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Intention to use e-commerce vs physical shopping. Difference between consumers in the post-COVID era

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ABSTRACT

The increase in the widespread use of e-commerce reveals a greater tendency towards online shopping. The objective of this research is to analyze the drivers and barriers of online channel usage intention and their implications for physical channels, based on a modification of the UTAUT2 model, as well as to identify the relevant segments of e-commerce consumers versus physical shoppers in the post-COVID-19 era, using Hierarchical Tree Regression applying the CHAID method through an online questionnaire on a final sample of 491 Portuguese and 345 Spanish users. The results confirm the differences in the adoption of the use of electronic channels between the two countries, the absence of influence of most socio-demographic variables on intention, and the importance of behavioral variables in the definition of segments in both populations. Finally, strategic recommendations are made for each of the identified groups to improve the intention to use e-commerce platforms.

1. Introduction

The pandemic provoked by COVID-19 and the effects it has had on health, society and the economy are producing a change to the buying habits of consumers in numerous sectors (Dionysiou et al., 2021; Bazi et al., 2022). Given this situation, it seems evident that the restrictions that countries have implemented caused a significant economic slowdown in most of the world during the years 2020 and 2021, which favored digital business activities which experienced a strong increase (Shareef et al., 2021; Modgil et al., 2022). In this sense, one of the highlights of this pandemic situation has been the increase in the widespread use of e–commerce, which revealed itself as one of the main solutions adopted by consumers to access the purchase of products and services, even among those who do not usually make use of these forms of acquisition (Nicewicz & Bilska, 2021; Kawasaki et al., 2022).

According to data published by the Spanish Foreign Trade Institute (ICEX, 2021), 84.5 % of households in Portugal had access to the Internet in 2020, that is, 3.6 percentage points more than in 2019. Likewise, the Internet penetration rate among the Portuguese population between the ages of 16 and 74 increased, going from 76.2 % in 2019 to 78.3 % in 2020 and, the penetration rate of online buyers was 56 %, below the EU-27 average of 72 %. According to Statista, Portugal ranked 43rd in the world income level in the B2C e-commerce market, with a turnover of € 3,054 M in 2020, experiencing a growth of 19.5 % compared to 2019. According to CaixaBank Research (2021), these figures show a reduction in in-store purchases and the willingness of Portuguese consumers to respect social distancing. This is also confirmed by Eurostat data (2021), where the percentage of people between the ages of 16 and 74 who made online purchases of goods and services over the last 12 months increased to 45 % in 2020 (it was 39 % in 2019), well above past growth trends. Portuguese adopters consider that the most important e-commerce qualities are detailed information, timeliness, ease of comparison and comfort (Oliveira & Reis, 2006).

On the other hand, in Spain, according to the National Statistical Institute (INE, 2021) 93.9 % of the population aged 16 to 74 has used the Internet in the last three months, 0.7 points more than in 2020. This represents a total of 33.1 million users. Internet use is a majority practice among young people aged 16 to 24, with 99.7 % for men and 99.6 % for women. Following Valarezo Unda et al. (2021), the Spanish online consumer is an employed male, with higher education and income levels and digital skills. As age increases, Internet use decreases in both men and women, with the lowest percentage corresponding to the group aged between 65 and 74 years old (74.6 % for men, and 72.0 % for women). Furthermore, according to the Spanish National Markets and Competition Commission (CNMC, 2022), e-commerce in Spain reached a turnover in the second quarter of 2021 that was 13.7 % higher in year-

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on-year terms, accruing a total of € 13,661 M, according to the most recent e-commerce data available on the website. Factors of concern include ease of access, detailed information, privacy and security and reliability (Gutiérrez-Rodríguez et al., 2020), as well as e-trust and online skills (Fernández-Bonilla et al., 2022), among other things.

The contribution made by this research is threefold. First, it addresses a gap in the recent academic literature by analyzing the drivers and barriers to e-commerce adoption by integrating into the UTAUT2 model other related variables analyzed in the scientific literature. In this sense, recent research has proposed different reviews of the importance of the UTAUT2 model (Taneja & Bharti, 2021; Tamilmani et al., 2021), concluding that it is one of the models most employed by the scientific literature in the study of technology adoption as well as in the use of new variables to improve its predictive capacity (Yawised et al., 2022; Kuriakose et al., 2022; Migliore et al., 2022). Secondly, although it is true that the adoption of e-commerce has been analyzed on different occasions, this research is novel because of the comparative analysis between two countries that are very close and with very similar behavior such as Spain and Portugal (Hofstede Insights, 2022). Thirdly, we contribute different findings for Spain and Portugal from the use of Hierarchical Tree-bases Regression (HTBR) in the definition of the profiles of online shoppers and physical shopping in both countries independently and comparatively after the end of the COVID-19 pandemic.

To understand the evolution of this online shopping trend, our research will be broken down into two sequenced stages. During the first stage we will analyze the factors assisting the adoption of electronic commerce in Spain and Portugal by preparing user profiles, continuing during the second stage to analyze the barriers that this sales format poses for users and how these affect the purchase intention in traditional commerce, once again defining customer segments.

To carry out this research we have elected to analyze side-by-side the adoption of e-commerce and that of traditional commerce using a broad theoretical framework. To analyze e-commerce, an analysis of a set of facilitators from the expanded UTAUT2 model is proposed, including trust as a fundamental element promoting or reducing the intention to make online purchases. Secondly, to analyze the intention to purchase in traditional stores, a set of variables relating to the barriers that users can encounter in e-commerce, and which consequently favor the use of traditional commerce is proposed. Finally, we have included some socio-demographic variables that previous research has verified as determinants when users are selecting the purchase channel. Specifically, addressing the following research questions are proposed:

RQ1: Based on the classic models of technology adoption, and more specifically the Unified theory of acceptance and use of technology 2 (UTAUT2), extended using trust and the suggested socio-demographic variables, it is proposed to analyze the profile of Portuguese and Spanish users regarding e-commerce.

RQ2: In parallel, it is proposed to analyze the behavior of Portuguese and Spanish users regarding traditional commerce from the perspective of the barriers that these users display regarding e-commerce.

RQ3: Discover whether there is an unobserved heterogeneity in consumer behavior and, if so, find relevant segments of e-commerce consumers versus physical shoppers in the post-COVID-19 era.

RQ4: Once the different behavioral segments influenced by the suggested dependent variables have been identified, a series of recommendations are made for improving e-commerce strategies for platforms and retailers to enhance consumer user intention.

To increase our understanding of consumer engagement in online and traditional shopping in Spain and Portugal and the relevant segments arising from them, we will use in both situations a set of classic variables to improve awareness of the differences between the profiles of Spanish and Portuguese buyers in the post-COVID-19 era. To this end, Hierarchical Tree-bases Regression (HTBR) will be used to determine the mutually exclusive and exhaustive subgroups of the target variable whose members share common characteristics.

To validate these research questions, an online survey was carried out with a final sample of 345 Spanish users and 491 Portuguese users in June and July 2020. The results reveal that the use of the proposed segmentation technique allows for the configuration of different segments of consumers when analyzing the intention to use e-commerce and physical stores in both the Spanish and Portuguese populations. Furthermore, significant differences were found between the average intention to use an online channel and the average intention to continue buying in physical stores between Spanish and Portuguese citizens. Finally, the socio-demographic variables influencing the formation of the segment were defined to predict behavior towards e-commerce or continuing to purchase in physical stores, which differ between one population and the other.

This research is developed as follows: in section two, a review of the literature is carried out based on the models of technology adoption and the proposed socio-demographic variables. Section three describes the methodology used for data collection, questionnaire design and analysis. Sections four and five show the analyses carried out, as well as the results obtained. Finally, in the last section, a discussion of the results, along with the implications, limitations, and future lines of research, respectively, is undertaken.

2. Literature review

In this section we review the literature corresponding to the UTAUT2 model understood as the e-commerce facilitators; then, we refer to barriers to e-commerce adoption and promoting traditional commerce; further on, we explain the role of sociodemographic variables in segmentation and, finally, we summarize these variables graphically in Fig. 1.

2.1. E-commerce facilitators: Extensions of the UTAUT2 model in e-commerce

There are multiple reviews that have used different technology adoption models over recent years (Patil et al., 2020; Tamilmani et al., 2020; Cabrera-Sánchez et al., 2021). Research has used anything from classical theories, such as the Theory of Reasoned Action (TRA; Fishbein; Ajzen, 1975; subjective norms, attitude, intention and use); the Theory of Planned Behavior (TPB; Ajzen, 1991; subjective norms, perceived control, attitude, intention and use); the Diffusion of Innovations (DOI) theory (Rogers, 2010; relative advantage, compatibility, complexity, testability and observed effects); and the Technology Acceptance Model (TAM; Davis et al., 1989; ease of use, usefulness, attitude, intention and use), to the Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh et al., 2003), which includes determinants such as performance expectancy, effort expectancy, social influence and other conditions facilitating acceptance, and the influence of gender and age, as well as experience and use.

