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The consumer intention to use e-commerce applications in the post-pandemic era: a predictive approach study using a CHAID tree-based algorithm

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Abstract

Purpose – This study proposes a hierarchic segmentation that develops a tree-based classification model and classifies the cases into groups. This allows for the definition of e-commerce user profiles for each of the groups. Additionally, it facilitates the development of actions to improve the adoption of the online channel that is in such high demand in the current pandemic COVID-19 context.

Design/methodology/approach – Regarding the created segments, two extreme segments stand out due to their marked differences and high volume. Segment 3 with 23% of the sample is the group with the most predisposition to use the online channel and is characterised by a high level of trust, more habitual use in comparison with other groups and the belief that its use implies high performance, which indicates they believe it to be useful, quick and helpful for more an effective shopping experience. The other extreme is found in segment 7. This group makes up 17.7% of the total and is the most reluctant to use the online channel. These users are characterised by the complete opposite: they have a low level of trust in this channel. However, the effort expectancy is low, i.e. they consider that the adoption of the online channel does not involve many difficulties in its learning and use. Nevertheless, they use it less regularly than the others.

Findings – Based on the conclusions reached in this study, in the current pandemic context in which consumer demand for online shopping channels for all types of products is on the rise, it is recommended that companies focus on the following aspects. It is essential to build trust with the user and show them the real benefits of e-commerce, how it would improve their life and why they should use it. Additionally, it is vital that the user perceives it as an easy procedure that does not require a significant learning curve. Other fundamental aspects would be to reduce any uncertainty the user might have about the online shopping process, to make it as easy as possible, and to design a simple, intuitive and user-friendly interface. It is also recommendable to manage data usage efficiently. To do so, the authors recommend asking the user for the least amount of information possible,

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offering a data protection policy and assuring them that their information will not be misused nor shared with third parties. All of this provides a series of facilities to modify the online shopping habits of users.

Research limitations/implications – As in most of the research, this study presents a series of limitations that should be debated and that could open future lines of investigation. Firstly, regarding the sample used that was limited to two neighbouring countries with similar profiles *a priori*; it would be necessary to compare their possible cultural differences according to Hofstede's dimensions as well as increase the number of European countries being analysed to reach a more generalised conclusions. Secondly, the variables used are a combination of those derived from the UTAUT2 model and others suggested in the literature as decisive in technology adoption by users, in this sense other theories and variables could be incorporated to complete a more holistic model.

Practical implications – This work contributes in a general way to (1) analysing the intention to use e-commerce platforms from a set of antecedents previously defined by their importance, after a period of economic and social restrictions derived from the pandemic; (2) determination of customer segments from the classification made by the CHAID analysis; (3) characterisation of the previously defined segments through the successive divisions that were proposed in the analysis carried out.

Social implications – Other fundamental aspects would be to reduce any uncertainty the user might have about the online shopping process to make it as easy as possible, and to design a simple, intuitive, and user-friendly interface. It is also recommended to manage data usage efficiently. To do so, the authors recommend asking the user for the least amount of information possible, offering a data protection policy, and assuring them that their information will not be misused or shared with third parties.

Originality/value – The results obtained have allowed us to establish predictive and explanatory models of the behaviour of the segments and profiles created, which will help companies to improve their relationships with online customers in the coming years.

Keywords User-intention, E-commerce, Segmentation, Trust, CHAID, COVID-19

Paper type Research paper

1. Introduction

The COVID-19 pandemic and the effects it has had on healthcare, society, and the economy are producing a change in consumer shopping habits. The increase in the general use of e-commerce reveals a greater tendency towards online shopping among consumers, even amongst those who would not usually make use of these forms of shopping. In Portugal, just 38.7% of the population between the ages of 16 and 74 years shopped online in 2019, a much lower percentage than the European average of 63%, or in the case of Spain which was close to 60% (Statista, 2020). However, the effect of the pandemic caused a 40%–60% increase in e-commerce, compared to the figures in 2019, especially in food-related products (ICEX, 2020). In the year of the pandemic, 2020, online retail sales, excluding food, grew in Europe by an average of 31%. Spain was the country with the second-highest increase, with growth reaching 38% (Wyman, 2021). According to this report, although physical stores will continue to be the primary retail channel in this decade, the observed growth in the online channel during the pandemic has demonstrated the ability of e-commerce to adapt to our environment, leading us to imagine a multi-channel future for retail. Consumers have increased their level of trust in online commerce, forcing physical distributors to include online functions to increase the attractiveness of their products that are increasingly integrated into the on-offline context.

