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The impact of COVID-19 on European tourists' attitudes to air travel and the consequences for tourist destination evoked set formation

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ABSTRACT

We study how risk conditions derived from the COVID-19 pandemic may impact on both the desire to travel and intention to visit of tourists and, therefore, on different stages of the destination choice process. We analyse 5134 million flight searches and 379 million flight picks during 2020 for the 17 largest European tourism source markets. An unweighted index number is employed to measure the average variation for searches and picks, for the year 2020, in relation to the reference base period (year 2019). This is done for air travel in general and to Spain specifically. The study then proceeds to conduct an analysis of 17 international travel destinations that are in the evoked sets of the two largest outbound markets in Europe (Germany and UK). We also identify which markets are most favourable to Spain. The research design can inform cost-efficient marketing decisions in a situation of high uncertainty.

1. Introduction

In the last two decades, health concerns in tourism have aroused a growing interest in the academic literature on tourism-related impacts (Chen, Law, & Zhang, 2021). For example, Mao, Ding, and Lee (2010) found that severe acute respiratory syndrome (SARS) has significant effects on tourism in South and Southeast Asia. Cooper (2006) and Zeng, Carter, and De Lacy (2005) analysed its influence on tourism in Japan and China, respectively. Kuo, Chen, Tseng, Ju, and Huang (2008) and McAleer, Huang, Kuo, Chen, and Chang (2010) analysed both Avian Flu and SARS, and found that the decrease in tourist arrivals had a greater influence on those countries affected by SARS than by Avian Flu. Blake, Sinclair, and Sugiyarto (2003) showed that the foot and mouth disease (FMD) outbreak led to a significant drop in tourism spending in the UK. Rosselló, Santana-Gallego, and Awan (2017) analysed the impact on tourist arrivals in countries affected by Malaria, Yellow Fever, Dengue and Ebola.

The risk of viral infection plays an important role in the choice of destinations and in health-preventive behaviours like travel avoidance (Huang, Dai, & Xu, 2020). Most of the research has focused on the latter stages of the decision-making process and only few studies, so far, have paid attention to the early stages of travel decision-making or the destination choice set. Furthermore, these works have focussed on specific regions and have employed structured surveys with different sampling procedures and methodologies, for different traveller groups and with a focus on specific destinations (Yang, Zhang, & Rickly, 2021). COVID-19 has demonstrated that we know little about how consumers make evoked set decisions under risk conditions. An evoked set is a small group of brands (or in our case, tourist destinations) that a consumer will consider before making a purchase. To address the gaps observed from the literature, the present study appears to be necessary since tourist destinations need to reconsider which source markets to target, based on a better understanding of how consumers in those markets may change their purchase considerations because of their perceptions of risk. Thus, this study aims to provide empirical evidence of how travellers' perceptions of the health-risks derived from COVID-19 are reflected in their evoked destination sets and in their travel decisions towards choosing a destination. To this end, the research questions (RQs) proposed are: RQ1) Which markets are more likely to travel abroad in 2020 (during the COVID-19 pandemic) in terms of their consumers' desires and intentions to travel? and RQ2) To what extent does predisposition to travel abroad change, in terms of the desire (evoked set) and intention to travel? On delving into these two research questions, more questions arise, whose answers might guide the Destination Marketing

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Organisations' (DMOs') marketing strategies, for example: i) Which are the source markets on which a specific tourist destination should focus their marketing efforts? This decision would be made according to whether the destination belongs to the evoked sets (desire to travel) and the late consideration sets (intention to travel); and ii) What other destinations are also in both sets (i.e., in the evoked and late consideration sets) and, therefore, competing with the specific tourist destination?

To respond these questions, unlike other studies, this study uses Big Data from Skyscanner; a search engine that provides timely, and accurate, worldwide data that is not subject to self-reporting biases. The method matches the concepts of flight searches (as a proxy for the desire to travel) and picks (as a proxy for the intention to travel) to the literature on the Choice Set (CS). The methodology is applicable to any source market or tourist destination. In our case, it has been applied to 17 European source markets to measure their predisposition to travel abroad. For Germany and the UK, the main European source markets, the study expands the analysis to compare inbound tourism demand for Spain with its competing destinations. The findings reflect the power of the methodology and dataset, and, hence, its managerial implications for DMOs. Thus, the present research study responds to a call from the literature to understand the inconsistent results achieved, when analysing the influence of risk perception on the destination choice (DC) process, due to a variety of research designs, sample, and data collection methodologies (Karl, 2018).

2. Literature review

2.1. Choice Set

The Choice Set (CS) assumes a funnel-like process that passes from recognition (awareness), through evaluation and reduction of alternative brands (evoked set), to arrive at a final choice (purchase). The decision rules that determine which products will enter the evoked set often acknowledges that final choice is a multi-stage process (Howard, 1963; Howard & Sheth, 1969).