Subsequently, the UTAUT model was expanded by emphasizing the hedonic value (intrinsic motivation) of users towards technology and incorporating three new constructs: hedonic motivation, price value and habit; this expanded model is popularly known as UTAUT2 (Venkatesh et al., 2012). Specifically, UTAUT2 and its subsequent extensions have recently been defined in the scientific literature as one of the most used models to analyze the innovation adoption process (Tamilmani et al., 2020). UTAUT2 theory is important for both researchers and practitioners (Tamilnmani et al. 2021) since it is a rigorous theory with well-defined parts that appeals to both the academic and professional communities, so it has been selected as a theoretical framework for this research. In line with Singh et al. (2020), UTAUT2 is considered appropriate for this study compared to other technology acceptance models, given that it allows for a better explanation of various constructs for measuring behavioral intent.

Based on the original model, there have been several research proposals that have expanded it in different fields (Kalinić et al., 2020). The research proposal for this study expands UTAUT2 adding trust in line

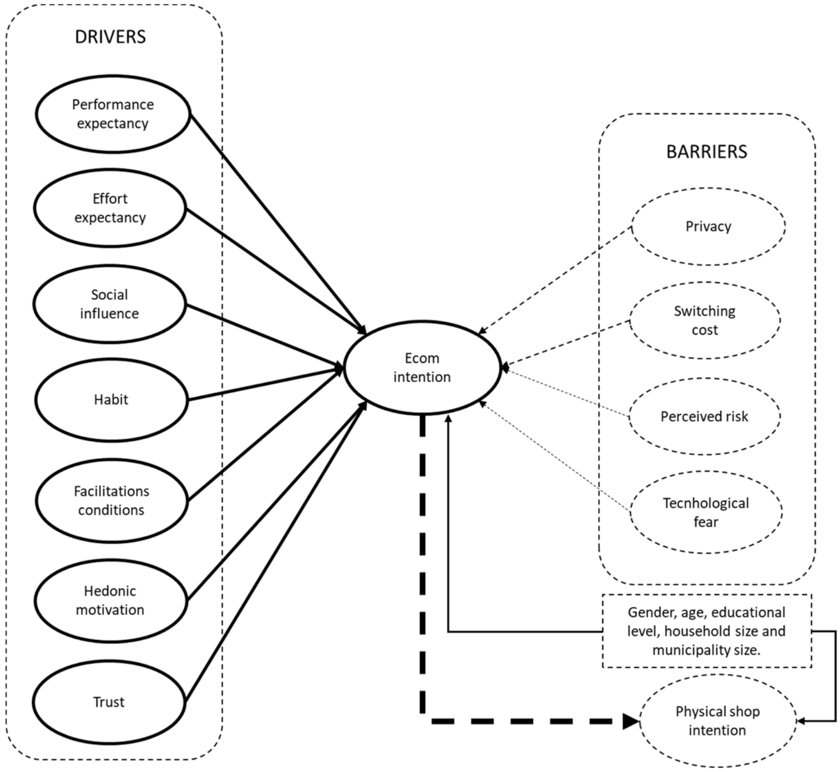

Fig. 1. Summary of the theoretical framework.

with the proposals of different researchers (Alalwan et al., 2017; Odusanya et al., 2019; Sim et al., 2021), since e-commerce is considered as an uncertain service.

Consequently, our research proposes the inclusion of the UTAUT2 model's variables extended with trust. These variables are defined in Table 1.

Table 1
Variables included in the e-commerce adoption analysis.

Variable	Definition	Author
Performance expectancy	The degree to which the use of a technology will provide benefits to users from its use.	Venkatesh et al. (2012)
Effort expectancy	The degree of ease associated with the use of technology by the customer using the technology.	Venkatesh et al. (2012)
Social influence	The individual's perception where the referents desire the individual to perform or not perform a behavior in question.	Venkatesh et al. (2003)
Habit	The degree to which people tend to perform behaviors that are automatic, based on learning.	Limayem et al. (2007)
Facilitation conditions	Describes the perceived importance of organizational and technical infrastructure to support systems use.	Venkatesh et al. (2003)
Hedonic motivation	Fun or pleasure derived from using a technology or system, and it is an important determinant of a consumer's technology acceptance and sustained use.	Tamilmani et al. (2020)
Trust	Trust refers to a subjective belief that a party will fulfil their obligations. It plays a crucial role in electronic financial transactions, where users are exposed to larger risks due to the uncertainty of the environment and a sense of loss of control.	Lu et al. (2011)

2.2. Barriers to e-commerce adoption and promoting traditional commerce

The COVID-19 pandemic has posed many challenges for businesses and also for consumers. Physical restrictions related to the COVID-19 pandemic meant limiting mobility. This caused a change in many buying habits, diverting them from traditional channels to online channels, fulfilling Cairncross's prediction (2001) regarding the death of geography in retail activities (Koch et al., 2020; Beckers et al., 2021).

In this sense, during the pandemic period consumers consider that making purchases online is a safer alternative to avoid coming into contact with the virus than in a physical store (Fihartini et al., 2021). Many studies have shown that, despite technological advances, its acceptance and influence on creating online purchase intent is limited in many sectors (Habib & Hamadneh, 2021), for example, due to factors such as perceived risk and consumer trust in online transactions. That is why it is essential to identify the barriers considered by buyers when deciding to use online commerce to meet their needs. To this end, a set of variables considered as barriers to the adoption of e-commerce systems were selected from a focus group with customers of the proposed nationalities. Specifically, the following were proposed as the main barriers: privacy, cost of change, perceived risk, and fear of technology.

Prior research indicates that, despite concerns about the privacy of online shoppers, they sometimes readily disclose their personal data or simply fail to consider all the recommended security measures (Kokolakis, 2017). This situation, whereby consumers behave contrary to their stated privacy concerns, is widely known as the privacy paradox (Dienlin & Trepte, 2015; Norberg et al., 2007). Therefore, we understand that privacy is a barrier when it comes to adopting e-commerce, being critical in the decision to purchase using traditional commercial channels (Bandara et al., 2020). A survey has revealed that 8 out of 10 users are worried about their personal data online (Ram Mohan Rao et al., 2018). In addition, there is a personal right to privacy which extends to protect e-commerce users' data privacy (Rajaretnam, 2022). It is therefore essential to take this into account.

Switching costs are the costs that a consumer incurs because of changing a service or product or the supplier of the same (Chang et al., 2014). Switching costs include the potential expenses and losses associated with the switch (Kim & Kankanhalli, 2009). Therefore, as these drawbacks increase, users are more likely to be reluctant to use a technology (Kahneman & Tversky, 2013; Hsieh, 2015), in our case e-commerce, and decide to continue buying using traditional commercial channels. Finally, the literature has demonstrated the importance of switching costs in e-commerce (Campbell, 2019).

Customer behavior explains perceived risk as a perception of the adverse consequences deriving from a particular behavior and the perception of uncertainty (Rehman et al., 2020). Perceived risk has been defined as the uncertainty of the customer associated with purchasing a product or service and the negative consequences deriving from it (Liébana-Cabanillas et al., 2020), more specifically regarding purchases made online (Herzallah et al., 2021). The perceived risk negatively affects customers' online shopping intentions (Ahmed et al., 2021). However, Arora and Rahul's (2018) research shows that perceived risk is not a significant factor influencing women's attitudes in India. Finally, numerous studies have shown how fear of technology is a driving force in decreasing enthusiasm to adopting said technology (Alhumaid et al., 2021). Despite the widespread use of technology by consumers in their daily lives, the fear of it, also called "technophobia" and "technology avoidance", remains a significant problem among the majority of the population worldwide (Martínez-Córcoles et al., 2017; Cabrera-Sánchez et al., 2021). A fear of the consequences of using e-commerce can hinder its adoption, and this situation can give rise to a feeling of insecurity and intimidation, its use being reduced. Furthermore, fear is a major barrier to intent to use, as proved by Heinssen Jr. et al (1989) and Cabrera-Sánchez et al. (2020).

2.3. Socio-demographic characteristics as segmentation variables

As far as socio-demographic variables are concerned, and in line with previous research related to technological innovations (Pobee & Opoku, 2018; Marinković et al., 2020; Handarkho, 2020), the gender, age, education level, household size and municipality size of the different users were analyzed.

The moderating effect of gender relating to technology adoption has been extensively reviewed in numerous studies (Kanwal et al., 2021). Much research has reported that men tend to be more motivated in tasks relating to achievements, such as utility, when making adoption decisions, while women are highly motivated and influenced by ease of use (Venkatesh & Morris, 2000). Traditionally, men have been more likely to engage in e-commerce than women (Liébana-Cabanillas et al., 2014). At the same time, men seem to have a higher degree of IT self-efficiency than women (Ong & Lai, 2006).

On the other hand, users' age also has a significant impact on their behavior regarding the adoption of a technology (Liébana-Cabanillas et al., 2021; Molinillo et al., 2021); in this sense, some studies have identified a positive relationship between the age of the consumer and their probability of buying online (Stafford et al., 2004), while others obtained negative results (Joines et al., 2003). In our view, these different opinions may be due to various factors such as cultural, temporal, and other factors.