The consumers' adoption of a technology is decisive in its success. Therefore, if we know the factors that affect their adoption and their intention of use, we will be able to facilitate an improved implementation in companies and a greater acceptance by the consumers/users. In this study we drew from the classic theories on acceptance of technology: The technology acceptance model, TAM (Davis, 1985, 1989) and the theory of planned behaviour, TPB (Ajzen, 1991), the proposed model in the Unified Theory of Adoption and Use of Technology, UTAUT (Venkatesh *et al.*, 2003) and its extended version UTAUT2 (Venkatesh *et al.*, 2012) that comprises the most significant contributions to the previous models. The changes caused by COVID-19 and its consequences suggest that there are other variables that increase and improve the intention of using e-commerce amongst online consumers.

This research analyses the gap generated the line between physical stores and e-commerce is ever more blurred. Based on the discussions we proposed the following research questions (RQs).

RQ1. This study will enable us to identify the factors that affect the adoption, and use of e-commerce by consumers and the decision to shop online. This investigation deepens the examination of the critical factors affecting the adoption of electronic commerce amongst these users.

RQ2. Additionally, it aims to discover if there is an unobserved heterogeneity in consumer behaviour and, if this is the case, to find relevant segments of e-commerce adopters in the post-COVID-19 era.

RQ3. Once we have identified the different behaviour segments that are influenced by the proposed variables in the model and understood the profile of these groups, we will recommend strategies to e-commerce platforms and app developers to improve consumer commitment to use said tools.

Consequently, the objective of the research is twofold. First, to increase our understanding of online consumer engagement and the relevant segments, we have added new original variables as inhibiting and influencing factors to obtain a more explanatory and predictive model of e-commerce adoption and usage in the post-COVID-19 era. Secondly, once the most relevant segments have been determined, strategies will be established for the different stakeholders involved in the online business.

In order to reach the objective of this research, two groups of variables were established: on one hand, a group of behaviour-related variables divided between facilitating variables (performance expectancy, effort expectancy, social influence, habit, facilitating conditions, hedonic motivation and trust) and variables considered to be obstacles in e-commerce (privacy risk, switching cost, perceived risk and technophobia); and on the other hand, a group of variables related to the socio-demographic characteristics of the users in both countries (gender, age, level of education, size of household and size of the municipality). In this way, this group of variables will enable the observation of both the behavioural variables, either facilitating or obstructing to adoption, and the socio-demographic variables.

To this effect, this investigation is structured in the following manner: following on from the introduction above, in the second section we analyse the fundamental concepts associated with the investigation and that are related to the segmentation in question; the third section presents the methodology framework used, while the fourth section analyses the major results of the empirical work. Finally, the last section presents the conclusions, implications, limitations, and future lines of research.

2. Literature review

2.1 Socio-demographic characteristics as segmentation variables

To reach the objectives of the investigation, it is proposed that the primary socio-demographic variables be included in the study in addition to those previously mentioned. The scientific literature reveals a strong association between socio-demographic characteristics and the adoption of different technologies (for example: Guttentag and Smith, 2020; Molinillo *et al.*, 2020; Choi, 2021). The socio-demographic factors of the respondents, such as gender, age, level of education, size of household and size of the municipality are influencing factors in the intention to adopt and the intention to continue using a technology.

Gender has been used as a segmentation variable in the scope of technology usage since the research done by Venkatesh and Morris (2000). Men and women have different commercial orientations that lead to different behaviours (Molinillo *et al.*, 2021). According to social psychology, men are more pragmatic and highly task and result-orientated than women are (Ramkissoon and Nunkoo, 2012) which implies behavioural differences in their actions. Traditionally, men have been more willing to participate in e-commerce than women (Susskind, 2004), make a greater number of purchases (Hasan, 2010), have a higher tendency to thoughtful purchasing (Zhou *et al.*, 2007), are more utilitarian and are more daring when making decisions (Lynott and McCandless, 2000) although women are more reliable (Escobar-Rodríguez *et al.*, 2017).

