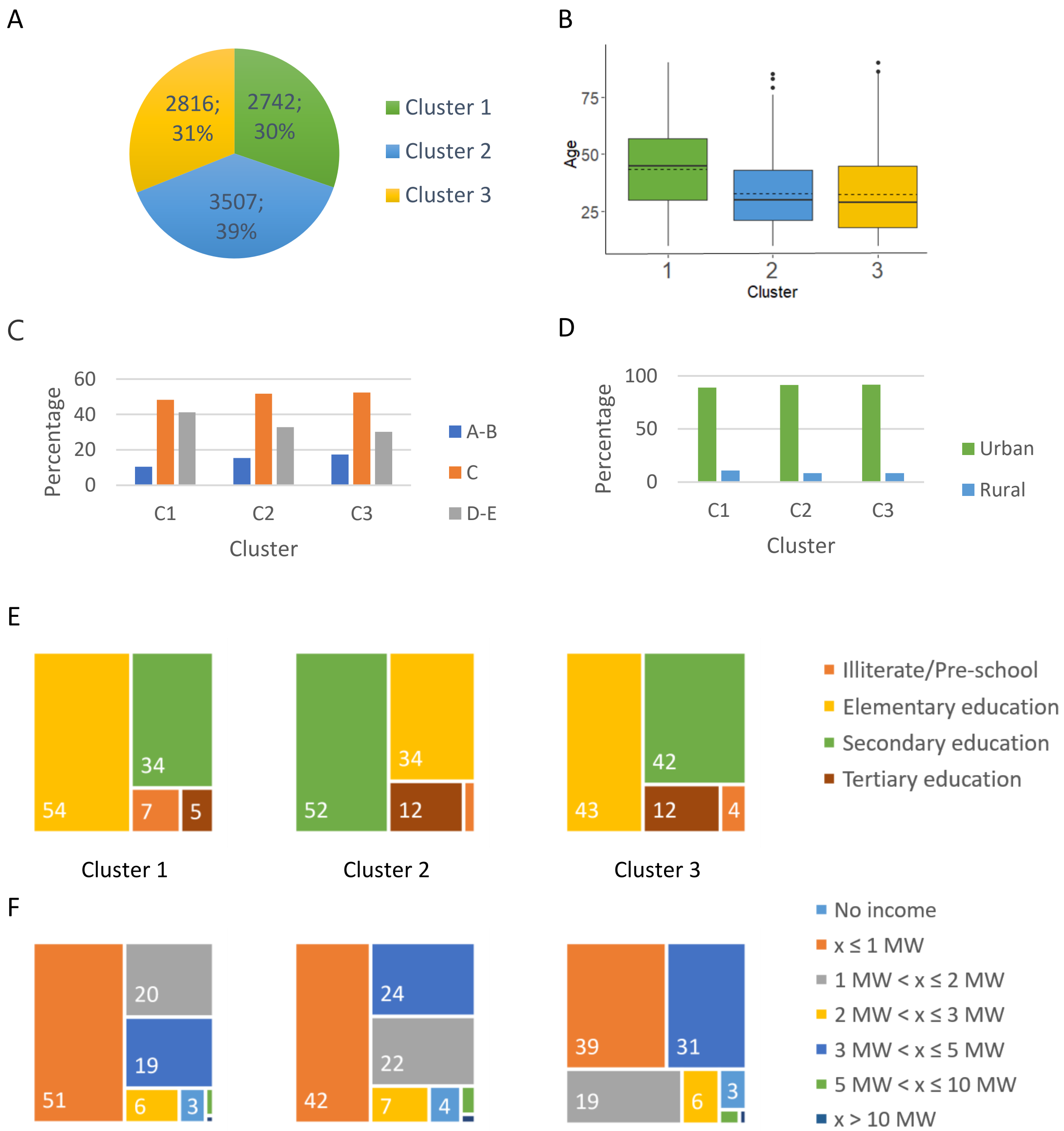

Fig. 2. An overview of the clusters and their description. (**A**) Pie chart showing the distribution of the sample between the clusters. (**B**) Boxplots comparing the age in each cluster. For C1, mean = 43.3 ± 17.1, mode = 48, and median = 45; for C2, mean = 32.9 ± 15, mode = 20; median = 30; and for C3, mean = 32.4 ± 17.1, mode = 11, median = 29. (**C**) Social class distribution in each cluster. (**D**) Distribution of the area of residence in each cluster. (**E**) Proportion of the level of education (given in percentage) in C1 (left), C2 (center), and C3 (right). (**F**) Proportion of family income (given in percentage) in C1 (left), C2 (center), and C3 (right).

