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International air travel attitude and travel planning lead times across 45 countries in response to the COVID-19 pandemic

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ABSTRACT

This paper explores global differences in travel risk perception based on i) attitudes towards travel abroad, and ii) the time required to plan travel. Baseline data from 2019 is compared with data from 2020, the first year of the COVID-19 pandemic. A methodology based on Big Data is developed through the Skyscanner metasearch engine, working with 20,756 million flight searches and 1979 million flight picks worldwide. We conduct an exploratory analysis by region, followed by a cluster analysis of 45 countries. We argue that the findings respond to uncertainty avoidance, with clear differences between Europe, America and Asia-Pacific. This knowledge has marketing implications for tourist destinations in terms of what marketing messages to convey and the best time to introduce marketing campaigns for each country or group of countries, so that the opportunity for reactivation of tourism is maximised.

1. Introduction

The tourism industry is highly vulnerable to unpredictable risks (Fuchs, 2013; Williams & Baláž, 2013), having a significant influence on travel planning and travel behaviour (e.g., Karl & Schmude, 2017; Neuburger & Egger, 2021; Rittichainuwat, Nelson, & Rahmafitria, 2018). In the last two decades, health concerns in tourism prompted a growing interest in the academic literature (e.g., Chen, Law, & Zhang, 2021; Novelli, Burgess, Jones, & Ritchie, 2018), and the publications have grown exponentially with the COVID-19 pandemic (Golets, Farias, Pilati, & Costa, 2021; Senbeto & Hon, 2019). While some studies have examined the impact of the COVID-19 outbreak on tourism industry outcomes (tourist arrivals, tourism spending, hotel occupancy rates) (e.g., Škare, Soriano, & Porada-Rochoń, 2021), others have analysed how risk perception influences tourists' behaviours such as desire to travel or intention to travel (e.g., Gallego, Font, & González-Rodríguez, 2022; Nazneen, Hong, & Ud Din, 2020; Neuburger & Egger, 2021). The global airline industry lost USD20.1 billion over three years, because of a drop of 46% in revenue from 2019 to 2021 (Habtemariam, 2020; IATA, 2021), making it the hardest hit industry across all sectors (Suau-Sanchez, Voltes-Dorta, & Cugueró-Escofet, 2020), in part because the industry was seen as an early vector for transmission, which led to flight suspensions (Sun et al., 2021a), with a greater impact on the international air transport industry than at domestic level (Sun et al., 2021b). In response, European airlines adopted a series of strategies of retrenchment, perseverance, innovation and exits in response to the evolving situation and depending on government levels of intervention (Albers & Rundshagen, 2020).

The literature has paid attention to how uncertainty avoidance (UA) affects both the process of searching information and the type of sources used. However, few studies analyse how UA affects the timing of planning trips, and the results achieved to date are inconclusive (Backhaus, Heussler, & Croce, 2022). According to the motivation protection theory, tourists manage their health risk perception according to their beliefs about health and their own risk prevention behaviour patterns (Quintal, Lee, & Soutar, 2010; Verkoeyen & Nepal, 2019). These beliefs and behaviours are somehow linked to their UA. The willingness to fly during and after COVID has been explained by four variables: perceived threat of COVID-19, agreeableness, affect, and fear (Lamb, Winter, Rice, Ruskin, & Vaughn, 2020). However, there is little discussion in the literature about how consumers from different countries address their intentions to travel in situations of health risk (Grupe & Nitschke, 2013; Tanovic, Gee, & Joormann, 2018). Rooted from the motivation protection theory, it might be expected that the detrimental effects that the

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COVID-19 pandemic has on people might be greater in those countries with a culturally high uncertainty and risk perception.

We aim to shed light on tourists' planning time behaviour under both ordinary and risk conditions, as well as the intention to travel under high-risk conditions. Destination Marketing Organizations (DMOs) must develop the appropriate marketing strategies to reactivate their international tourism demand. Particularly, marketers face the dilemma of either standardising or adapting their marketing strategies. A thorough understanding of travellers' planning processes and their behaviour resulting from high-risk perceptions can help DMOs prioritise international demand and to determine marketing strategies. To comprehend the complexity in travel planning, it is necessary to understand travel planning horizons across countries and cultures (Backhaus et al., 2022), especially as the risk of viral infection continues to play an important role in health-preventive behaviours, such as travel avoidance (Huang, Dai, & Xu, 2020). To our knowledge, no studies have those essential aspects together as a measure to reactivate tourist demand. Furthermore, some gaps are observed in relation to the role of uncertainty avoidance (UA) on planning time and travel preventive behaviour in relation to cultural backgrounds. The current research addresses these gaps.

2. Literature review

2.1. Trip-planning behaviour under ordinary circumstances

Travel planning results from interrelated decisions responding to the motives of travel, information search, information acquisition, trip distance, duration of the trip, mode of travel, type of accommodation, and booking each component of the trip (Rahman, Crouch, & Laing, 2018). Travel planning helps potential tourists to reduce perceived risks and avoid uncertainty while travelling (Jordan, Norman, & Vogt, 2013). Thus, while the criteria to evaluate potential destinations in the earliest stage is based mainly on the ability of destinations' attributes to meet tourists' motives, the criteria used to evaluate destinations in the later stages, leading to the final destination choice, are clearly determined by both constraints (personal, social and financial) and concerns (uncertainty, travel risk and safety) (Karl, Muskat, & Ritchie, 2020). In international travels, uncertainty avoidance is considered the most influential cultural dimension in all the stages of travel decision-making (Litvin, Crotts, & Hefner, 2004). And it is also recognized to have a relevant impact on trip planning behaviour (Jiang, Scott, Tao, & Ding, 2019; Li & Cai, 2012). Uncertainty avoidance refers to the feeling of being threatened by ambiguity and is a measure of intolerance for risk. Individuals from societies with high UA can feel anxious or threatened by situations with a high level of uncertainty and, therefore, would spend more time in planning their trip to reduce the uncertainties of travelling (Karl, 2018).

A growing body of studies claim that travel planning behaviour is not homogeneous across cultures leading to different planning time/horizon behaviour (e.g. Kim, Bai, Kim, & Chon, 2018). However, early literature focused more on two determinants of time planning, namely traveller-related (sociodemographic and psychographic factors) and trip-related variables, rather than on its cultural antecedents. While sociodemographic variables such as age are highly correlated with planning time (Huh & Park, 2010; Zalatan, 1996), psychographic factors better explain planning time frame (Schul & Crompton, 1983).