On the other hand, age is another fundamental variable for defining the intention of technology usage (Phang *et al.*, 2006). In this regard, older users usually tend to be relatively relaxed in terms of using technology to carry out transactions because they are sceptical about technology and rely more on offline transactions (Chawla and Joshi, 2020). On the contrary, younger users typically have more technological experience and give better responses in terms of trust, security, etc. and consequently have an elevated final intention (Liébana-Cabanillas *et al.*, 2020; Arfi *et al.*, 2021).

In addition to the previous variables, level of education also has a positive effect on intention, meaning that the higher the user's level of education, the greater their intention and usage of technology will be (Nasri, 2011; Yan *et al.*, 2013; Arora and Sandhu, 2018). Typically, users with a greater level of education will have less resistance towards the usage of new technology and will therefore be more accepting towards new innovations (Leong *et al.*, 2020).

Likewise, size of household and size of municipality are relevant when it comes to defining the user intention of usage. On one hand, it has been proven that the number of people residing in one house is negatively related to the intention of usage, since those living in smaller households (less than 3 members) probably have a lower average age and as a result are more prone to using new technology, and vice versa (McLean and Osei-Frimpong, 2019). On the other hand, the size of the municipality is also related to the adoption of innovations. Some studies have positively correlated the size and the adoption intention arguing that, since the size of the company affects adoption significantly, the relationship between the size of the city and that of the companies should also influence the diffusion of innovations (Diebolt *et al.*, 2016). These studies have predicted a premature adoption the same size as the biggest city because it gives a greater probability of receiving information about innovations (Pedersen, 1970) and consequently adopting them.

Finally, the nationality of the users also determines the intention of usage of a particular technology. In this sense, since Hofstede's weekly studies (2001) up to the current day, multiple studies have confirmed how the different cultural dimensions of the users influence the adoption of digital technologies (Gvili and Levy, 2021).

2.2 Behavioural characteristics as segmentation variables

Behavioural segmentation is based on the client's behaviour towards products and services (Goyat, 2011). Behavioural intention is one of the most studied dependent variables in scientific literature relating to the cognitive-behavioural approaches (Vallespín *et al.*, 2017). In this study, we analyse the intention of adopting e-commerce.

With the arrival of the internet and Smartphones, information technology has become an indispensable tool for both users and companies. Despite the numerous investigations already carried out on the adoption and diffusion of technology, many researchers continue to analyse the influence of factors that impact the acceptance and individual use of emerging information technology (Hughes *et al.*, 2020). This approach has given rise to numerous theories and models such as the TAM, the Diffusion of Technology (DOI), the TPB and the Theory of Task-technology Fit (TTF), that were used primarily to examine a series of questions related to adoption and diffusion. As a continuation of these approaches, Venkatesh *et al.* (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) in an organisational context, placing emphasis on the utilitarian value (extrinsic motivation) of the organisation's users after having eliminated the similar/redundant constructs.

The peak of consumer technology made it necessary to extend the UTAUT model into the context of consumption, emphasising the hedonic value (intrinsic motivation) of users of technology. This led to the incorporation of three new constructs such as hedonic motivation, price value and habit into the original UTAUT, resulting in the new amplified version known as UTAUT2 (Tamilmani *et al.*, 2021). This new theory predicts more comprehensively the variance of the behavioural intention of consumers. This has enabled numerous researchers to use very recently in very diverse disciplines (Ramírez-Correa *et al.*, 2019; Andrew *et al.*, 2021; Gansser and Reich, 2021; García-Milon *et al.*, 2021; Thaker *et al.*, 2021; Cabrera-Sánchez *et al.*, 2021; Erjavec and Manfreda, 2022; Migliore *et al.*, 2022). In our research, we have included the following variables in the analysis: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit.

In addition to the above-mentioned variables, the UTAUT2 model was broadened by including the variables: Trust, Perceived risk, Privacy, Switching cost and Technophobia. These variables are closely related to adoption and have been included in similar studies. Over the last few decades, research carried out in the marketing sector has highlighted the importance of trust between the parties as a tool for enhancing the relationship, this being a very important aspect in the business world. Trust in online markets implies the belief that the company will fulfil their commitments without taking advantage of the purchasing party, which will favour its intention to adopt or continue its usage (Vimalkumar *et al.*, 2021). This exact variable has been widely studied together with Perceived Risk in virtual settings (Irimia-Diéguez *et al.*, 2023). Perceived risk is defined as the perception a consumer has about the uncertainty and adverse consequences of carrying out a transaction with a vendor in a specific setting (Liébana-Cabanillas *et al.*, 2023). When combined with these two variables, privacy refers to the right of everyone to control the collection and use of their personal digital or non-digital information (Merhi *et al.*, 2019). Finally, switching cost and technophobia have been defined as obstacles to the adoption of new technologies that stem from the effort required to modify a current behaviour (Subero-Navarro *et al.*, 2022) and from insecurity and the feeling of intimidation that new technology may produce (Talukder *et al.*, 2020).