In parallel, education level has also been studied as a determining factor in consumer behavior regarding technology (Ou, 2007). In this sense, individuals with a better education level will be more exposed to technologies and will develop a greater predisposition towards them (Sánchez-Torres et al., 2017).

Furthermore, the effect of household size has also been investigated. Various studies have shown that the greater the number of family members is, the greater the probability of using an online shopping service is (Wang & Somogyi, 2019), although other proposals state the opposite, arguing that the greater the number of family members is, the greater the probability that individuals are available to go to the market and buy food in a traditional manner is (Dominici et al., 2021).

On the other hand, the municipality size is also related to the adoption of innovations. Some studies have positively related size to adoption intention arguing that since firm size significantly affects adoption, the relationship between city size and firm size should also have an impact on the diffusion of innovations (Diebolt et al., 2016). Studies have predicted an early adoption of the larger city size as it offers a higher probability of receiving information about the innovation (Pedersen, 1970) and consequently being adopted.

3. Methodology

3.1. Sample and data collection

Data collection was carried out through a self-administered, pre-coded online questionnaire. First, a pre-test was conducted among expert researchers and potential participants to ensure that the survey was well conceptualized. Data were collected during June and July 2020 through convenience sampling whose target population had to have made an online purchase in the last three months. The valid response rate was 94 %. After the necessary data cleaning, the final sample consists of 491 Portuguese and 345 Spanish participants. The socio-demographic characteristics of the sample are shown in Table 2.

3.2. Measurement scales

All measurement scales used were adapted from previous studies. The variables used to segment the intention to buy using e-commerce are mostly from the UTAUT2 model. Specifically, they are performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, and habit. They were adapted from Venkatesh et al. (2003), Davis (1989) and Venkatesh et al. (2012). In addition, trust in e-commerce adapted from Pavlou and Gefen (2004).

On the other hand, the following variables, which are considered as e-commerce detractors and, therefore, facilitators to shopping in physical shops were applied to the segment regarding the intention to continue shopping in physical shops. Fear of technology (Heinssen Jr. et al. 1987), privacy risk and perceived risk (Featherman & Pavlou, 2003) and switching cost (Hsieh, 2015). Moreover, the socio-demographic variables were included. The measurement scales are detailed in Annex.

Table 2
Sample characteristics.

	Portugal		Spain	
Gender	**N**	**%**	**N**	**%**
Male	220	44.8	234	67.8
Female	271	55.2	111	32.2
Age				
Up to 40 years old	329	67	76	22
More than 40 years old	162	33	269	78
Education				
Lack	9	1.8	–	–
Primary	213	43.4	12	3.5
Secondary/ Bachelor	173	35.2	91	26.4
University	78	15.9	159	46.1
Post-graduate	15	3.1	83	24.1
Household size				
Up to 3 people	297	60.5	180	52.2
More than 3 people	194	39.5	165	47.8
Municipality size (inhabitants)				
<10,000	97	19.8	22	6.4
10,000–20,000	116	23.6	59	17.1
20,000–50,000	78	15.9	99	28.7
50,000–100,000	71	14.5	129	37.4
100,000–500,000	79	16.1	33	9.6
greater than500,000	50	10.2	3	0.9

3.3. Data analysis

Hierarchical Tree-bases Regression (HTBR) is applied for data analysis. HTBR appeared in the 1960 s in a study by Morgan and Sonquist (1963). It is a non-parametric statistical technique that determines mutually exclusive and exhaustive subgroups of the target variable whose members share common characteristics. This procedure has proven to be a powerful tool for dealing with prediction and classification problems (Lemon et al., 2003). Therefore, it is an efficient method to explore the relationship between dependent and independent variables. HTBR creates a tree-based classification model using the CART (Classification and Regression Trees), CHAID (Chi-squared Automatic Interaction Detection) or QUEST (Quick, Unbiassed, Efficient and Statistical Tree) algorithm.

The HTBR methodology does not require variables to be selected in advance since it uses a stepwise method to determine the optimal splitting rules. In this case, the CHAID method is applied which constructs regression-type trees that allow for splits in which each (non-terminal) node identifies a splitting condition to produce an optimal prediction (Breiman et al., 1984). In this way, node formation and segment configuration are carried out, ending when there is no significant relationship between the criterion and the explanatory variables. Finally, the HTBR technique is suitable since it treats nonadditive and nonlinear behavioral data better than other methods like ordinary least squares regression. Furthermore, HTBR can handle mixed mode (discrete and continuous) independent variables more optimally. In addition, HTBR is much more effective in dealing with multicollinearity since it handles it automatically within the tree construction process (Washington & Wolf, 1997). The HTBR methodology and specifically CHAID has been applied in the field of marketing. For example, to explain the profile of users of a bicycle-sharing system (Molinillo et al., 2020), and of carsharing of battery-powered electric vehicles (Wang et al., 2017). It has also been applied in the digital environment, for example, in e-mail marketing (Qabbaah et al., 2019) or in mobile banking (Wang & Petrounias, 2017), as well as in the context of tourism (Agapito et al., 2012; Amir et al., 2015).

4. Results

The results obtained reveal that the CHAID algorithm technique shows a significant relationship when analyzing the intention to use e-commerce or physical shopping in both the Spanish and Portuguese population. Prior to this analysis, the reliability and validity of the measurement scales used were tested, giving satisfactory values in all cases. In addition, a test of mean differences was carried out to analyze whether there are significant differences between the average intention to use online channels between Spanish and Portuguese participants and the average intention to continue shopping in physical shops between Spanish and Portuguese participants. The results show that there are significant differences in the first case, if the intention to use the online channel is higher in Spain than in Portugal, while in the second case no significant differences were found.

4.1. Spanish e-commerce intention

In this segmentation analysis, the dependent variable or criterion is e-commerce intention. The independent variables are socio-demographic: gender, age, education level, household size and municipality size. The behavioral variables from the UTAUT model are performance expectancy, effort expectancy, social influence, habit, facilitating conditions, hedonistic motivation, and trust in e-commerce. When there are variables with a high level of reliability, summary variables can be obtained, so the mean of the items of each variable was calculated (Rifon et al., 2005). Then, based on the mean of each of the variables concerned, the behavioral variables were re-coded by establishing a “high” and “low” hierarchy in order to facilitate their interpretation.

The final tree structure (Fig. 2) assumes three splitting variables: habit, trust, and effort expectancy. Therefore, only these three variables imply significant differences in segment formation. The rest of the variables do not influence the dependent variable.

The first split refers to habit, starting at node 0 (Chi-square = 105.747; df = 1; p-value = 0.000). The root node is divided into two subsidiary nodes: node 1 (low habit) and node 2 (high habit). At the second level, the best predictor for node 1 (low habit) is effort expectancy (Chi-square = 10.100; df = 1; p-value = 0.001), while the best predictor for node 2 (high habit) is trust (Chi-square = 7.284; df = 1; p-value = 0.007). Both are subdivided into high and low trust.

The characteristic profile of the terminal nodes is detailed below:

- Segment 1 (node 3). This is the smallest group with 15.4 % of the sample. 61.3 % of users have a low adoption intention to use e-commerce. They are characterized by low usage habits and high effort expectancy.
- Segment 2 (node 4). This group is the largest with 34.8 % of the total. In this case, 84.2 % of them have a low intention to use e-commerce. Their behavior is determined by low habit and low effort expectancy.
- Segment 3 (node 5). This is the second largest group with 33.9 % and has the highest average intention, since 83.8 % of them have a high intention to adopt. This segment has high habit and high trust towards e-commerce.
- Segment 4 (node 6). This group is made up of 15.9 % of the sample. They have a high habit, but low trust in the online channel. In this group, 65.5 % have a high adoption intention.

The risk estimate, as a measure of the tree’s goodness of prediction, is 0.223 (22.3 %). Therefore, it can be affirmed that the analysis allows the correct classification of 77.7 % of the cases; in such a way that the tree has a very good predictive capacity, since it exceeds the limit recommended by Luque (2014).

4.2. Spanish physical shop intention

In this segmentation analysis, the dependent variable or criterion is intention to shop in physical shops. The independent variables are the socio-demographic variables: gender, age, education level, household size and municipality size and the behavioral variables are privacy, switching cost, perceived risk, and fear of technology. When there are variables with a high level of reliability, summary variables can be obtained, so the mean of the items of each variable was calculated (Rifon et al., 2005). Then, based on the mean of each of the variables, the behavioral variables were re-coded by establishing a “high” and “low” hierarchy to facilitate their interpretation.

The final tree structure involves two splitting variables: switching cost and perceived risk. Therefore, only these two variables imply significant differences in segment formation. The rest of the variables do not influence the dependent variable (see in Fig. 3).

The first split refers to switching cost, starting at node 0 (Chi-square = 35.652; df = 1; p-value = 0.000). The root node is divided into two branch nodes: node 1 (low switching cost) and node 2 (high switching cost). At the second level, the best predictor for node 2 (high switching cost) is perceived risk (Chi-square = 10.404; df = 1; p-value = 0.001). This node is also subdivided into high and low perceived risk.