However, we know little about the effect of UA culture on the time spent in travel planning and, the findings achieved are far from being conclusive (Golets et al., 2021). Some studies in international travel behaviour have demonstrated that individuals with high UA and long-term orientation tend to pre-pay tours and pre-book accommodation well in advance, compared to individuals from low UA and short-term oriented cultures (Crotts & Litvin, 2003; Jordan et al., 2013). However, other studies of planning time/horizon deviate from these findings. Money and Crotts (2003) defined trip planning time with two indicators: days before the decision to travel; and days before reservation. They found that the trip planning measured with any of these two indicators was longer among the medium UA group members than the high UA group. Litvin et al. (2004) replicated Money and Crotts (2003)'s research, extending the sample of visitors to U.S from 58 countries who were sorted by UA as high and low groups. Similarly, they reported fewer days in trip planning for high UA respondents. Elsewhere, studies did not find significant evidence of the role of UA on planning time/horizon: Crotts (2004) did not find significant differences between US nationals travelling to high or low UA country, while Backhaus et al. (2022) found that UA only had a marginal effect on travel planning travel to European countries.

Research on travel planning has relied on structured surveys (Backhaus et al., 2022; Huh & Park, 2010; Litvin et al.,2004; Mone & Crotts, 2003) or scenario-base experiments (Rahman et al., 2018) with a sample design delimited in nature and size to observe differences in trip planning time/horizon between individuals from different countries and between traveller-related or trip-related determinants. These studies also differ in how travel planning time/horizon is defined and operationalized. Unlike previous studies, Rahman et al. (2018) defined planning time as timing of booking intentions (early vs late) and related this timing to traveller-related (age, gender, income level, education, prior trips,) and trip-related antecedents such as the framing of price-deal information. However, this study did not consider contextual antecedents such as UA as a determinant of planning time. To date, no studies have used large secondary datasets to detect differences in the efforts of potential travellers to mitigate uncertainty about travel choices under ordinary circumstances, such as before the pandemic period. Hence, a research gap is addressed by this study. Furthermore, travel metasearch engines are more reliable to operationalise planning time variables, compared with survey-based studies with inherent biases. Particularly, metasearch engines allow researchers to retrieve data for any period of time and location that is of interest. Thus, the following research question is formulated:

RQ1: Do individuals from a culture with high level of uncertainty avoidance behave differently in terms of the planning travel time between flight search and flight travel dates?

2.2. Travel attitude under high-risk conditions

The perception of travel risk is usually conceptualised as a subjective determinant of potential harm or the possibility of a loss that stems from the uncertainty of the tourism activity (Golets et al., 2021). The tourism literature has reported the following perceived travel risks as common: functional (the need is not met); financial (poor value for money); physical (infectious diseases, natural disasters); political (instability, terrorism); social (loss of social status); psychological (self-esteem damages, anxiety, and stress); and time (waste of time) (Floyd, Gibson, Pennington-Gray, & Thapa, 2004; Huang et al., 2020; Schmude, Zavareh, Schwaiger, & Karl, 2018). However, among all tourism-related risk, health travel risk is one of the concerns with most impact on both domestic (Abraham, Bremser, Carreno, Crowley-Cyr, & Moreno, 2020) and international travel (Chien, Sharifpour, Ritchie, & Watson, 2017; Jonas, Mansfeld, Paz, & Potasman, 2011). Health travel risk refers to the probability assessment that health problems might occur at a destination in a certain period (Chien et al., 2017). A vast body of research have demonstrated that disease outbreaks create a high level of anxiety, which undoubtedly affects tourist decision-making and travel behaviour (Grupe & Nitschke, 2013; Senbeto & Hon, 2019; Tanovic et al., 2018; Zenker, Braun, & Gyimothy, 2021). Empirical studies have also shown evidence that disease outbreaks have a larger impact on perceived risks associated with international travel than with domestic travel (Cahyanto, Wiblishauser, Pennington-Gray, & Schroeder, 2016).

Protection motivation theory explains how people assess threats and perform protective behaviours (Rogers & Prentice-Dunn, 1997). Accordingly, individuals develop preventative behaviours when fear and perceived risk is high. The tourism literature confirms that protection motivation is triggered by fear, threat vulnerability, and threat severity (Lu & Wei, 2019). Individuals' assessment of travel safety in a health crisis leads them to develop cautious travel or to adopt temporal travel avoidance as self-protective measures to reduce risk (Chua, Al-Ansi, Lee, & Han, 2021; Huang et al., 2020). Rooted in protection motivation theory, Nazneen et al. (2020) explained that the fear of COVID-19 among Chinese citizens increased both the travelling risk perception and the health and security protection, leading to travel avoidance. Zheng, Luo, and Ritchie (2021) and Zheng, Luo, and Ritchie (2022) indicate that threat severity and threat susceptibility influence travel fear and risk perception among Chinese citizens, which in turn impact their tourist destination choices and activities. Hence, protection motivation and resilience are found to significantly influence both travel avoidance and cautious travel behaviours (Zheng et al., 2021).

Further research provides empirical evidence that health risk perception has increased considerably during the COVID-19 pandemic, affecting both individuals' travel intentions (Kock, Nørfelt, Josiassen, Assaf, & Tsionas, 2020; Zenker & Kock, 2020) and mobility patterns (Borkowski, Jażdżewska-Gutta, & Szmelter-Jarosz, 2021; Rahman, Gazi, Bhuiyan, & Rahaman, 2021). The pandemic outbreak impacted both the desire to travel and intention to visit Europe, with a reduction on flight searched and picks of 36.2% and 42.6% respectively, in the period 2019–2020 (Gallego et al., 2022). Travel risk perception and therefore individuals' willingness to change travel plans or to avoid trips and events, significantly increased in two weeks (1–4 March 2020 to 15–19 March 2020) in Germany, Austria and Switzerland (Neuburger & Egger, 2021). The fear of the COVID-19 pandemic affected travel risk and management perception, with tourists avoiding risk and overpopulated tourist destinations (Rahman et al., 2021).