By way of summary, the set of variables included in the research is presented graphically (see Figure 1).

Sociodemographic	Behavioural
•Gender •Age •Educational level •Household size •Municipality size •Culture	•Performance expectancy •Effort expectancy •Social influence •Facilitating conditions •Hedonic motivation •Habit •Trust •Privacy risk •Perceived risk •Technophobia •Switching cost •Intention to use ecommerce

Source(s): Prepared by the authors

Figure 1. Variables included in the research

3. Research methodology

3.1 Measurement scales

For the variables prior to the behavioural intention to use e-commerce, we used measurement 7-POINT LIKERT scales adapted from Venkatesh *et al.* (2003), Davis (1989) and Venkatesh *et al.* (2012) and we took six into account: (1) performance expectancy, defined as the degree to which using technology offers benefits (utility) when performing certain activities; (2) effort expectancy, which measures the degree of ease (ease of usage) associated with the use of technology; (3) social influence measures the way in which consumers perceive the opinion of their friends and family who believe they should use a specific technology; (4) the facilitating conditions, such as the consumers' perceptions about resources and help available to develop a behaviour; (5) hedonic motivations, measured by the perception of enjoyment as a decisive factor in the usage of technology; and (6) habit, measured by the frequent and natural usage of technology.

This model enables the inclusion and evaluation of the effect of different moderating variables (Arenas-Gaitán *et al.*, 2019). In our case, we incorporated the following variables as limiting factors to broaden the model and improve its explicative ability: technophobia (Heinssen *et al.*, 1987), privacy risk, perceived risk (Featherman and Pavlou, 2003), switching costs (Hsieh, 2015) and trust (Pavlou and Gefen, 2004) as an influencing factor. In all the cases, it used 7-point Likert scales. The measurement scales are detailed in Table 1.

3.2 Data collection

The sample used for the investigation comes from individuals that answered the self-administered survey *with* online collection that was circulated among the Spanish and Portuguese populations (Iberian Peninsula) during the months of June to September 2020. To eliminate possible ambiguities in the survey, a pre-test of 150 participants in each population was carried out among and expert researchers. The survey was sent out in Spanish for the sample in Spain, and in Portuguese for the sample in Portugal.

The total number of valid surveys obtained was 836 observations. Table 2 shows the socio-demographic characteristics of the bulk sample.

3.3 Data analysis

The objective of this research is to develop a classification model to predict the profile of online buyers. To achieve this, Hierarchical Tree-Based Regression (HTBR) was applied. HTBR is a non-parametric procedure that does not require a predefined relationship between the dependent and independent variables to identify the comprehensive and selective sub-assemblies of the objective variable (Zhan *et al.*, 2016). It is called tree analysis because the target variable node (tree trunk) is divided into predictor nodes (branches).

Decision trees are a data mining technique that organises the data to reveal the information they hide. The division method used for the tree is the Chi-Square Automatic Interaction Detector (CHAID). There are also other methods such as CHAID exhaustive, classification and regression trees and Quick, unbiased, efficient, statistical tree. However, the CHAID method was chosen because of the nature of the data since this technique can handle nonparametric data and does not presume that the data are normally distributed. Decision trees predict the values of a dependent variable (criteria) based on the values of the independent variables (predicting). Thus, in each step, CHAID proposes the independent variable that presents the strongest interaction with the dependent variable in such a way that each predictor will be significantly different in relation to the dependent variable (Magidson, 1994). The definition of the different sub-groups and their profiles enables the attribution of a specific type of information to each group. As a result, the procedure can be used to segment, stratify, predict, and reduce the data. Furthermore, CHAID clearly shows