The characteristic profile of the terminal nodes is detailed below:

- Segment 1 (node 1). This is the most numerous groups with 49.3 % of the sample, where 63.5 % of them have a low predisposition to continue shopping in physical shops. These users are characterized by a low cost of switching from the traditional channel to the electronic channel.
- Segment 2 (node 3). This group has the lowest volume with 18.8 % of the total. Out of these, 53.8 % have a high intention to continue

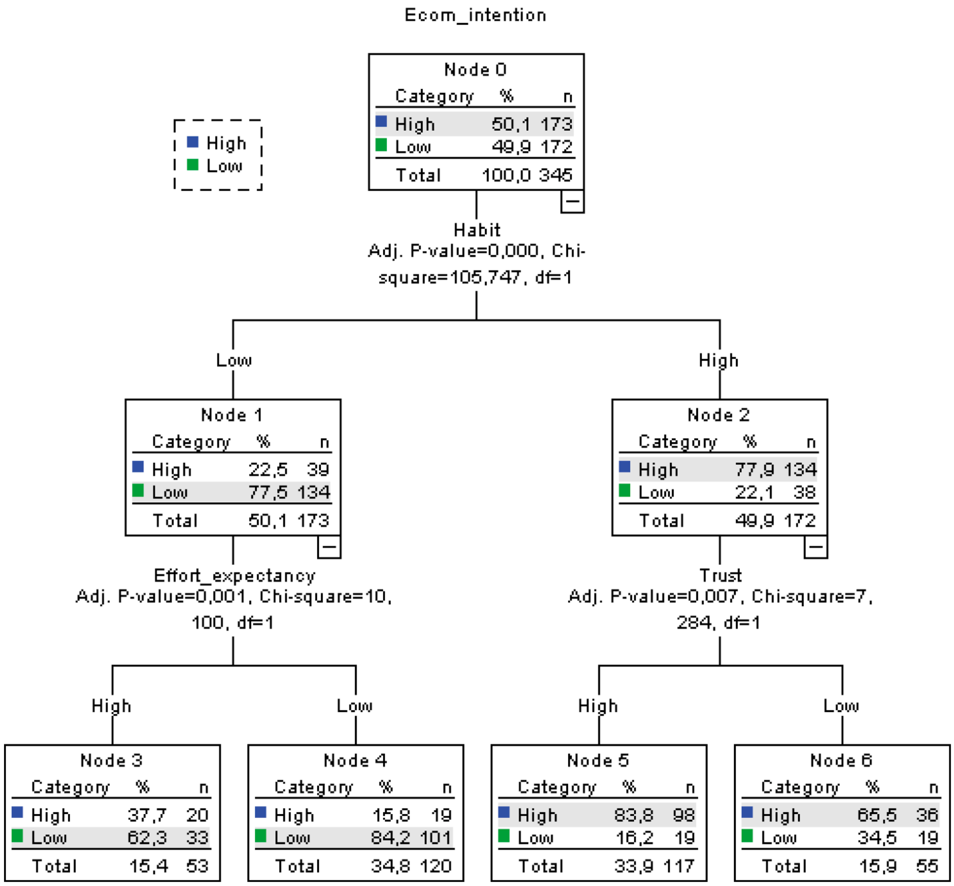

Fig. 2. CHAID results for Spanish e-commerce intention.

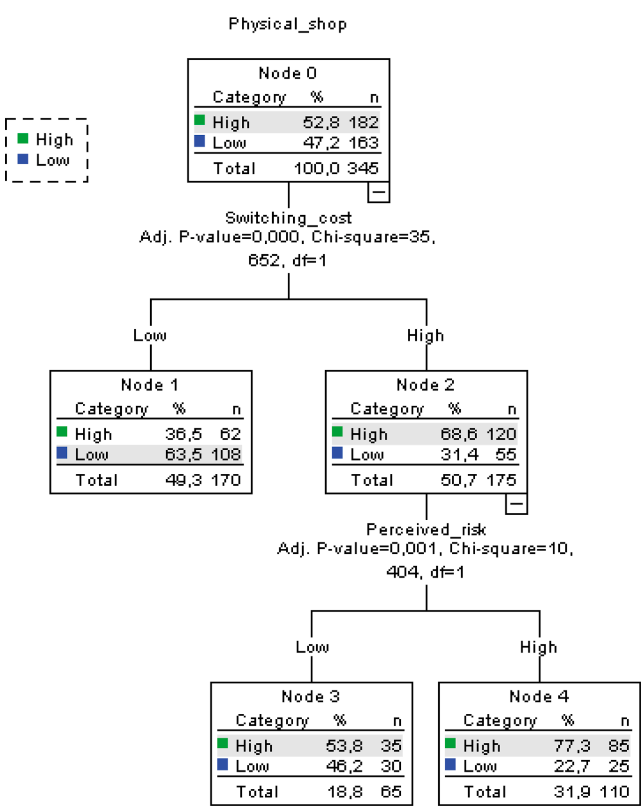

Fig. 3. CHAID results for Spanish physical shop intention.

shopping in physical shops. Their behavior is determined by a high switching cost, but low fear of technology.

- Segment 3 (node 4). Consists of 31.9 % of the sample and has the highest average intention since 77.3 % of them have a high intention to continue shopping in physical shops. This segment has a high switching cost and high fear of technology.

The risk estimate, as a measure of the tree's goodness of prediction, is 0.339 (33.9 %). Therefore, it can be affirmed that the analysis allows 66.1 % of the cases to be classified correctly, in such a way that the tree has a good predictive capacity, since it exceeds the limit recommended by Luque (2014).

4.3. *Portuguese e-commerce intention*

In this segmentation analysis, the dependent variable or criterion is, once again, e-commerce intention. The independent variables are the same as in the case of the Spanish population. On the one hand, the socio-demographic variables are gender, age, education level, household size and municipality size. On the other hand, the behavioral variables from the UTAUT model are performance expectancy, effort expectancy, social influence, habit, facilitating conditions and hedonistic motivation, as well as trust. Likewise, the procedure is similar. When there are variables with a high level of reliability, summary variables can be obtained, so the mean of the items of each variable was calculated (Rifon et al., 2005). Then, based on the mean of each of the variables, the behavioral variables were re-coded by establishing the hierarchy "high" and "low" in order to facilitate their interpretation.

The final structure of the tree (Fig. 4) involves four splitting variables: trust, facilitating conditions, social influence, and habit. Thus, four variables imply significant differences in segment formation. The

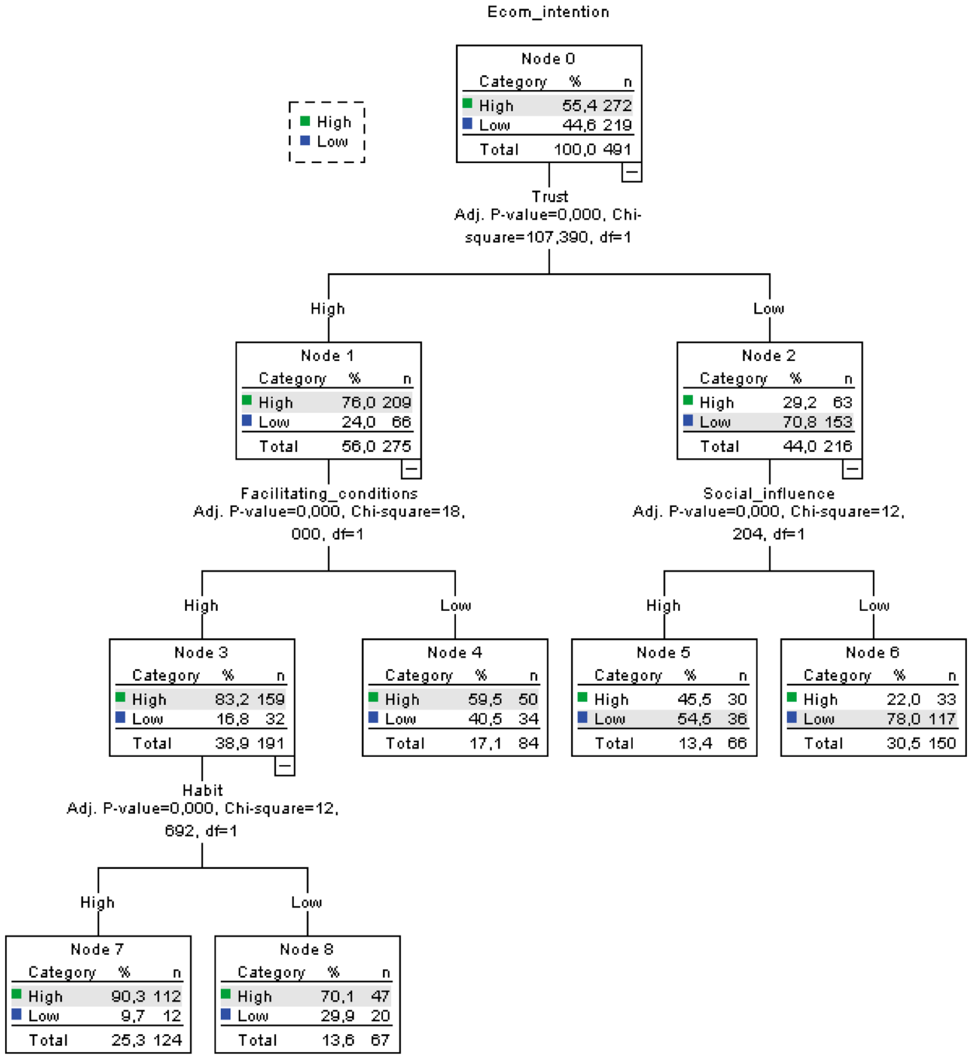

Fig. 4. CHAID results for Portuguese e-commerce intention.

remaining variables do not influence the dependent variable.