Due to the inherent risks involved in international travel, the extent to which tourists try to reduce such risks will depend not only on their personal and psychological characteristics but also on their cultural orientations (Golets et al., 2021; Reisinger & Mavondo, 2005). According to protection motivation theory, risk perception is particularly influenced by the cultural value of UA (Karl, 2018; Quintal et al., 2010). There is empirical evidence prior to COVID-19 that cultural differences and specifically UA influence travel behaviour (Dolnicar, 2007; Litvin et al., 2004; Money & Crotts, 2003; Woodside & Ahn, 2007). However, these studies focus more on how the cultural background influences risk avoidance in the pre-travel stage, i.e., in the planning time frame, trip duration, and travel style, than on travel intention (Backhaus et al., 2022; Rahman et al., 2018). Studies assume that the COVID-19 pandemic affected tourists homogenously, which fails to identify the impact of sociodemographic and regional background differences, such as the impact of cultural values when travel planning (Zheng et al., 2022). Few of the studies have investigated the influence of UA on intention to travel under extreme, high-risk situations (unlike Golets et al., 2021). Furthermore, the studies mentioned above are cross-sectional case study surveys of specific target groups, rather than employing large data sets that comprehensively study multiple countries over a long period. To gain a more complete understanding of consumer behaviour under risk conditions, it is beneficial to analyse how different countries react to the same perceived risk and uncertainty as that of COVID-19 pandemic. Hence, the following research questions are formulated:

RQ2: How does travel intention differ between individuals from cultures with high and low uncertainty avoidance?

RQ3: What countries present homogeneous behaviours according to their travel intention during the COVID-19 pandemic and their behaviour in terms of the time span between the flight search and flight travel dates?

3. Methodology

We reiterate that the aim of this study is to explore whether there are common patterns of behaviour by country in terms of aversion to travel due to the COVID-19 pandemic and planning time. To address this aim, we use a global and homogeneous data source that allows a comparative analysis. The methodology is developed following four phases: (1) Database analysis; (2) Variable selection; (3) Data extraction; and (4) Methods: normalisation, descriptive analysis, and clustering.

3.1. Phase 1: Database analysis

Researchers increasingly use Big Data from mobile applications, social networks and web tools to better monitor and understand the needs of tourists (Li & Law, 2020; Li, Xu, Tang, Wang, & Li, 2018). This study uses data from Skyscanner, a travel metasearch engine used monthly by >100 million people worldwide (Giachino, Bollani, Bonadonna, & Bertetti, 2021). Skyscanner allows users to define the search parameters (origin, destination, travel dates, number of travellers, etc.) that best suit their wishes. It then generates a query to each of its hundreds of partners (including airlines and online travel agencies (OTAs)) and returns all the possible options to the user so that they can compare and choose the best solution for their trip.

In addition to the volume that characterises Big Data, a Skyscanner data set also meets other properties (El Alaoui, Gahi, Messoussi, Todoskoff, & Kobi, 2017; Gandomi & Haider, 2015), such as: speed, due to its daily update process; variability, referring to the variation in data flow rates; veracity, as it reports real data instead of estimates or extrapolations; visualisation, as the data is easy to understand; and value, since data is transformed into knowledge to improve the management of tourist destinations. However, Skyscanner does have a limitation; although the aeroplane is one of the most common means of international transport, the Skyscanner database does not capture trips through other forms of transport, so it offers a biased view.

3.2. Phase 2: Variable selection

Skyscanner's flight search process provides information on consumer behaviour in two aspects: i) the consumer's desired trip based on their searches (Where are you thinking of travelling?), and ii) the option that best fits their desired trip based on the selection they make from all the possible options (Where have you finally decided to travel to?). Thus, data is available on two stages of the purchase process: search and picks (Middleton, Fyall, Morgan, & Ranchhod, 2009), which are identified as the desire and intention to travel, respectively (Gallego et al., 2022). In no case is it known if the reservation and/or purchase of the flight is made, since Skyscanner redirects the user to the corresponding partner to complete the process.

To respond to RQ1, a more structural variable is sought, since we intend to use the variable to measure, in a normal year (similar to a reactivation period), how the consumers of different countries plan their trips abroad. Specifically, information is sought on the length of time that consumers take, in advance of travelling, to prepare for/plan their trips. The Skyscanner database provides information on the date when a user makes a search to travel abroad on specific future dates. Thus, the variable "Lead Time" (LT) refers to the concept of trip-planning behaviour under ordinary circumstances (see section 2.1 Literature Review) and is measured by the number of days that elapse between the search date and the trip date. To calculate the LT, flight searches are chosen, not flight picks, because searches are a better fit with our objective to measure the beginning of the purchase process. For this variable, 2019 is taken as the study's reference period, i.e., activity during this year represents the structural, or habitual, behaviour of consumers and, therefore, represents the level of activity that, when reached post-pandemic, will denote the demand's reactivation and a return to normality. The LT variable is dichotomous: short-term travel plans are trip searches with a LT of less than a month and long-term travel plans are searches with a LT of more than a month.

To respond to RQ2, a variable is sought that allows us to see how different countries react to the situation of uncertainty caused by COVID-19. To do this, the variable " Aversion to Travel " (AT) refers to the concept of travel attitude under high-risk conditions (see section 2.2 Literature Review) and is measured by the change in international flight selections between 2019 and 2020. AT is an indicator of perceived risk. The selected variable is flight picks, instead of flight searches, because flight picks is closer to the final intention of the consumer. Thus, for a country, we can deduce that the greater the decrease in flight picks in 2020, compared to 2019, the more uncertainty has affected that country, the more that a country avoids risks, unstructured situations or situations that are out of the ordinary and, therefore, the greater their aversion to travel.

It is the joint analysis of LT and AT that answers RQ3, allowing destination marketeers to know where and how to launch marketing strategies (through the AT variable) and when to do so (through the LT variable).

3.3. Phase 3: Data extraction

Data extraction occurs in two phases: i) data aggregated by regions, and ii) data aggregated for 45 countries (15 countries per region). The 15 countries with the highest number of searches in Skyscanner in three regions in 2019 are selected. Together, these countries account for 97.7% of the total searches made in the American region [U.S.A. (USA), Canada (CAN), Puerto Rico (PR), Brazil (BRA), Mexico (MEX), Argentina (ARG), Cuba (CUB), Colombia (COL), Chile (CHL), Peru (PER), Costa Rica (CR), Ecuador (ECU), Venezuela (VEN), Panama (PAN) and Dominican Republic (DO)], 92.8% for the Asia-Pacific region [South Korea (KOR), Japan (JPN), Australia (AUL), Taiwan (TAI), Thailand (THA), Hong Kong (HOK), India (IND), Singapore (SIG), Philippines (PHI), Malaysia (MAL), United Arab Emirates (UAE), China (CHI), Saudi Arabia (SA), Indonesia (IDO) and Vietnam (VIE)], and 88.4% for the European region [United Kingdom (UK), Italy (ITA), Spain (SPA), Germany (GER), Russia (RUS), France (FRA), Netherlands (NET), Turkey (TUR), Greece (GRE), Poland (POL), Israel (ISR), Ireland (IRE), Switzerland (SWI), Portugal (POT) and Belgium (BEL)].