Performance expectancy (Venkatesh *et al.*, 2012)
I think E-COM is useful in my daily life
I think E-COM increases my possibilities of reaching the things important to me
I think E-COM helps speed up my purchases
I think E-COM improves my performance when shopping
Effort expectancy (Venkatesh *et al.*, 2012)
Learning to use E-COM tools is easy for me
My interaction with E-COM tools is clear and understandable
I find it easy to use E-COM
I think learning to use E-COM applications is easy for me
Social influence (Venkatesh *et al.*, 2003)
Important people in my life think I should use E-COM
People who influence my behaviour think I should use E-COM
People whose opinion I value and take into account believe I should use E-COM
Facilitating conditions (Venkatesh *et al.*, 2012)
I have the resources necessary to be able to shop online
I have the knowledge necessary to be able to shop online
E-COM is compatible with other applications I use
When I have trouble while using E-COM, I can get help
Hedonic motivation (Venkatesh *et al.*, 2012)
Shopping online is fun
I enjoy shopping online
Shopping online is entertaining
Habit (Limayem *et al.*, 2007)
Shopping online has become a habit of mine
I am addicted to E-COM
I have to use E-COM applications
Using E-COM has become a natural activity for me
Trust (Pavlou and Gefen, 2004)
E-COM is reliable
When I shop online, the company always fulfils what it promises
E-commerce is responsible for satisfying the user
Technophobia (Heinssen *et al.*, 1987)
I doubt when shopping online because I fear making mistakes that I cannot correct
I dislike working with machines that are smarter than me
I feel afraid when shopping online
I fear becoming dependent on E-COM and losing some of my abilities
I feel anxious when shopping online
I feel insecure in my ability to understand E-COM
I have avoided shopping online because it is not familiar to me and, in some way, it intimidates me
I have difficulty understanding the technical aspects of online shopping
Privacy risk (Featherman and Pavlou, 2003)
I worry that the information I give when shopping online will be misused
I worry that somebody could find private information about me on the internet
I worry about giving out personal information on E-COM because of how it might be used
Perceived risk (Featherman and Pavlou, 2003)
In general, shopping online is risky
It is dangerous to use E-COM
Shopping online puts me at risk
Switching cost (Hsieh, 2015)
We have already allocated a lot of time and effort to dominating the current online shopping format
A lot of time and effort is required to change to using E-COM
Changing to E-COM could generate unexpected costs
Intention of using e-commerce (Venkatesh *et al.*, 2012)
I intend on using E-COM in the near future
I will always attempt to use E-COM in my daily life
I plan to use E-COM frequently

Source(s): Prepared by the authors

Table 1.
Measurement scales

Gender	N	%
Male	454	54.31%
Female	382	45.69%
Age		
Up to 40 years old	405	48.44%
More than 40 years old	431	51.56%
Education		
None	12	1.44%
Primary	225	26.91%
Secondary/Bachelor	264	31.58%
University	237	28.35%
Post-graduate	98	11.72%
Household size		
Up to 3 people	477	57.06%
More than 3 people	359	42.94%
Municipality size (inhabitants)		
<10,000	119	14.23%
10,000–20,000	175	20.93%
20,000–50,000	177	21.17%
50,000–100,000	200	23.92%
100,000–500,000	112	13.40%
>500,000	53	6.34%

Source(s): Prepared by the authors

Table 2. Socio-demographic characteristics

which segmenting variable should be the first and fundamental variable. In addition, the advantages of using decision trees include their easy interpretation and great flexibility. Thanks to the visual representation of decision trees, they are very easy to understand, quickly identifying the most important variables, which is not always so easy with other algorithms. IBM SPSS Statistics 20 software was used to run the CHAID model.

Applying the CHAID algorithm has been used, *inter alia*, in political marketing (Walker *et al.*, 2017), tourism (Díaz-Pérez *et al.*, 2020; Legohérel *et al.*, 2015), digital marketing (Gupta and Pal, 2019; Liébana-Cabanillas and Alonso-Dos-Santos, 2017; Natarajan *et al.*, 2015; Sabaitytė *et al.*, 2019) and ecological marketing (Ali *et al.*, 2019; García-Maroto and Muñoz-Leiva, 2017; Higueras-Castillo, 2021).

4. Results

Firstly, an analysis of the viability and validity of the measurement scales was carried out. The results generated satisfactory levels in all cases, exceeding the limits established by the literature (Cronbach, 1951). In the same way, we performed a factor analysis that established the appropriate indicators in each of the proposed dimensions.