The first split refers to trust, starting at node 0 (Chi-square = 107.390; df = 1; p-value = 0.000). The root node is divided into two subsidiary nodes: node 1 (high trust) and node 2 (low trust). At the second level, the best predictor for node 1 (high trust) is facilitating conditions (Chi-square = 18.000; df = 1; p-value = 0.000). While the best predictor for node 2 (low trust) is social influence (Chi-square = 12.204; df = 1; p-value = 0.000). Both are subdivided into high and low. At the third level, the best predictor for node 3 (high facilitating conditions) is habit (Chi-square = 12.692; df = 1; p-value = 0.000). It is also subdivided into high and low habit.

The characteristic profile of the terminal nodes Is detailed below:

- Segment 1 (node 7). This is one of the largest groups with 25.3 % of the sample. Their average intention to use e-commerce is the highest, with 90.3 % being highly predisposed. These users are characterized by high trust in the channel, with the necessary resources to use this tool, i. e., high facilitating conditions and high habit.
- Segment 2 (node 8). This is the smallest group with 13.6 % of the total. In this case, 70.1 % have a high intention to use the online channel. Their behavior is determined by high trust, high facilitating conditions but low habit.
- Segment 3 (node 4). This is made up of 17.1 % of the sample, and out of these 59.5 % have a high intention to adopt. This segment has high trust but low facilitating conditions.
- Segment 4 (node 5). This group consists of 13.4 % of the sample. They have low trust but are highly influenced by the social group. In this case, 54.5 % have a low intention to use e-commerce.
- Segment 5 (node 6). This is the largest group with 30.5 % of the sample, and has the lowest average adoption, with 78 % having a low predisposition. In this case both trust and social group influence are low.

The risk estimate, as a measure of the tree's goodness of prediction, is 0.263 (26.3 %). Therefore, it can be affirmed that the analysis allows 73.7 % of the cases to be classified correctly; in such a way that the tree has a very good predictive capacity, since it exceeds the limit recommended by Luque (2014).

4.4. Portuguese physical shop intention

In this segmentation analysis, the dependent variable or criterion is physical shop intention. The independent variables are the socio-demographic variables: gender, age, education level, household size and municipality size. The behavioral variables from the privacy model, are switching cost, perceived risk, and fear of technology. When there are variables with a high level of reliability, summary variables can be obtained, so the mean of the items of each variable was calculated (Rifon et al., 2005). Then, based on the mean of each of the variables, the behavioral variables were re-coded by establishing the hierarchy "high" and "low" in order to facilitate their interpretation.

The final structure of the tree involves three splitting variables: privacy, fear of technology and gender. Therefore, only these three variables imply significant differences in segment formation. The rest of the variables do not influence the dependent variable (see in Fig. 5).

The first split refers to privacy, starting at node 0 (Chi-square = 88.739; df = 1; p-value = 0.000). The root node is divided into two branch nodes: node 1 (high privacy) and node 2 (low privacy). At the second level, the best predictor for node 2 (low privacy) is fear of technology (Chi-square = 6.153; df = 1; p-value = 0.013). This node is also subdivided into high and low. At the third level, the best predictor for node 3 (high fear of technology) is gender (Chi-square = 4.401; df = 1; p-value = 0.036), which is subdivided into male and female.

The characteristic profile of the terminal nodes is detailed below:

- Segment 1 (node 1). This is the most numerous groups with 54.4 % of the sample. 70.8 % of them have a high intention to continue shopping in physical shops and it is the highest of all segments. These users are characterized by a high fear regarding data privacy.
- Segment 2 (node 5). This group has the lowest volume with 11.2 % of the total. In this case, 87.3 % of them have a low intention to continue shopping in physical shops. Their behavior is determined by a low fear regarding data privacy, but a high fear of technology. Moreover, they are male.
- Segment 3 (node 6). It consists of 13.6 % of the sample where 71.6 % also have a low predisposition. Like the previous one, this segment has a low fear regarding data privacy but a high fear of technology, with the difference that they are women.
- Segment 4 (node 4). Formed by 20.8 % of the total, where the majority (63.7 %) have a low intention to continue shopping in physical shops. They are characterized by a low fear regarding data privacy and a low fear of technology.

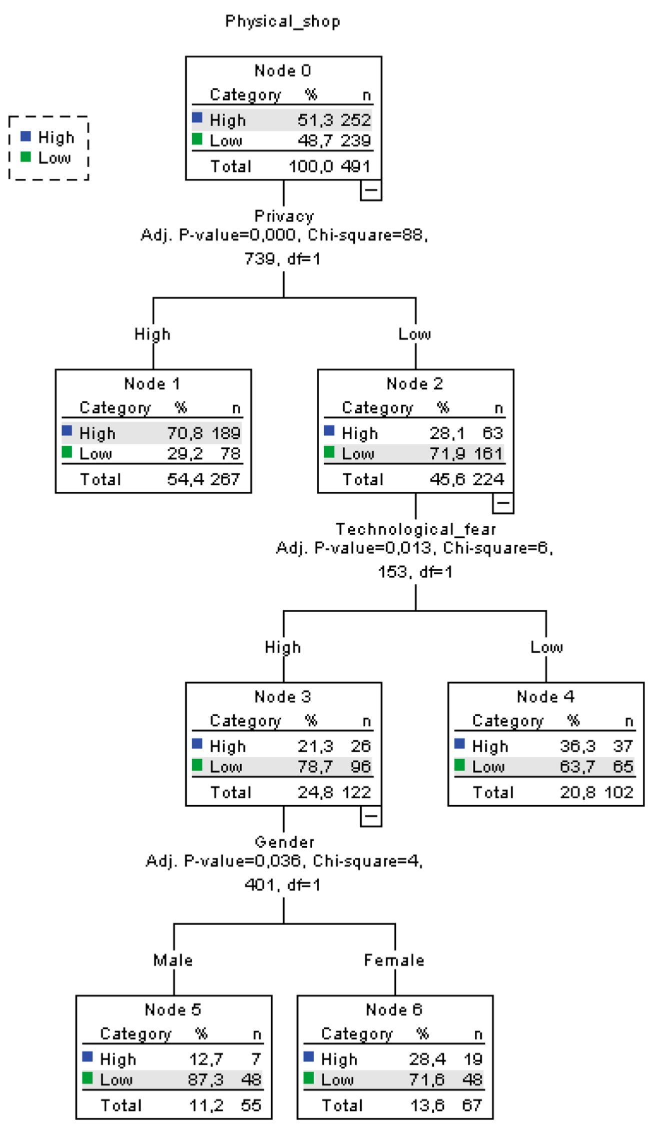

Fig. 5. CHAID results for Portuguese physical shop intention.

The risk estimate, as a measure of the tree's goodness of prediction, is 0.287 (28.7 %). Therefore, it can be affirmed that the analysis allows the correct classification of 71.3 % of the cases; in such a way that the tree shows good predictive capacity since it exceeds the limit recommended by Luque (2014).

5. Discussion

Whilst it is true that e-commerce has increased in importance over recent years as we have had the opportunity to verify, reality shows that offline and online shopping behaviors are different depending on each country's culture. In this sense, an in-depth awareness of buyers' profiles in both scenarios will be essential for designing appropriate commercial strategies to improve companies' profitability.

This study aims to analyze the factors impacting the intent to use e-commerce and the barriers preventing it, and which, therefore, also represent an incentive to continue buying in physical stores. By using the UTAUT2 model extended with trust, the intent to use the online channel is analyzed using Hierarchical Tree bases Regression applying the CHAID method. On the other hand, factors such as fear of technology, data privacy, perceived risk and switching costs work as detractors for using online channels and, therefore, as facilitators for continuing to shop in physical stores. In both cases, the analysis is supplemented with socio-demographic variables such as gender, age, education level, household size and municipality size. This analysis is carried out from a sample composed of Spanish and Portuguese citizens and identifies the type of factors influencing every case and whether the segments created have similarities or differ in each population. The research's theoretical and management contributions are explained below.

5.1. Theoretical contributions

The major social and economic changes experienced in recent years in the face of the health situation resulting from COVID-19 have led to major changes in the purchases of citizens in all the world's economies (Bhatia et al., 2022). Precisely the use of new sales formats such as e-commerce has favored the lack of interaction between buyers and sellers, to a certain extent reducing possible contagions.