The traditional CS literature that suggests three sequential stages in the tourist destination selection process (Crompton, 1992). First, an initial set of destinations, called an early consideration set (awareness set), is formed from those destinations that consumers are aware of either from their own previous experience (familiarity) or due to their proximity or by gathering information passively from external sources. Those destinations are defined as possible vacation destinations within a period. Second, a smaller, late consideration set (evoked set) is formed by reducing the awareness set. The evoked set is defined as including those destinations that the consumer would consider travelling to and has actively gathered information about. Third, the late consideration set is composed of those destinations considered as probable destinations for travelling to and it is from this set that the traveller will make their final choice of destination.

Although the traditional CS models have been widely adopted in the tourism decision making literature, Decrop (2010) goes one step further to define the formation of DC through four dimensions, instead of stages, by assuming that the decision-making process is not always sequential. Awareness or consideration set is the first dimension. The second dimension leads to three categories, namely: i) an evoked set (based on preference or expectations); ii) a surrogate set (based on tolerance level) formed by destinations that are assessed positively; and iii) an exclusion set that includes destinations evaluated negatively. The third dimension considers the main constraints for choosing a destination, through which the evoked set is categorised into: i) the dream set formed by destinations with one or more structural constraints; ii) the unavailable set with destinations suffering situational inhibitors; and iii) the available set with destinations that either do not experience any constraints or are more realistic (i.e., the constraint, although being a barrier to travel, might not prevent the DC due to the opportunities offered by the destination (Karl & Reintinger, 2017)). The final choice (fourth dimension) can be made either from the available set, the surrogate set or directly from the awareness set. Thus, unlike the traditional CS literature, the formation of CSs can be viewed as a dynamic process driven by constraints and opportunities.

2.2. Destination choice sets and constraints

Tourism academics have explored the processes of information searching and choice reduction during complex decision making (Dellaert, Arentze, & Horeni, 2014). In doing so, they have acknowledged that the formation of CSs is not linear as initially suggested, but it can be viewed as a dynamic process driven by constraints and opportunities, and considers that there may be an unavailable set with destinations suffering situational inhibitors; and an available set with destinations that either do not experience any constraints or are more realistic (i.e., the constraint, although being a barrier to travel, might not prevent the DC due to the opportunities offered by the destination (Decrop, 2010; Karl & Reintinger, 2017). According to the CS, the DC process is based on the allocation of alternatives into groups, which in turn are structured according to the tourist's desire to visit a destination and the feasibility of that destination in terms of constraints (Karl, Muskat, & Ritchie, 2020). However, more research on DC influences has been undertaken based on tourist characteristics rather than based on destination attributes (Karl, Reintinger, & Schmude, 2015; Sönmez & Graefe, 1998) and even less on constraint conditions (Karl & Reintinger, 2017). The CS concept assumes that the psychological states of the consumers are shaped by the interaction of consumer characteristics with the search activity and the subsequent alternative evaluation process. Yet relatively little is known about the role of perceived risk (as an influential constraint) in reducing the destinations that they are choosing.

With the COVID-19 pandemic, there is a growing body of literature that explains that tourist's perceived risk, anxiety and risk attitude play a role in determining their health risk tolerance level, but this literature has not been used to understand decisions about the DC process. We know that COVID-19 influences perceived health risk, impacting on mental wellbeing and inducing uncertainty perception (Chua, Al-Ansi, Lee, & Han, 2020), and that "travel anxiety and risk attitude moderate the indirect impacts between fear of COVID-19 and travel intention" (Luo & Lam, 2020). The anxiety/uncertainty management theory (Gudykunst & Hammer, 1988) can be used to explain why the perception of uncertainty/risk induces anxiety towards making choices that will make it difficult to adapt to a new environment, and why this anxiety is reduced by consumers choosing tourist destinations that they are already familiar with. Likewise, individual characteristics, social structures and cultural orientation determine the acceptable level of risk perception (Sjöberg, Moen, & Rundmo, 2004) and culture, personality and motivation to travel are viewed as the main antecedents of anxiety (Reisinger & Mavondo, 2005). Thus, under situational constraints conditions, these personal factors influence the evaluation of destinations, and their subsequent allocation into sets, at each stage of the DC process. However, we still have limited research on how personal factors shape the risk tolerance level in the COVID-19 period (Graham, Kremarik, & Kruse, 2020; Neuburger & Egger, 2020).

While recognising that risk constitutes a relevant factor in DCs, the questions of how and when (at which step in the DC process) this factor affects the DC, have not been sufficiently researched (Karl, 2018). Travellers mention perceived risks and safety in few studies, arguably, because those factors will already have been considered early on and will have ruled out destinations from the evoked set (Karl et al., 2015). This argument is in accordance with the motivation-hygiene theory (Herzberg, Mausnes, Peterson, & Capwell, 1957), which suggests that some external/situational factors are almost assumed as pre-conditions and, while in most circumstances they will not influence customers to choose a product, if they are not met, they will lead to dissatisfaction and product/service avoidance. Thus, for some studies travel risk has been treated as a marketing hygiene factor, such that tourist destinations that do not meet a threshold level of perceived safety will be discarded by travellers at an early stage of the DC process (Perdue & Meng, 2006).