The data set extracted from Skyscanner and used in this study has 20,756 million searches and 1979 million flight picks made by users around the world during the years 2019 and 2020. This volume of data cannot be captured, saved and processed with conventional technologies, so, for its extraction, the company ForwardKeys (2022) was used, which offers a payment platform that enables the monitoring, analysis and prediction of world airport traffic in a comfortable environment for the analyst.

3.4. Phase 4: Methods

3.4.1. Normalisation

Given the large sample of selected countries and the study's aim to make comparisons between countries, a standardisation process is developed. There are several normalisation methods recommended in the literature (Freudenberg, 2003; Jacobs, Smith, & Goddard, 2004). In our case, the distance to a reference country method (Joint Research Centre-European Commission, 2008) is chosen since this is the most appropriate approach to quantify the distance between each country and those reaching the most extreme values in both AT and LT. For the Aversion to Travel variable, a AT Index (0−100) is calculated, where the maximum value (100) is defined as a reference point, being the most pronounced decrease in the number of flight searches among the 45 countries analysed (reference country: Hong Kong). The higher the index value, the greater the aversion to travel of a country's consumers.

$$\text{AT Index}_{pc}^{t} = \frac{x_{pc}^{t}}{x_{p\bar{c}}^{t}}$$

Where x_{pc}^{t} is the value of indicator p (pick) for country c at time t and $\bar{c}$ is the reference country.

For the Lead Times variable, the LT Index (0–100) is calculated, where the maximum value (100) is defined by the country that presents the highest percentage of long-term flight searches, i.e., with more than a month LT between the search and travel dates (reference country: Costa Rica). The higher the index value, the greater the long-term orientation of the country's consumers in their travel planning.

$$\text{LT Index}_{sc}^{t} = \frac{x_{sc}^{t}}{x_{s\bar{c}}^{t}}$$

Where x_{sc}^{t} is the value of indicator s (search) for country c at time t and $\bar{c}$ is the reference country.

3.4.2. Descriptive analysis and clustering

Once the variables that best fit the objective are defined, and the corresponding indices calculated, the last step is to analyse the data and identify behaviour patterns. To do this, the analysis is carried out at two levels: first, a descriptive analysis focuses on the four regions (Africa, America, Asia-Pacific, and Europe) and, second, a cluster analysis is calculated at the country level, as described in the following section.

4. Results

Firstly, we examine whether there are significant differences in the behaviour of consumers by region based on how they reacted to the uncertainty caused by COVID-19 in their trips abroad and according to the time they needed to start planning their trips. Then, we evaluate whether the differences (if they exist) can be transferred to the country level, with the aim of identifying and grouping homogeneous behaviours in the countries. If this approach proves to be successful, tourist destination managers will be able to develop different, adapted strategies for different countries, according to the types of behaviour identified within each market, to make their marketing budgets deliver greater benefit.

The world population made a total of 20,756 million searches on Skyscanner to travel during the years 2019 and 2020, and, from the results of these searches, a total of 1979 million flights were selected by users (picks). The figures for 2020 show decreases of −39.5% in searches and − 48.4% in flight picks worldwide, compared to the previous year. Table 1 shows that, although consumers worldwide drastically reduced their searches and flight picks because of the pandemic, the largest drops occurred in the Asia-Pacific region. Conversely, with a difference of almost 20 percentage points for both searches and picks, the two American continents together registered the smallest decreases in their intentions to travel during 2020. In all cases, the decreases are less abrupt in searches than in flight picks. This is due to the decision-making process itself, where the consumer first searches for their flight options and then picks a flight that is closest to their wishes. The flight pick represents progress in the decision-making process and is, therefore a closer approximation, than searches, to the consumer's final decision.

Analysing the monthly evolution of flight picks, the decision closest to the real intention of the consumer (Fig. 1), it is confirmed that citizens from the Asia-Pacific region showed the lowest rates throughout 2020.

Table 1
Interannual variation rates, in 2020 compared to 2019, of flight searches and picks. Global and regions.

	% variation 2020/2019	
	Searches	Picks
GLOBAL	−39.5%	−48.4%
EUROPE	−37.3%	−42.8%
AMERICA	−28.7%	−39.3%
ASIA - PACIFIC	−48.2%	−58.9%
AFRICA	−39.0%	−52.1%

Source: Authors, based on Skyscanner (2021).

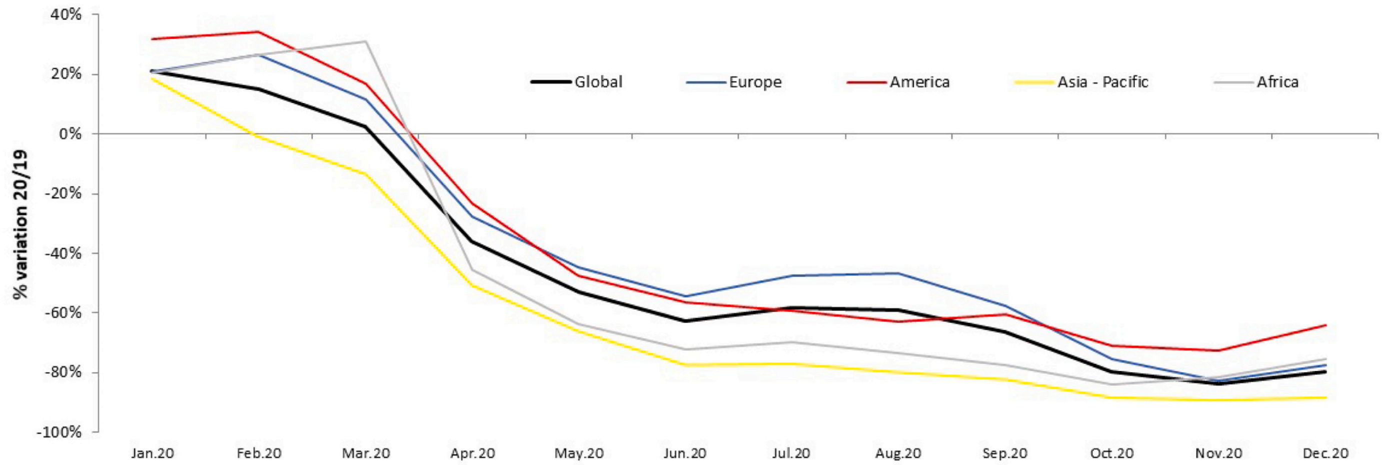

Fig. 1. Year-on-year variation rates. Consumer intention (Picks) to travel. Global and regions.
Source: Authors, based on Skyscanner (2021).