4.4. Understanding the Clusters: Main Features and Names

C1 had 2,742 (30%) members, consisted of 61% females, and had an average age of 43.3 ± 17.1. The members of this cluster scored the highest in all the dimensions, standing out in the disinterest and inability dimensions. Somehow, they are slightly confused about purchasing online, since all the reasons seem to affect them. Their average age coincides predominantly with Generation X and the Baby Boomers. This finding is consistent with previous studies (Gilly, Celsi, & Schau, 2012; Hough & Kobylanski, 2009; Lissitsa & Kol, 2016; Moorthy et al., 2017) suggesting that members of those generations are more resistant to technology and have more trouble with it than the members of subsequent generations. Considering all these features, C1 was named **aversive generations**.

C2 had 3,507 (39%) members, consisted of 58% females, and had an average age of 32.9 ± 15. Based on the scores in each dimension, in general, the members of this cluster scored either near the average or above it in every dimension except inability. In other words, they do not stand out in any dimension but score in all of them, which suggests that, in summary, e-commerce does not work for them. Thus, C2 was named **disbelievers** because even though its members are not restricted by a lack of digital skills, they are not interested in e-commerce, nor do they have the desire to give up tangibility; they do not want to wait for the product to arrive nor are they willing to deal with problems if something goes wrong. They do not want to provide their data, nor do they trust that the product will be delivered. In summary, they do not believe that e-commerce works.

Finally, C3 had 2,816 (31%) members, consisted of 53% females, and had an average age of 32.4 ± 17.1. Its main characteristic stands out in Table 3: the members of this cluster are not interested in purchasing online. They scored the highest on the variable 'preference for shopping in person' (46%), which means that tangibility is, by far, the most critical factor for them. Moreover, this group values shop tangibility and human interactions, meaning that they prefer to speak to an actual person over chatting with a bot, even to hire a service, which is not tangible at all. For all these reasons, C3 was named **doubting Thomas** because they have to see it to believe it.

5. DISCUSSION AND CONCLUSION

We have found heterogeneous groups of e-commerce nonusers in Brazil. Although the clusters overlap each other in a few instances, the tendency to cluster is noticeable. More importantly, our findings do not provide evidence that socioeconomic factors are important determinants of e-commerce nonusers' behavior. Instead, together with age, these factors are only weakly associated with the clusters. Overall, our findings suggest that merchants have failed to attract customers' attention and that tangibility is the major hurdle to be overcome.

Previous attempts to segment e-commerce nonusers found four types of online nonshoppers (Iglesias-Pradas et al., 2013; Swinyard & Smith, 2003) or found four factors that constitute barriers to e-commerce access (Anckar, 2003). In our study, three clusters of nonusers have been identified out of four dimensions of reasons not to shop online. **Aversive generations** are the most intriguing group. Several demographic factors historically associated with technology adoption (H. Li et al., 1999; Venkatesh, Sykes, & Zhang, 2020; Zhu & Chen, 2013) are present in the cluster. The members tend to be less educated, to belong to lower classes, and are older than the members of the other clusters. Additionally, they are impacted by all dimensions. Compared with Swinyard and Smith's (2003) classification, **aversive generations** are a mix of shopping avoiders and technology muddlers.

Such a variety of characteristics in this group poses great challenges in how to encourage its members to be more interested in, and comfortable with, purchasing online. All of these factors have been identified before by previous studies (Laukkanen, 2016; Venkatesh et al., 2020; Venkatesh, Thong, & Xu, 2012; Zhu & Chen, 2013), so they are not novel. However, they continue to affect people in terms of technology adoption. To address the dimensions by considering these demographics, we recommend that online merchants should focus on the dimensions that are common to most of the clusters, that is, distrust and tangibility. For example, dedicating efforts to offering consumers a memorable experience might be a start (W. L. Chang, Yuan, & Hsu, 2010).