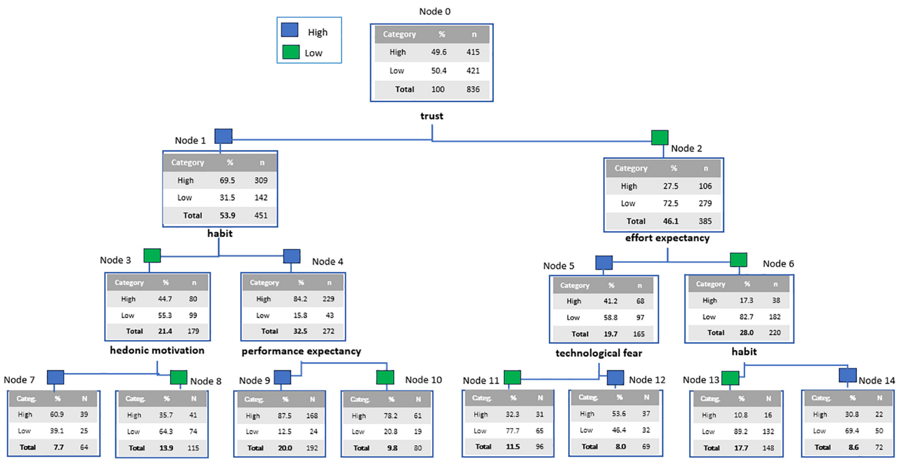
In the segmentation analysis (under the CHAID algorithm), the dependent or predictor variable is the intention to use electronic commerce. The independent variables are all of those previously described. On one hand, the variables considered to facilitate electronic commerce: performance expectancy, effort expectancy, social influence, habit, facilitating conditions, hedonic motivation, and trust; on the other hand, the variables considered to be obstacles to e-commerce: privacy risk, switching cost, perceived risk, and technophobia; lastly, the socio-demographic variables: gender, age, level of education, size of household and size of municipality. Moreover, the country variable (Spain and Portugal) is included with the aim to discern if significant differences exist with regards to nationality. When there are variables with high levels of reliability, summary variables can be obtained, and for this we calculated the average of the items of each variable (Rifon *et al.*, 2005). After this, to facilitate their interpretation, the behavioural variables were recoded establishing a hierarchy of "high" and "low", according to the average of each one of the variables.

The final structure of the tree contains seven division variables (see Figure 2): trust, habit, effort expectancy, hedonic motivation, performance expectancy, technophobia, and habit once again. Therefore, only the behavioural variables, especially facilitating variables, imply significant differences. The rest of the dependent variables included in the analysis do not have a significant effect.

The first division at node 0 refers to trust (Chi-square = 139,540; df = 1; p-value = 0.000). The root node was divided into two subsamples. Node 1: high trust and node 2: low trust. In the second level, the best predictor for node 1 (high trust) is habit (Chi-square = 78,075; df = 1; p-value = 0.000), whilst the best predictor for node 2 (low trust) is effort expectancy (Chi-square = 27,082; df = 1; p-value = 0.000). Both are subdivided into high and low. In the third level, the best predictor for node 3 (low habit) is hedonic motivation (Chi-square = 10,635; df = 1; p-value = 0.001), for node 4 (high habit); it is performance expectancy (Chi-square = 5,370; df = 1; p-value = 0.020). On the other hand, for node 5 (high effort expectancy), the best predictor is technophobia (Chi-square = 7,540; df = 1; p-value = 0.006). Lastly, for node 6 (low effort expectancy), once again habit is significant (Chi-square = 13,215; df = 1; p-value = 0.000). All of these are, in turn, subdivided into high and low.

The character profile of the terminal nodes is elaborated hereafter:

(1) *Segment 1* (node 7). It is the smallest group with 7.7% of the sample. 60.9% of this sample has an elevated intention to use e-commerce. These users are characterised by having a high level of trust in e-commerce and low habit, but they are motivated by the enjoyment and pleasure of using online channels, that is, they have high hedonic motivation.



Source(s): Prepared by the authors based on data from the *IBM SPSS Statistics 20* software

Figure 2. CHAID result of the intention to adopt electronic commerce

(2) *Segment 2* (node 8). This group makes up 13.8% of the total sample, of which 64.3% has low adoption of e-commerce usage. They are users with high levels of trust in e-commerce, low habit, and low hedonic motivation toward online shopping.

(3) *Segment 3* (node 9). This is the largest group with 23.0% of the sample, of which 87.5% have high adoption. They are users with a high level of trust, high habit and high-performance expectancy of the online shopping channel.