This study examines the influence of socio-demographic and behavioral characteristics on the intention to use e-commerce based on two groups of factors (drivers and barriers) and their implications for purchases in traditional commerce. Data were obtained through an online survey of a sample of 491 Portuguese and 345 Spanish users and analyzed using a hierarchical tree-based regression (CHAID) method (Gokhan et al., 2019). Some important results were obtained.

First, the mean difference test concludes that there are significant differences between the mean adoption for using electronic channels between Spanish and Portuguese citizens. The intent of Spanish citizens is greater (4,383) than that of Portuguese citizens (3,826).

Second, the research shows that of most of the socio-demographic variables are not significant when defining behavior. Behavioral variables predominate in the formation of segments in both populations. The following table (Table 3) shows the differences between both commercial formats and populations.

Table 3
Summary of drivers and barriers for both populations.

	E-commerce intention	Physical shop intention
Spain	Habit, trust and effort expectancy	Switching cost and perceived risk
Portugal	Trust, facilitation conditions, social influence and habit	Privacy, technophobia and gender

As can be seen, in the case of e-commerce, the habit and confidence variables appear in the definition of the segments resulting from the application of Hierarchical Tree-bases Regression between both populations. In addition to these variables, effort expectancy in the Spanish case and facilitating conditions and social influence in the case of the Portuguese population are decisive. On the other hand, in the case of intention to use physical shop, the results of the analysis applied to the two countries show there is no common variable. Specifically, the barriers to the use of e-commerce and consequently the intensification of traditional commerce are the cost of change and perceived risk for the Spanish sample and privacy, technophobia and gender for the Portuguese case. The rest of the variables do not influence the dependent variable in any of the cases.

Third, the study reveals that the variables influencing the formation of segments when predicting behaviors towards e-commerce or continuing to shop in physical stores differ between one population and the other. Therefore, this justifies that the segments of each population should receive specific actions based on those aspects that matter most to them.

In general, for the Spanish population, the most important predictor when using e-commerce is habit, followed by trust and effort expectancy, whereas, for the Portuguese population, the most important thing is trust, followed by facilitating conditions, followed by the influence of social groups and habit. On the other hand, the factors most influencing the Spanish user to continue buying in physical stores instead of switching to online channels is switching costs and perceived risk. However, for the Portuguese user, the most important thing is privacy, fear of technology and gender.

Finally, and as explained above, the importance of the extended UTAUT2 model (Kalinić et al., 2019; Agarwal & Sahu, 2022) with the trust variable, improves the explanation of the intention to use e-commerce as the previous literature had proposed (Iqbal et al., 2022), since it has been found to be determinant for both population groups.

5.2. Management contributions

On a practical level, companies or institutions that wish to improve the adoption of online channels, and which are aimed at the Spanish user are recommended to focus their strategy on improving customer habit behaviors. In general, online shopping involves more uncertainty than purchases in physical stores, so it means a change in buying habits. This is related to the finding that switching costs constitutes the main barrier to e-commerce. Therefore, it is important that the user learns and standardizes the activities necessary to make the purchase online. When online shopping behavior becomes normal, the need for undertaking a cognitive assessment of brand perception is eliminated (Chiu et al., 2012). Therefore, if the purchase process is simplified, as indicated in this study, it will improve the intent to use online channels.

When addressing Portuguese users, the importance of trust has been proved. Although for Spaniards it is the second most important factor, in the case of the Portuguese population it differs markedly. Therefore, it is highly recommended that the website be aesthetically pleasing and well-organized with the aim of making it easy for the user to use, as well as offering users the opportunity to recommend the tool or giving the website the capacity to respond to possible queries raised by users. All this will increase trust in e–commerce and also increase sales.

Other important factors for Spanish users are trust and effort expectancy. Therefore, the shopping experience and the web platform should be user-friendly. While for Portuguese users it would be of greater value to work on the facilitating conditions and social influence.

Regarding the factors considered as a barrier to e-commerce or those encouraging the consumer to continue purchasing using traditional channels, we must also carry out an analysis according to each population group. For Spanish citizens, as has already been pointed out above, switching costs and the perceived risk are critical. Therefore, following the above recommendations, an attempt should be made to reduce uncertainty and the effort involved in using these means. However, for the Portuguese consumer, privacy and fear of technology are more important. This has to do with how important it is for them to be able to trust the online channel. Thus, good use of information should be made and be transparent. Finally, it is also advisable to focus efforts on people of the male sex.

5.3. Limitations and future lines of research

Like most research papers, this one shows a series of limitations which should be discussed, and which may involve future lines of research.

In the first place, regarding the context in which the research has been undertaken, the study has been carried out in two population groups which, although they certainly have significant differences, also have significant similarities. In this sense, it is proposed to include other cultures from different continents to contrast and externally validate the results of the current research.

Regarding the data collection method, a cross-section review has been developed which prevents the analysis of the evolution of user behavior over time. A longitudinal approach would make it possible to check the robustness of any conclusions and to verify, from a temporal perspective, the evolution of the effects of the variables analyzed.

Finally, the used methodology refers to a statistical analysis of data collected using a questionnaire, so the research has sample bias. To avoid this type of bias, analyses applying neuroscience techniques could be included, where the analysis of the measures is more objective since it is collected directly from users' psycho-physiological records, although, logically, these measures hinder analysis due to the complexity of the techniques employed and make it more expensive due to their high cost.

CRediT authorship contribution statement

Elena Higueras-Castillo: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Francisco J. Liébana-Cabanillas:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Ángel F. Villarejo-Ramos:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

ANNEX: *QUESTIONNAIRE ITEMS*.

Performance expectancy
I think the E-COM is useful to me in my daily life.
I think the E-COM increases my chances of achieving things that are important to me.
I think the E-COM helps me to make my purchases more quickly.
I think the E-COM improves my shopping performance.
Effort expectancy
Learning to use E-COM tools is easy for me.
My interaction with the E-COM tools is clear and understandable.
I find it easy to use E-COM.
I find learning applications to use E-COM easy for me.
Social influence
The people I care about think I should use E-COM.
People who influence my behaviour think I should use E-COM.
People whose opinion I value and consider think I should use E-COM.
Facilitating Conditions
I have the necessary resources to be able to buy online.
I have the necessary knowledge to be able to shop online.
The E-COM is compatible with other applications I use.
When I have difficulties using the E-COM I can get help.
Hedonic motivation
Shopping online is fun.
I enjoy shopping online.
Shopping online is a lot of fun.
Habit
Online shopping has become a habit for me.
I am an E-COM addict.
I must use E-COM applications.
Using E-COM has become second nature to me.
Trust
E-COM can be trusted.
When I buy online the company delivers what it promises.
Online shopping is about satisfying the user.
Technology fear
I hesitate to buy online as I am afraid of making mistakes that I cannot correct.
I dislike working with machines that are smarter than me.
I am afraid to shop online.
I fear being dependent on E-COM and losing some of my skills.
I feel anxious about shopping online.
I feel insecure about my ability to understand E-COM.
I have avoided shopping online because it is unfamiliar and somewhat intimidating.
I have difficulty understanding the technical aspects of shopping online.
Privacy risk
I am concerned that the information I give you in an online purchase will be misused.
I am worried that someone might find private information about me on the internet.
I am worried about giving personal information to the E-COM because of the use they might make of it.
Perceived risk
Overall, online shopping is risky.
E-COM is dangerous to use.
Shopping online exposes me to risk.
Switch cost
We have already spent a lot of time and effort in mastering the current way of shopping.
E-COM requires a lot of time and effort to switch to the new way of buying.
Switching to E-COM could lead to unexpected costs.
e-commerce intention to use
I intend to use E-COM soon.
I will always try to use the E-COM in my daily life.
I plan to use the E-COM frequently.
Physical shop intention
We will continue to shop in physical shops.
It would be very stressful for me to switch to a new way of shopping.
In our house we like to shop in physical shops the way we do.
I will continue to shop in physical shops even though I know it is not the best way to do. things and that we would get more benefits from ecom.

References

Agapito, D., Do Valle, P. O., & Mendes, J. D. C. (2012). Understanding tourist recommendation through destination image: A CHAID analysis. *Tourism & Management Studies, 7*, 33–42.

Agarwal, V., & Sahu, R. (2022). Predicting repeat usage intention towards O2O food delivery: Extending UTAUT2 with user gratifications and band wagoning. *Journal of Foodservice Business Research, 25*(4), 434–474.

Ahmed, S. Y., Ali, B. J., & Top, C. (2021). Understanding the Impact of Trust, Perceived Risk, and Perceived Technology on the Online Shopping Intentions: Case Study in Kurdistan Region of Iraq. *Journal of Contemporary Issues in Business and Government, 27*(3), 2136–2153.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*, 179–211.

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management, 37*(3), 99–110.

Alhumaid, K., Habes, M., & Salloum, S. A. (2021). Examining the factors influencing the mobile learning usage during COVID-19 Pandemic: An Integrated SEM-ANN Method. *IEEE Access, 9*, 102567–102578.

Amir, S., Osman, M. M., Bachok, S., & Ibrahim, M. (2015). Understanding domestic and international tourists' expenditure pattern in Melaka, Malaysia: Result of CHAID analysis. *Procedia-Social and Behavioral Sciences, 172*, 390–397.