Also, the monthly variation rates highlight the greater propensity to fly overseas shown by the Europeans in the summer months (July–September), the holiday period par excellence of this region, while the Americans registered a better evolution in the last quarter of the year.

For any tourist destination to plan its marketing campaigns, it is especially relevant to know when consumers are looking for information about future trips. Obviously, this behaviour can vary depending on the situation and planning is not the same in periods of stability as in periods of uncertainty. In our case, a “normal” year (2019) is taken as a reference, without the effects of the pandemic, to capture the typical behaviours of consumers not affected by an atypical and conjunctural situation. Eventually, when travel is reactivated, consumer behaviour is expected to return to normality, i.e., to be like that of 2019. Table 2 shows that, despite the absence of significant differences between regions, Europeans showed a greater predisposition to plan in the long-term, while residents from Africa and Asia-Pacific tended to plan in the short-term. We therefore identify clear behaviour patterns across the four regions by combining the variables of aversion to travel (AT) and lead time (LT). Citizens from Africa and Asia-Pacific showed greater risk aversion and tended to plan their trips in the short-term, while citizens from Europe and the Americas coped somewhat better with the uncertainty and planned in the long-term, especially the Europeans.

Next, we descend into analysis at the country level, excluding countries from the African continent, which are no longer considered due to the lower volume of data available. Our objective is to check if the changes in behaviour detected at the regional level are also reflected at the country level and if there is homogeneous behaviour across the countries according to the region to which they belong. As described in the methodology, to facilitate the analysis, two indices are calculated. First, the AT Index that shows the reaction to the perceived risk in each country, taking the value 100 for the country that registers the highest drop in rate of picks and, therefore, shows the greatest aversion to travel. Among the 45 countries analysed, Hong Kong takes the value 100 for registering the greatest drop (−70% compared to 2019). Second, the LT Index shows the orientation of a country’s consumers towards short- or long-term planning, taking the value 100 to be the country that reaches the highest percentage of long-term flight searches (with more than a month lag between search and travel dates). Among the 45 countries analysed, Costa Rica takes the value 100, as 70.7% of its flight searches were made more than a month before the trip.

To offer a joint analysis of both indices, the results are shown in scatter plots (X, Y). The AT Index is shown on the X axis; the further to the right the country is (closer to value 100) the more that country’s consumers are averse to travel, which indicates the greater they are affected by uncertainty. The Y axis displays the value that the country takes in the LT Index; the higher the position that the country occupies (closer to value 100) the greater its consumers’ orientations to long-term planning. Fig. 2 represents the position that each country occupies within its own region. For countries in the Americas, it is noted that all the consumers tend more towards long-term planning (LT Index >74) and that the majority are between a value of 60 to 80 for the AT Index. Puerto Rico (PR) is an exception and registers the lowest index, which implies a low aversion to risk, while Venezuela (VEN) is at the other extreme, with a AT Index close to 100.

Except for Russia and Turkey, consumers in European countries also have a long-term planning orientation (LT Index >82), although there is greater dispersion in the AT values. AT values range from the United Kingdom (UK), which is less affected by uncertainty and has residents that are more willing to travel, to Russia (RUS), which reaches the highest value in this index. Citizens of countries in the Asia-Pacific region have relatively homogeneous behaviours in terms of their aversion to travel (AT Index >74), yet they show substantial dispersion in their lead times to plan trips, from Taiwan (TAI), which is clearly oriented to the long-term, to Saudi Arabia (SA), whose consumers tend more towards the short-term.

In Fig. 3, all the countries are shown together and a fairly homogeneous pattern within, and differentiated between, regions is observed. Consumers from America and Europe show less aversion to travel and

Table 2
Percentage distribution of lead times for travel in 2019.

		Europe	America	Asia - Pacific	Africa
Lead times (days between search and flight date)	0 to 4 days	6.8%	7.5%	7.1%	**12.8%**
	5 to 14 days	15.0%	15.5%	15.9%	**20.4%**
	15 to 29 days	14.3%	14.4%	**15.1%**	**15.1%**
	30 to 44 days	11.5%	11.5%	**12.0%**	10.7%
	45 to 59 days	9.2%	9.1%	**9.3%**	7.7%
	60 to 89 days	**13.4%**	13.2%	13.2%	10.7%
	90 to 119 days	**9.1%**	8.9%	8.9%	7.1%
	120 to 364 days	**20.8%**	19.8%	18.6%	15.4%
	TOTAL	100.0%	100.0%	100.0%	100.0%

The highest percentages by row appear in bold.
Source: Authors, based on Skyscanner (2021).