(4) *Segment 4* (node 10). It makes up 9.6% of the total, of which 76.2% has an above-average level of adoption. They are users with high trust towards e-commerce, high habit, and low performance expectancy.

(5) *Segment 5* (node 11). This group consists of 11.5% of the sample. In this case, 67.7% has low adoption. They are characterised by a low level of trust, high effort expectancy and low technophobia.

(6) *Segment 6* (node 12). Formed by 8.3% of the total, of which 53.6% possesses a high adoption level. They are users with low trust, high effort expectancy and high technophobia.

(7) *Segment 7* (node 13). It is made up of 17.7% of the sample, making it the second largest group, of which 89.2% have low adoption. These users have low trust towards e-commerce, low effort expectancy and low habit.

(8) *Segment 8* (node 14). It makes up 8.6% of the sample, of which 69.4% has low adoption. They are users with low trust, low effort expectancy, but low habit.

Figure 2 shows the results from the *IBM SPSS Statistics 20* software.

The estimation of risk, as a measurement of the tree's goodness-of-fit for prediction, is 0.251 (25.1%). Therefore, the analysis allows for correct classification in up to 74.9% of cases; thus, the tree presents a very good predictive ability in that it exceeds the limit recommended by Luque Martínez (2012).

5. Discussion and conclusions

5.1 Conclusions

This study proposes a hierarchic segmentation that develops a tree-based classification model and classifies the cases in groups. This allows for the definition of e-commerce user profiles for each of the groups. Additionally, it facilitates the development of actions to improve the adoption of the online channel that is in such high demand in the current pandemic context.

To achieve the goals of this study, we categorised variables into two distinct groups. First, we organised a set of variables pertaining to consumer behaviour. These variables were further divided into those that enhance the e-commerce experience, including factors such as performance expectancy, effort expectancy, social influence, habit, facilitating conditions, hedonic motivation, and trust. Conversely, we also examined variables that might impede e-commerce adoption, encompassing concerns like privacy risks, switching costs, perceived risks, and technophobia. Secondly, we considered a cluster of variables related to the demographic and socio-economic characteristics of participants in both nations. These encompassed factors such as gender, age, educational attainment, household size, and the population size of their place of residence.

The results show the existence of 8 segments with different characteristics. The main decision variable is trust, followed by habit and effort expectancy, while socio-demographic variables do not make significant differences.

5.2 Theoretical implications

Firstly, it must be pointed out that, although the sample comes from two different countries (Spain and Portugal, Iberian Peninsula), no significant differences between the two population groups were observed given that the independent variable of nationality turned out to be insignificant. Therefore, the identified groups form segments that come from a homogenous population.

Secondly, this study combines behavioural and socio-demographic variables. The results show that the socio-demographic variables have no impact on behaviour and the creation of segments. It can be deduced that the behavioural variables are much more important when predicting behaviour. In this respect, the most important variable is trust. In line with previous studies on the adoption of electronic commerce, trust is a fundamental attribute when it comes to adopting and expanding the online channel for shopping (Alalwan *et al.*, 2017; Chandra and Jhonsons, 2019). The next most important variables in behaviour prediction are habit and performance expectancy (Escobar-Rodríguez and Carvajal-Trujillo, 2013). Lastly, hedonic motivation, effort expectancy and technophobia also significantly influence the formation of segments. Hence, there are four facilitating factors and two opposing factors.

Regarding the created segments, two extreme segments stand out due to their marked differences and high volume. Segment 3 with 23% of the sample is the group with most predisposition to use the online channel and is characterised by a high level of trust, more habitual use in comparison with other groups and the belief that its use implies high performance, which indicates they believe it to be useful, quick, and helpful for more an effective shopping experience. The other extreme is found in segment 7. This group makes up 17.7% of the total and is the most reluctant to use the online channel. These users are characterised by the complete opposite: they have a low level of trust in this channel. However, the effort expectancy is low, i.e. they consider that the adoption of the online channel does not involve many difficulties in its learning and use. Nevertheless, they use it less regularly than the others. Segments 6 and 2 are found within the median interval regarding the level of predisposition. Segment 6 has low trust in e-commerce and high effort expectancy, that is, they find it more difficult than the rest to understand and use these new tools. Furthermore, they are greatly influenced by their technophobia. On the other hand, segment 2 has high trust, but low habit and low hedonic motivation. Additionally, four segments were created, two of which have a high level of adoption for the most part (segment 4 and segment 1). The other two have a low adoption level in general (segment 2, segment 5 and segment 8).