Likewise, the existence of the **disbelievers** group reinforces the need for (i) more accurate marketing strategies, (ii) better customer care, (iii) better delivery systems, and (iv) more attention to customer experience and engagement. Our findings confirm that customers are not alike, and that simple nonuser labeling is inappropriate. In contrast, various factors may or may not influence consumers' behaviors and must be considered to design effective, customized strategies. These points notwithstanding, in the face of the current global pandemic, online purchasing is a necessary mechanism for ensuring the acquisition of products and services while respecting physical distancing – especially among high-risk groups – and fighting the negative effects caused by the current crisis.

The **disbelievers** cluster roughly brings together three types of nonshoppers from Iglesias-Pradas et al.'s (2013) study, namely, skeptical/distrustful, risk-avoiders, and hesitant. In both cases, despite the resistance identified, there is still room to engage the members in online shopping due to the drivers that can be used as motivations for them to make online purchases, such as making them know the seller better, having them perceive security in online transactions, and reducing their skepticism about product tangibility.

Finally, we also found the **doubting Thomas** cluster. A curious phenomenon occurs in this cluster. It has proportionally more members from the upper and lower classes than the other clusters (Fig. 2C), has more illiterate individuals than the **disbelievers** cluster (Fig. 2E, right), has a modal age of eleven but an average age of 32.4, and is mostly affected by only one of the dimensions of reasons not to shop online (Table 3). The fact that its modal age is eleven explains the higher proportion of incomeless members compared to the other clusters (Fig. 2F) and why its members do not score in almost any dimension investigated. Because they are younger (from Generation Y on), they are less afraid to provide personal information (Gewald et al., 2017) and are usually more digitally skilled (Lissitsa & Kol, 2016). Nonetheless, the members of the **doubting Thomas** cluster value tangibility.

Considering the demographic aspects of all the clusters, our findings do not provide evidence that such aspects inhibit e-commerce adoption. Hence, we propose that tangibility and the feeble marketing strategies of enterprises, which have failed to attract customers' attention, are far more important factors causing resistance to e-commerce. This hypothesis should be further investigated in future studies.

Previous studies have documented that individuals may resist, not adopt (Hernandez et al., 2009; Laumer & Eckhardt, 2012), or not be interested in technology (Mainardes et al., 2020) due to social influence, perceived ability, or lack of trust (Faqih, 2016; Y. Li et al., 2020; Liu & Wei, 2003; Pavlou, 2003). We have confirmed some of those findings and extended them by demonstrating that operational aspects also lead many individuals to take such attitudes.

Our most important finding is the size of the **doubting Thomas** cluster. As shown, it consists of 31% of the total sample, which means that nearly one-third of Brazilian e-commerce nonusers may be reached just by focusing on tangibility. This large number of consumers, if converted into e-commerce users, may greatly boost electronic sales, revenues, and the national market.

One limitation of our study is the lack of control over variables with respect to what they intended to measure. Because we used secondary data, we were limited to the variables provided by the CGI.br. Therefore, other questions that might also be of interest with regard to the context could not be addressed in the present study. For example, we were unable to ask whether the respondent had an unpleasant online experience prior to his/her decision not to shop online. Additionally, the CGI.br (2019) did not measure the same variables in previous ICT Households waves, which would have allowed us to use different years to confirm or reject the results. Thus, we are temporally limited by this cross-sectional view.

In conclusion, our results have focused on the large electronic market that remains idle in Brazil. According to the CGI.br (2019), most e-commerce nonusers identified here are Internet users already, which means that they are halfway to becoming e-commerce users as well. Our findings also support the notion that e-commerce nonusers are heterogeneous segments with at least three natural clusters. We encourage researchers to undertake further analysis to determine what other factors have the strongest effects on nonshoppers, particularly carefully examining what may have changed since the beginning of the pandemic. Perhaps people have become more susceptible to engaging in the online market and some factors may no longer be relevant.

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