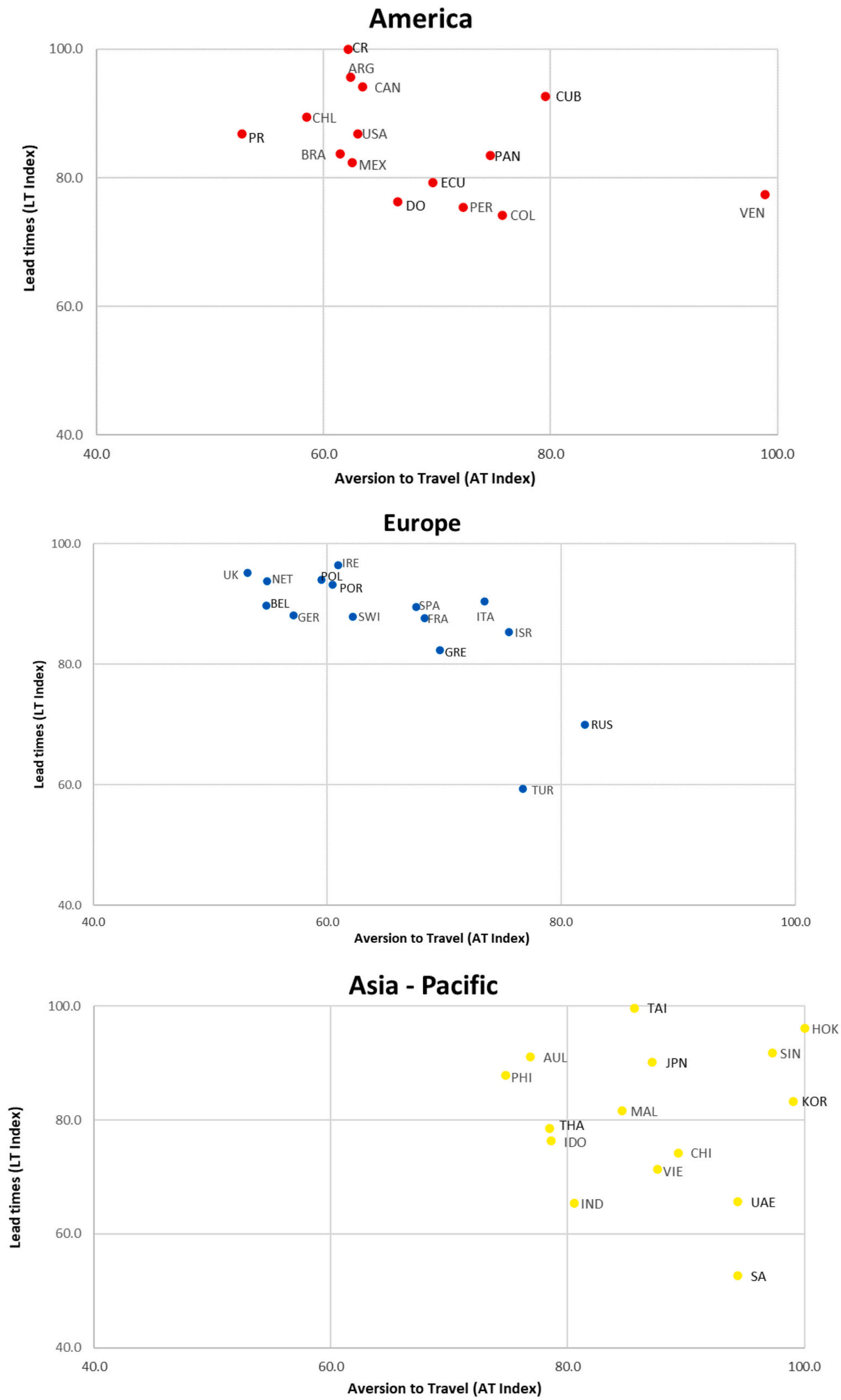

Fig. 2. Positioning matrix by country and region according to Aversion to Travel (AT Index) and Lead Times (LT Index).

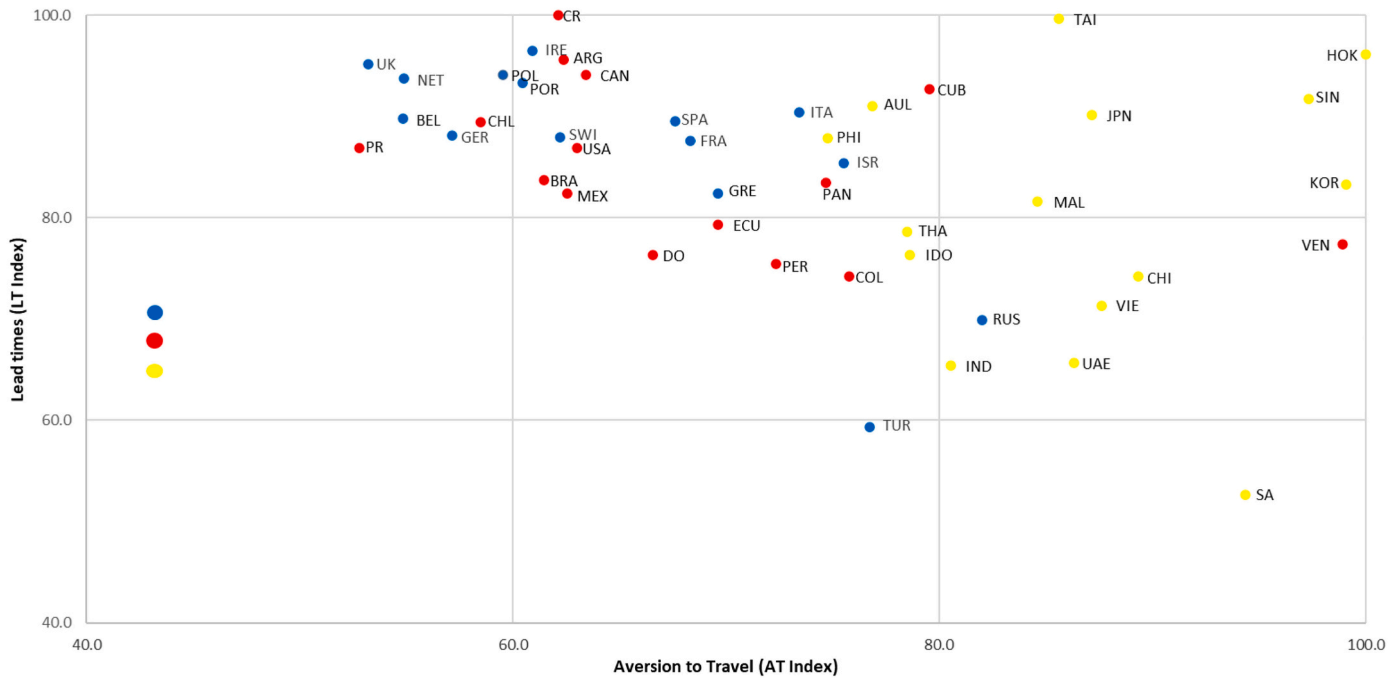

Fig. 3. Joint positioning matrix according to the indices: Aversion to Travel (AT Index) and Lead Times (LT Index).

plan more ahead of travel time than those from Asia-Pacific. Citizens from countries in the Asia-Pacific region are more likely to avoid uncertainty overall, while showing substantial variability in their travel planning lead times. Despite the homogeneous behaviour shown by European and American consumers, it is worth noting some significant differences within: i) the North and South American countries, where Ecuador (ECU), Dominican Republic (DO), Peru (PER) and Colombia (COL) all move more towards planning in the short-term; and ii) the European countries, where Russia (RUS) and Turkey (TUR) differ from the other European countries in both dimensions and are closer to Asian behaviour in terms of their greater aversion to travel and short-term planning.

A cluster analysis is performed to identify groups with similar response patterns. Of the 45 countries selected, only Saudi Arabia (SA) is removed from the analysis because it is classified as an outlier, and the Ward method is applied to the rest. Fig. 4 show that the first cluster is made up primarily of European countries, the second cluster is made up of a similar number of countries from America and Asia-Pacific, while the third cluster is primarily made up of countries from Asia-Pacific plus Venezuela, Russia, and Turkey.