Arora, N., & Rahul, M. (2018). The role of perceived risk in influencing online shopping attitude among women in India. *International Journal of Public Sector Performance Management, 4*(1), 98–113.

Bandara, R., Fernando, M., & Akter, S. (2020). Explicating the privacy paradox: A qualitative inquiry of online shopping consumers. *Journal of Retailing and Consumer Services, 52*, Article 101947.

Bazi, S., Haddad, H., Al-Amad, A., Rees, D., & Hajli, N. (2022). Investigating the Impact of Situational Influences and Social Support on Social Commerce during the COVID-19 Pandemic. *Journal of Theoretical and Applied Electronic Commerce Research, 17*(1), 104–121.

Beckers, J., Weekx, S., Beutels, P., & Verhetsel, A. (2021). COVID-19 and retail: The catalyst for e-commerce in Belgium? *Journal of Retailing and Consumer Services, 62*, Article 102645.

Bhatia, S., Singh, N., & Liébana-Cabanillas, F. (2022). Intermittent continued adoption of digital payment services during the COVID-19 induced pandemic. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2022.2087671

Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). *Classification and regression trees*. Chapman and Hall: Wadsworth Inc., Co. Florida.

Cabrera-Sánchez, J. P., Ramos-de-Luna, I., Carvajal-Trujillo, E., & Villarejo-Ramos, Á. F. (2020). Online Recommendation Systems: Factors Influencing Use in E-Commerce. *Sustainability, 12*(21), 8888.

Cabrera-Sánchez, J. P., Villarejo-Ramos, Á. F., Liébana-Cabanillas, F., & Shaikh, A. A. (2021). Identifying relevant segments of AI applications adopters–Expanding the UTAUT2's variables. *Telematics and Informatics, 58*, Article 101529.

Cairncross, F. (2001). *The death of distance: how the communications revolution will change our lives, No. C20–21*. Harvard Business School.

CaixaBank Research (2021). Comercio electrónico en Portugal a lo largo de la pandemia: ¿un amortiguador para la caída del consumo? Retrieved from https://www.caixabankresearch.com/es/economia-y-mercados/analisis-coyuntura/comercio-electronico-portugal-lo-largo-pandemia-amortiguador.

Campbell, D. E. (2019). A relational build-up model of consumer intention to self-disclose personal information in e-commerce B2C relationships. *AIS Transactions on Human-Computer Interaction, 11*(1), 33–53.

Chang, I. C., Liu, C. C., & Chen, K. (2014). The push, pull and mooring effects in virtual migration for social networking sites. *Information Systems Journal, 24*(4), 323–346.

Chiu, C. M., Hsu, M. H., Lai, H., & Chang, C. M. (2012). Re-examining the influence of trust on online repeat purchase intention: The moderating role of habit and its antecedents. *Decision Support Systems, 53*(4), 835–845.

CNMC (2022). El comercio electrónico supera en España los 57.700 millones de euros en el año 2021, un 11,7% más que el año anterior. Spanish National Markets and Competition Commission. Retrieved from https://www.cnmc.es/prensa/comercio-electronico-iv-2021-20220701#:~:text=El%20comercio%20electr%C3%B3nico%20supera%20en,que%20el%20a%C3%B1o%20anterior%20%7C%20CNMC.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science, 35*(8), 982–1003.

Diebolt, C., Mishra, T., & Parhi, M. (2016). *Dynamics of distribution and diffusion of new technology. A Contribution to the Historical, Economic and Social Route of a Developing Economy. India Studies in Business and Economics book series (ISBE)*. Springer.

Dienlin, T., & Trepte, S. (2015). Is the privacy paradox a relic of the past? An in-depth analysis of privacy attitudes and privacy behaviors. *European journal of social psychology, 45*(3), 285–297.

Dionysiou, G., Fouskas, K., & Karamitros, D. (2021, March). The Impact of Covid-19 in E-Commerce. Effects on Consumer Purchase Behavior. In Strategic Innovative Marketing and Tourism in the COVID-19 Era: 9th ICSIMAT Conference 2020 (pp. 199-210). Springer International Publishing.

Dominici, A., Boncinelli, F., Gerini, F., & Marone, E. (2021). Determinants of online food purchasing: The impact of socio-demographic and situational factors. *Journal of Retailing and Consumer Services, 60*, Article 102473.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International. Journal of Human Computer Studies, 59*(4), 451–474.

Fernández-Bonilla, F., Gijón, C., & De la Vega, B. (2022). E-commerce in Spain: Determining factors and the importance of the e-trust. *Telecommunications Policy, 46*(1), Article 102280.

Fihartini, Y., Helmi, R. A., Hassan, M., & Oesman, Y. M. (2021). Perceived health risk, online retail ethics, and consumer behavior within online shopping during the COVID-19 pandemic. *Innovative Marketing, 17*(3), 17–29.

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior; An Introduction to Theory and Research.* Addison-Wesley, Reading, MA.

Gokhan, A. K. S. U., & Keceoglu, C. R. (2019). Comparison of results obtained from logistic regression, CHAID analysis and decision tree methods. *Eurasian Journal of Educational Research, 19*(84), 115–134.

Gutiérrez-Rodríguez, P., Villarreal, R., Valiño, P. C., & Blozis, S. (2020). A PLS-SEM approach to understanding E-SQ, e-satisfaction and e-loyalty for fashion e-retailers in Spain. *Journal of Retailing and Consumer Services, 57*, Article 102201.

Habib, S., & Hamadneh, N. N. (2021). Impact of perceived risk on consumers technology acceptance in online grocery adoption amid covid-19 pandemic. *Sustainability, 13*(18), 10221.

Handarkho, Y. D. (2020). The intentions to use social commerce from social, technology, and personal trait perspectives: Analysis of direct, indirect, and moderating effects. *Journal of Research in Interactive Marketing., 14*(3), 305–336.

Heinssen, R. K., Jr, Glass, C. R., & Knight, L. A. (1987). Assessing computer anxiety: Development and validation of the computer anxiety rating scale. *Computers in human behavior, 3*(1), 49–59.

Herzallah, D., Leiva, F. M., & Liébana-Cabanillas, F. (2021). To buy or not to buy, that is the question: Understanding the determinants of the urge to buy impulsively on Instagram Commerce. *Journal of Research in Interactive Marketing*. https://doi.org/10.1108/JRIM-05-2021-0145

Hofstede insights (2022). Country comparison. Retrieved from https://www.hofstede-insights.com/country-comparison/portugal,spain/.

Hsieh, P. J. (2015). Healthcare professionals' use of health clouds: Integrating technology acceptance and status quo bias perspectives. *International Journal of Medical Informatics, 84*(7), 512–523.

ICEX (2021). Informe e-País: El comercio electrónico en Portugal. Retrieved from file:///C:/Users/Fran/Dropbox/PC%20(2)/Downloads/ResumenEjecutivo_e-Pais_2021.pdf.

INE (2021) *Población que usa Internet (en los últimos tres meses)*. *Tipo de actividades realizadas por Internet*. National Statistical Institute, Spain. Retrieved from https://acortar.link/Y1kEqj.

Iqbal, U. P., Jose, S. M., & Tahir, M. (2022). Integrating trust with extended UTAUT model: a study on Islamic banking customers' m-banking adoption in the Maldives. *Journal of Islamic Marketing,* (ahead-of-print). https://doi.org/10.1108/JIMA-01-2022-0030.

Joines, J. L., Scherer, C. W., & Scheufele, D. A. (2003). Exploring motivations for consumer Web use and their implications for e-commerce. *Journal of Consumer Marketing., 20*(2), 90–108.

Kahneman, D., & Tversky, A. (2013). Prospect theory: An analysis of decision under risk. In *Handbook of the fundamentals of financial decision making*: Part I (pp. 99-127).

Kalinić, Z., Marinković, V., Djordjevic, A., & Liebana-Cabanillas, F. (2019). What drives customer satisfaction and word of mouth in mobile commerce services? A UTAUT2-based analytical approach. *Journal of Enterprise Information Management, 33*(1), 71–94.

Kanwal, M., Burki, U., Ali, R., & Dahlstrom, R. (2021). Systematic review of gender differences and similarities in online consumers' shopping behavior. *Journal of Consumer Marketing., 39*(1), 29–43.

Kawasaki, T., Wakashima, H., & Shibasaki, R. (2022). The use of e-commerce and the COVID-19 outbreak: A panel data analysis in Japan. *Transport Policy, 115*, 88–100.

Kim, H., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo bias perspective. *Management Information Systems Quarterly, 33*, 567–582.

Koch, J., Frommeyer, B., & Schewe, G. (2020). Online shopping motives during the COVID-19 pandemic—lessons from the crisis. *Sustainability, 12*(24), 10247.

Kokolakis, S. (2017). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. *Computers & security, 64*, 122–134.

Kuriakose, A., Sajoy, P. B., & George, E. (2022). In *February). Modelling the Consumer Adoption Intention towards Unified Payment Interface (UPI): An Extended UTAUT2 Model with Relative Advantage, Add-on Services and Promotional Benefits* (pp. 1–7). IEEE.