5.3 Practical implications

The results of the present research also have important managerial implications based on the need to segment consumers to ensure the effectiveness of marketing policies in an environment that is in continuous change and with a high level of competition (Ruiz-Molina *et al.*, 2021). Therefore, the present work contributes in a general way to: (1) Analysing the intention to use e-commerce platforms from a set of antecedents previously defined by their importance, after a period of economic and social restrictions derived from the pandemic; (2) Determination of customer segments from the classification made by the CHAID analysis; (3) Characterisation of the previously defined segments through the successive divisions that were proposed in the analysis carried out.

During the pandemic, a large part of the population changed many consumer habits. Among them, the consumer turned to the electronic channel for shopping. This continues to have an impact on their current shopping behaviour. Consumers are more inclined to shop online and to use apps. This change in shopping behaviour has significant implications for companies operating in the e-commerce environment. In the light of the results obtained from the analysis, the importance of trust, habit, effort expectancy, hedonic motivation, performance expectancy and technophobia, as variables that allow the classification of the analysed sample, is demonstrated.

It is essential to build trust with the user and show them the real benefits of e-commerce, how it would improve their life and why they should use it. Additionally, it is vital that the user perceives it as an easy procedure that does not require a significant learning curve. All of this provides a series of facilities to modify the online shopping habits of users. Other fundamental aspects would be to reduce any uncertainty the user might have about the online shopping process, to make it as easy as possible and to design a simple, intuitive, and user-friendly interface. It is also recommendable to manage the data usage efficiently. To do so, we recommend asking the user for the least amount of information possible, offering a data protection policy and assuring them that their information will not be misused nor shared with third parties. These strategies are essential to build user confidence and promote a positive online shopping experience.

In addition to the general recommendations given above, each segment has some characteristics in common with different groups and others that are unique (Wedel and Kamakura, 2002), and therefore require specific marketing actions to improve the adoption of each one of the groups. For example, segment 7 has great growth potential since we observed that they find it easy to learn and use these tools, however, it is essential that their trust improves and progressively modify their shopping habits. Segments 4 and 1, whose intention of use is high, could be improved by focussing on their lower values. In segment 4, it is recommendable to focus on improving the performance expectancy that is, convincing the user of its utilities and benefits. For segment 1 it is essential to create habit. Although they enjoy shopping online and using the electronic channel, they do not do it regularly and have not incorporated it into their shopping habits. On the other hand, segments 2, 5 and 8 have low adoption. However, segment 2 has high trust, which has the most important predictor. This segment needs to normalise the use of the electronic channel and turn their shopping experience into a fun and entertaining activity that is seen as something positive. In turn, for segment 5, with low trust, high effort expectancy and low technophobia. Comparatively, they have the worst values in each the significant variables. Lastly, in the case of segment 8, the strong point is their high habit and low effort expectancy, but its weak point is the trust in said tool, therefore it should be improved.

In conclusion, these findings can be used by all companies marketing their product or service online, considering which variables are most important to the consumer and improving them accordingly.

5.4 Limitations and future research

As in most of the research, this study presents a series of limitations that should be debated and that could open future lines of investigation. Firstly, regarding the sample used that was limited to two neighbouring countries with similar profiles *a priori*; it would be necessary to compare their possible cultural differences according to Hofstede's dimensions as well as increase the number of European countries being analysed to reach more generalised conclusions.

Secondly, the variables used are a combination of those derived from the UTAUT2 model and others suggested in literature as decisive in technology adoption by users, in this sense other theories and variables could be incorporated to complete a more holistic model. For example, using psychographic, geographic, product and financial variables or even other variables related to the navigation through the different e-commerce websites (navigation, presentation, or brand).

With regards to the data collection method, a cross-sectional investigation has been carried out which prevents analysing the evolution of user behaviour over time. A longitudinal approach would allow for the verification of the sturdiness of the relationships and constructs established, and the evolution of the obtained results from a temporal perspective.

Lastly, it would be interesting to consider, from the perspective of consumer behaviour studies, the implementation of new measurements through other methodologies in such a way that would allow for the broadening of the conclusions through data mining or big data techniques.

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