Analysing the averages of the two dimensions (Table 3), we observe that the clusters are formed from lesser to greater repercussion of

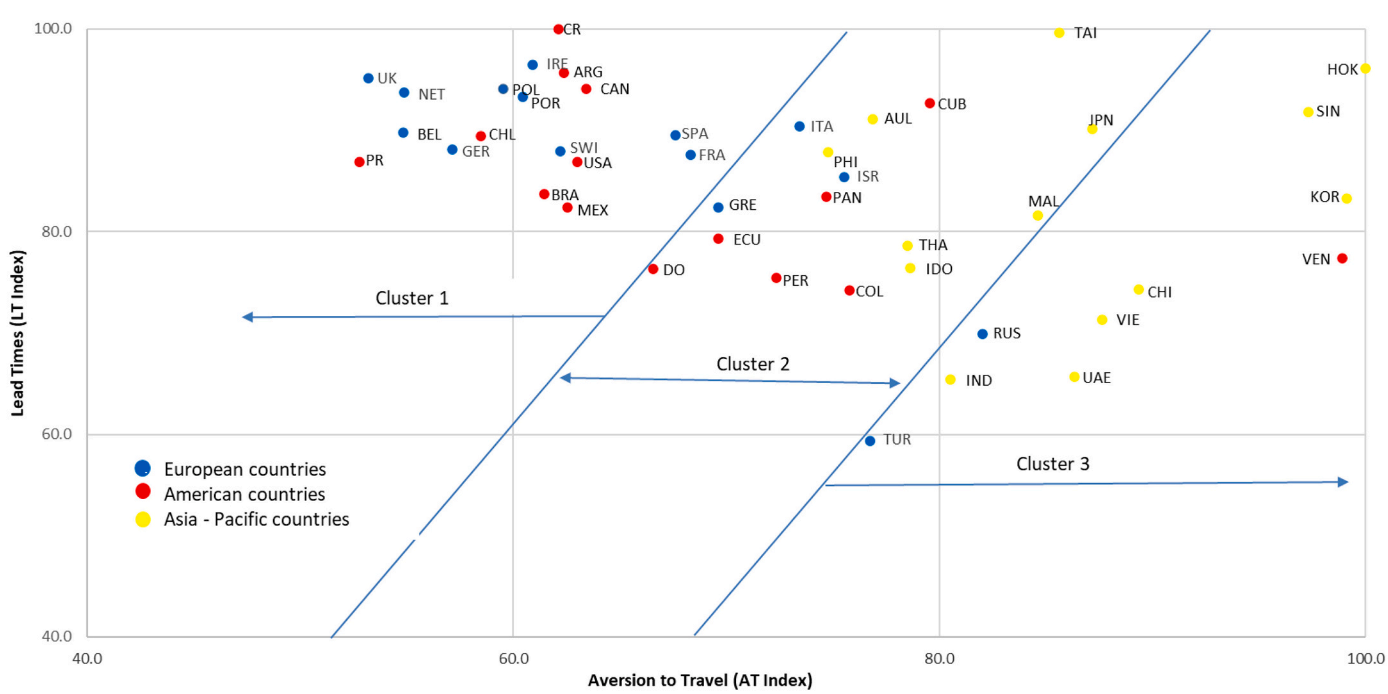

Fig. 4. Classification of countries into three clusters.

Table 3
Average indices and ANOVA - Post-hoc Scheffe test of the three clusters in the two dimensions analysed.

Ward Method		AT Index		LT Index	
		Media	Sig	Media	Sig
Cluster 1	Cluster 2	60.29	0.000	90.81	0.050
	Cluster 3		0.000		0.000
Cluster 2	Cluster 1	76.45	0.000	84.05	0.050
	Cluster 3		0.000		0.030
Cluster 3	Cluster 1	89.78	0.000	75.44	0.000
	Cluster 2		0.000		0.030

uncertainty in their intentions to travel and from greater to lesser orientation in their long-term planning. To give robustness to the analysis and verify that stable groups are behind the nature of the data, other different agglomeration methods are applied, and we conclude that two of them yield similar results: the complete link (or furthest neighbour) method and the method of the median, while the rest generate very unbalanced groups, without a coherent interpretation.

In summary, the results suggest that there is homogeneous behaviour among most countries belonging to the same region. However, there are significant differences in consumer behaviour between regions. These patterns of behaviour are corroborated when analysed at the country level. Consumers from Asia-Pacific are more averse to travel and have a greater range in the lead times for planning their trips, while European countries have more homogeneous consumer behaviour, plan ahead of time and have less aversion to travel. American countries have less homogeneous consumer behaviour, with North American countries (USA, Canada and Mexico), and some South American countries (Chile, Brazil, Argentina, Puerto Rico and Costa Rica) behaving similarly to the European countries. These findings have important implications when it comes to defining international marketing strategies to promote and reactivate tourism in the recovery period after the COVID-19 pandemic. The results indicate that it is not necessary to establish strategies by country, but that it is optimal and more cost-effective, to reduce the number of strategies orienting them to regions.

5. Conclusion and discussion

The present study responds to calls for a better understanding of the role of travellers' cultural background in travel decision making and travel behaviour (Backhaus et al., 2022; Karl, 2018) and for the usage of novel methodologies (Zenker & Kock, 2020). This study analyses the perceived risk to air travel based on two variables: aversion to travel, and travel planning lead times. We compare data from 2020 against the 2019 baseline because of the global, and almost uniform, closure of international air travel flights in 2020, when the UNWTO (2020) recommended domestic and land-based trips instead of international air travel in response to the COVID-19 pandemic. Using 2021 data would have introduced confounding variables due to travel restrictions that varied between countries that would have affected the travel search patterns. Unlike other studies in the tourism literature that focus on laboratory designed experiments or case studies referring to specific destinations, this research uses Big Data to deepen our understanding of the behaviour of potential tourists before and during the COVID-19 pandemic and, therefore, overcomes the shortcomings of surveys and experiments. The Skyscanner database allows us to identify and analyse, under the same prism, the reaction to travel of consumers from different regions and different countries within those regions, as well as investigate whether there is homogeneous behaviour of the consumers according to their origins and, therefore, their cultures.