Lemon, S. C., Roy, J., Clark, M. A., Friedmann, P. D., & Rakowski, W. (2003). Classification and regression tree analysis in public health: Methodological review and comparison with logistic regression. *Annals of behavioral medicine, 26*(3), 172–181.

Liébana-Cabanillas, F. J., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2014). Role of gender on acceptance of mobile payment. *Industrial Management & Data Systems, 114*(2), 220–240.

Liébana-Cabanillas, F., Japutra, A., Molinillo, S., Singh, N., & Sinha, N. (2020). Assessment of mobile technology use in the emerging market: Analyzing intention to use m-payment services in India. *Telecommunications Policy, 44*(9), Article 102009.

Liébana-Cabanillas, F., Singh, N., Kalinic, Z., & Carvajal-Trujillo, E. (2021). Examining the determinants of continuance intention to use and the moderating effect of the gender and age of users of NFC mobile payments: A multi-analytical approach. *Information Technology and Management, 22*, 133–161.

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly, 31*(4), 705–737.

Lu, Y., Yang, S., Chau, P. Y., & Cao, Y. (2011). Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. *Information & Management, 48*(8), 393–403.

Luque Martínez, T. (2014). *Técnicas de análisis de datos en investigación de mercados*. Ediciones Pirámide.
Marinković, V., Đorđević, A., & Kalinić, Z. (2020). The moderating effects of gender on customer satisfaction and continuance intention in mobile commerce: A UTAUT-based perspective. *Technology Analysis & Strategic Management, 32*(3), 306–318.
Martínez-Córcoles, M., Teichmann, M., & Murdvee, M. (2017). Assessing technophobia and technophilia: Development and validation of a questionnaire. *Technology in Society, 51*, 183–188.
Migliore, G., Wagner, R., Cechella, F. S., & Liébana-Cabanillas, F. (2022). Antecedents to the adoption of mobile payment in China and Italy: An integration of UTAUT2 and innovation resistance theory. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10237-2
Modgil, S., Dwivedi, Y. K., Rana, N. P., Gupta, S., & Kamble, S. (2022). Has Covid-19 accelerated opportunities for digital entrepreneurship? An Indian perspective. *Technological Forecasting and Social Change, 175*, Article 121415.
Molinillo, S., Aguilar-Illescas, R., Anaya-Sánchez, R., & Liébana-Cabanillas, F. (2021). Social commerce website design, perceived value and loyalty behavior intentions: The moderating roles of gender, age and frequency of use. *Journal of Retailing and Consumer Services, 102404*.
Molinillo, S., Ruiz-Montañez, M., & Liébana-Cabanillas, F. (2020). User characteristics influencing use of a bicycle-sharing system integrated into an intermodal transport network in Spain. *International Journal of Sustainable Transportation, 14*(7), 513–524.
Morgan, J. N., & Sonquist, J. A. (1963). Problems in the analysis of survey data, and a proposal. *Journal of the American Statistical Association, 58*(302), 415–434.
Nicewicz, R., & Bilska, B. (2021). Analysis of Changes in Shopping Habits and Causes of Food Waste Among Consumers Before and During the COVID-19 Pandemic in Poland. *Environmental Protection and Natural Resources, 32*(3), 8–19.
Norberg, P. A., Horne, D. R., & Horne, D. A. (2007). The privacy paradox: Personal information disclosure intentions versus behaviors. *Journal of consumer affairs, 41*(1), 100–126.
Odusanya, K., Aluko, O., & Lal, B. (2019). Understanding the Adoption and Use of E-tail Websites: An Empirical Analysis Based on the Revised UTAUT2 Model Using Risk and Trust Factors. In *International Working Conference on Transfer and Diffusion of IT* (pp. 191–211). Cham: Springer.
Oliveira, S. V. D., & Reis, A. P. D. (2006). How do Portuguese college students perceive e-commerce? Instituto Superior de Economia e Gestão. *Departamento de Gestão*, 3–06. Working papers series n°.
Ong, C. S., & Lai, J. Y. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Computers in Human Behavior, 22*(5), 816–829.
Ou, W. M. (2007). Moderating effects of age, gender, income and education on consumer's response to corporate reputation. *Journal of American Academy of Business, 10*(2), 190–194.
Patil, P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. *International Journal of Information Management, 54*, Article 102144.
Pavlou, P. A., & Gefen, D. (2004). Building Effective Online Marketplaces with Institution-Based Trust. *Information Systems Research, 15*(1), 37–59.
Pedersen, P. O. (1970). Innovation diffusion within and between national urban systems. *Geographical Analysis, 2*(3), 203–254.
Pobee, F., & Opoku, D. (2018). The moderating effects of gender on E-commerce systems adoption factors. *International Journal of Strategic Decision Sciences (IJSDS), 9*(4), 86–104.
Qabbaah, H., Sammour, G., Vanhoof, K., Voronin, A., Ziatdinov, Y., Aslanyan, L., … Honchar, A. (2019). Decision Tree Analysis to Improve E-Mail Marketing Campaigns. *International Journal of Information Theories and Applications, 26*(4), 3–36.
Rajaretnam, T. (2022). *Information Privacy Governance and Regulation in Australia: An Ecommerce Perspective*. Western Sydney University.
Ram Mohan Rao, P., Murali Krishna, S., & Siva Kumar, A. P. (2018). Privacy preservation techniques in big data analytics: a survey. *Journal of Big Data, 5*, 33.
Rehman, Z. U., Baharun, R., & Salleh, N. Z. M. (2020). Antecedents, consequences, and reducers of perceived risk in social media: A systematic literature review and directions for further research. *Psychology & Marketing, 37*(1), 74–86.
Rifon, N. J., LaRose, R., & Choi, S. M. (2005). Your privacy is sealed: Effects of web privacy seals on trust and personal disclosures. *Journal of Consumer Affairs, 39*(2), 339–362.
Rogers, E. M. (2010). *Diffusion of innovations*. New York, NY: Simon and Schuster.
Sánchez-Torres, J. A., Varon-Sandobal, A., & Sánchez-Alzate, J. A. (2017). Differences between e-commerce buyers and non-buyers in Colombia: The moderating effect of educational level and socioeconomic status on electronic purchase intention. *Dyna, 84*(202), 175–189.
Shareef, M. A., Dwivedi, Y. K., Wright, A., Kumar, V., Sharma, S. K., & Rana, N. P. (2021). Lockdown and sustainability: An effective model of information and communication technology. *Technological Forecasting and Social Change, 165*, Article 120531.
Sim, J. J., Loh, S. H., Wong, K. L., & Choong, C. K. (2021). Do We Need Trust Transfer Mechanisms? An M-Commerce Adoption Perspective. *Journal of Theoretical and Applied Electronic Commerce Research, 16*(6), 2241–2262.
Singh, N., Sinha, N., & Liébana-Cabanillas, F. J. (2020). Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence. *International Journal of Information Management, 50*, 191–205.
Stafford, T. F., Turan, A., & Raisinghani, M. S. (2004). International and cross-cultural influences on online shopping behavior. *Journal of Global Information Technology Management, 7*(2), 70–87.
Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2020). Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2. *Information Systems Frontiers, 23*(4), 987–1005.
Tamilmani, K., Rana, N. P., Wamba, S. F., & Dwivedi, R. (2021). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation. *International Journal of Information Management, 57*, Article 102269.
Taneja, B., & Bharti, K. (2021). Mapping unified theory of acceptance and use of technology (UTAUT) 2: A taxonomical study using bibliometric visualisation. *Foresight, 24,* 2, 2022, 210-247.
Valarezo Unda, Á. E., López Zorzano, R. A., & Pérez-Amaral, T. (2021). Adoption of e-commerce by individuals and digital divide: Evidence from Spain. *Ene, 11*, 46.
Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly, 24*(1), 115–139.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.
Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extended the unified theory of acceptance and use of technology. *MIS Quartely, 36*(1), 157–178.
Wang, O., & Somogyi, S. (2019). Determinants for consumer food choice with the New Retail e-commerce mode (No. 2186-2019-1368).
Wang, S., & Petrounias, I. (2017). Big data analysis on demographic characteristics of Chinese mobile banking users. In *In 2017 IEEE 19th Conference on Business Informatics (CBI)* (Vol. 2, pp. 47–54). IEEE.
Wang, Y., Yan, X., Zhou, Y., Xue, Q., & Sun, L. (2017). Individuals' acceptance to free-floating electric carsharing mode: A web-based survey in China. *International Journal of Environmental Research and Public Health, 14*(5), 476.
Washington, S., & Wolf, J. (1997). Hierarchical tree-based versus ordinary least squares linear regression models: Theory and example applied to trip generation. *Transportation Research Record, 1581*(1), 82–88.
Yawised, K., Apasrawirote, D., Chatrangsan, M., & Muneesawang, P. (2022). Factors Affecting SMEs' Intention to Adopt a Mobile Travel Application based on the Unified Theory of Acceptance and Use of Technology (UTAUT-2). *Emerging Science Journal, 4*, 207–224.

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