To our knowledge, no previous studies have used lead time between flight searches and travel as a measure to understand risk perceptions. We acknowledge that any analysis of secondary data has the limitation of developing a theoretical framework to interpret the patterns identified. Skyscanner does not allow us to track whether someone has conducted a single search, or whether they search multiple times at different points in time. We tried to reduce this limitation by analysing the variable of flight picks, which is less likely to occur repeatedly than flight searches. We also operationalise the time-related aspect of travel planning as "the time span between the search flights and travel dates (called "Lead Times"); and travel intention under high-risk condition as the change in international flight selections between 2019 and 2020 (called "Aversion to Travel"), yet we acknowledge that our data set will not include the whole period of planning a trip, which starts with the idea/inspiration, as our data is limited to the step of searching for flights. We argue that the originality and timeliness of this study, together with the rigour of the methodology, outweigh this limitation, which is common to all Big Data studies.

To our knowledge, no other study has conducted such an extensive comparison of travel search behaviours, comparing before and during COVID-19 behaviours. The analysis of a global phenomenon allows us to draw theoretical implications in relation to the impact of intolerance of uncertainty in travel intentions (Chien et al., 2017; Golets et al., 2021; Huang et al., 2020; Senbeto & Hon, 2020; Zenker et al., 2021). Knowledge of which countries are more resistant to crises is essential for destination marketers to inform recovery plans post-COVID (Golets et al., 2021). Previous studies on health travel risk have shown how specific regions affected by pandemics have seen reduced travel, but the decreases were often at the expense of consumers redirecting their travel to other destinations (Chien et al., 2017; Jonas et al., 2011; Wilks, 2006; Wilks, Pendergast, & Leggat, 2006). The COVID-19 pandemic is the first opportunity to study a risk condition that has not resulted simply in redirection of international travel to other destinations. This pandemic has resulted in the entire globe adjusting its travel expectations according to a shared threat, with the resultant adjustments and changes in behaviour patterns reflecting how different cultures experience risk.

5.1. Theoretical implications

We contribute to the literature on motivation protection theory by showing how uncertainty avoidance behaviours manifest differently across cultures and how individuals from countries with a low risk tolerance change their travel search behaviours more than those from high risk tolerance countries (Grupe & Nitschke, 2013; Quintal et al., 2010; Tanovic et al., 2018; Verkoeyen & Nepal, 2019). Our study demonstrates the extent to which uncertainty avoidance is a culturally specific dimension, and contributes to the previous literature on risk and uncertainty in travel information search behaviour (Backhaus et al., 2022; Gursoy & McClearly, 2004; Gursoy & Umbreit, 2004; Kah, Vogt, & MacKay, 2008; Quintal et al., 2010; Senbeto & Hon, 2019; Zheng et al., 2022). Our study shows how uncertainty avoidance specifically manifests itself in the lead time between the start day of trip planning and the departure date, as a further tool to mitigate risk and, in doing so, contributes to the literature on how risk affects trip planning (Backhaus et al. ., 2022; Golets et al., 2021; Jordan et al., 2013). In doing so, we provide the most comprehensive analysis to date of how uncertainty avoidance affects the process of searching for flight information (Crotts & Litvin, 2003; Litvin et al., 2004; Money & Crotts, 2003) and avoidance of travel more broadly (Backhaus et al. ., 2022; Nazneen et al., 2020; Neuburger & Egger, 2021; Senbeto & Hon, 2019; Zheng et al., 2022). Moreover, unlike recent research (Backhaus et al. ., 2022) our results are consistent with the findings achieved by Money and Crotts (2003) and Litvin et al. (2004) who reported fewer days in trip planning for high UA respondents. As reported by Money and Crotts (2003:199), "risk-reducers would tend to spend more time in planning their trips in order to lessen the uncertainties of traveling to a new destination. However, risk avoiders may also have a harder time making a decision and take longer because of their search process".

5.2. Managerial implications

Marketers are faced with the dilemma of either standardising or adapting their marketing strategies. A cost-conscious approach is to deploy a standardised global marketing strategy, whereby a DMO uses the same marketing strategy and mix elements for all international demand. Adapting that global approach requires adjusting the marketing strategy and the mix elements. Despite requiring greater investment in the short-term, adaptation leads to a greater market share and return in the long-term (Theodosiou & Leonidou, 2003). The key to successful adaptation is to gain deeper knowledge of each international target country and identify how to segment the demand, particularly when faced with consumer behaviour changes from external shocks. This study has implications for destination marketing managers, as we recommend they introduce two different marketing strategies and campaigns according to the risk perceptions of target demand. First, destinations ought to target consumers from most European and American countries, who are more risk tolerant of travelling abroad, encouraging them to return to normal travel, making up for lost time. Second, destinations should introduce a campaign aimed at consumers in the Asia-Pacific countries, who are the most fearful, and at those who have reduced their trips abroad the most during the pandemic. These groups should receive messages focused on the safety of the destination and the possibility of carrying out risk-free activities. Both campaigns should help remove/reduce the perceived risks by providing consumers with up-to-date information about the destination and its products that enhance their sense of safety and security. The lead time data should inform the dates of when campaigns should be launched, with campaigns targeting most European and American consumers being launched well in advance of the time when consumers are expected to travel. Complementary to these early marketing campaigns, action should be taken in a different way for consumers from the Asia-Pacific countries, with marketers opting to target adverts in the short- or long-term by country, since these countries are less homogeneous than those in Europe or the Americas.

5.3. Limitations and future research

We acknowledge, however, that there will be other variables that affect travel search patterns, besides the cultural values of uncertainty avoidance, that should be investigated in further studies. For example, we cannot say that all countries in Asia-Pacific share the same culture, surely the reasons why residents of Australia searched for fewer flights during 2020 than the residents from the UK and the US will differ from the reasons of residents in Hong Kong. The availability of flights since COVID-19 has not been consistent across countries, as a result from variations in border closures (UNWTO, 2021). Still, we argue that there are regional policies and patterns determined by groupthink and that the actions taken by the more dominant countries in any given region will have knock-on effects on others. In addition, it is important to test how other variables known to influence the trip planning horizon may affect flight patterns post-COVID, such as the purpose (Fodness & Murray, 1997), length and distance of the trip (Zalatan, 1996), as well as the mode and cost of transportation (Chen & Hsu, 2000; Huh & Park, 2010). While our dataset did not allow us to test for the relative importance of different variables, this study provides several research questions to further validate with other methodologies.

Credit author statement

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Dr. M. Rosario González-Rodríguez: Writing- original draft, writing-review & editing.

Prof Xavier Font: Writing- original draft, writing- review & editing.

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