However, other studies have assumed that an individual's constraints have more influence on the later stages of the DC process. Decrop (2010) admitted that constraints (structural and situational) play a vital role in the third dimension of the DC process. He also mentioned that the tolerance level, with respect to certain constraints, determines the surrogate set. Otherwise, Um and Crompton (1992) found that the merits of destination attributes (termed as facilitators), in terms of their ability to meet tourist needs, are the dominant criteria for constructing the late consideration set from the early set (evoked set). In contrast, situational constraints such as cost, health problems, safety and physical accessibility (termed as inhibitors), are the dominant criteria for the final DC from the late consideration set.

In summary, set theory suggests that deciding on DC is a hierarchical, or dynamic, multistage process that consists of allocating alternative destinations into groups. The groups are allocated hierarchically, mainly based on the individual's levels of desire to visit the various destinations and the feasibility of them doing so. There is no consensus on whether risk perception has a stronger influence at the beginning of the DC process (evoked set) or at the last stage of the process, when tourists choose their final destination from the late consideration set (Karl, 2018). However, what is generally accepted is that risk perception is a key factor that relates to both desirability (at the initial stage of the DC process) and feasibility (at the final stage). Hence, the present study aims to respond:

RQ1: Which markets are more likely to travel abroad in 2020 (COVID-19 period), in terms of desire and intention to travel?

RQ2: To what extent does COVID-19 affect the desire (evoked set) and intention to travel (late consideration set)?

3. Methodology

Previous studies employ mostly surveys that lead to segmenting potential tourists based on hypothetical (rather than realistic) alternative destinations in both their evoked set and the late consideration set. Instead, this study employs Big Data with timely, accurate and real information on destination choices during the pandemic period. The use of Big Data avoids the bias caused by the social desirability factor in surveys.

The Skyscanner metasearch engine allowed us to: i) analyse demand, in terms of flight search, from any origin to any destination, and ii) work with a high volume of real data in real time. The Skyscanner platform provided us with two moments of interest during the purchase decision process. First, the consumer defined their search by indicating a desired destination, regardless of the actual availability of that service by the airlines, thus generating the variable "searches" whose destinations were identified with the "evoked set" of the CS. Secondly, from the available options that the search provided, the consumer may, or may not, have chosen the option that best suited their requirements in terms of hours, stopovers, price, etc.; thus, generating the variable "picks" and the selected destinations were identified with the "available set" of the CS. The variables show an intention to travel at two different stages of the decision process, regardless of the reason for the trip, and, therefore, allow us to know the predisposition or attitude of the potential tourist towards travelling to certain destinations. However, the data does not tell us if the flight booking has been confirmed since, once the flight has been selected, Skyscanner redirects the consumer to the corresponding website to make the reservation and payment.

Our data set consists of 5134 million flight searches and 379 million flight picks made by European consumers to travel during the year 2020, whose capture, management and processing is carried out through the payment platform ForwardKeys (2020), a Big Data company that monitors the aviation industry. Contrasting the evolution of these variables with the evolution of the pandemic, through the data provided by the World Health Organization (WHO, 2020) on cases of COVID-19 contagion in Europe, we observe in Graph 1 that an increase of cases entails a reduction in flight searches and picks. Likewise, a low level of contagion translates to higher results in both variables. In short, the better or worse the pandemic implies a greater or lesser predisposition to travel.

Once the variables to be measured in relation to travelling attitudes have been identified and the effect of the pandemic on them has been demonstrated, we proceed to identify an indicator that allows us to know the variations in the travelling attitude during 2020. For this, we have opted for the calculation of index numbers as a statistical measure that allows us to study the changes that occur in a magnitude with respect to time and their comparison between different territories. This measure compares a series of observations with respect to an initial situation that is arbitrarily set; this base or reference period, which is taken as the origin of the comparisons, conditions the result of these, so the choice of base period must be carefully selected as the most suitable possible according to the objectives pursued. In our case, the month of January 2020 is taken as the base period because: i) in Europe, travel at this time was not yet affected by the pandemic, ii) it is the natural start of the calendar year, and iii) traditionally, January is low season for travel as well as a month with a low volume of flight searches and picks for European countries under analysis in a normal situation. Therefore, by selecting January 2020 as the base period, we are comparing the evolution during the pandemic to a low level of activity during a normal period without a pandemic.

First, the simple index numbers are calculated for each month of the variables search (*si*) and pick (*pi*) for country i. For the base period (0), which takes the value 100 and is defined by the month of January, and the current period (t) for all months of the year, it would be:

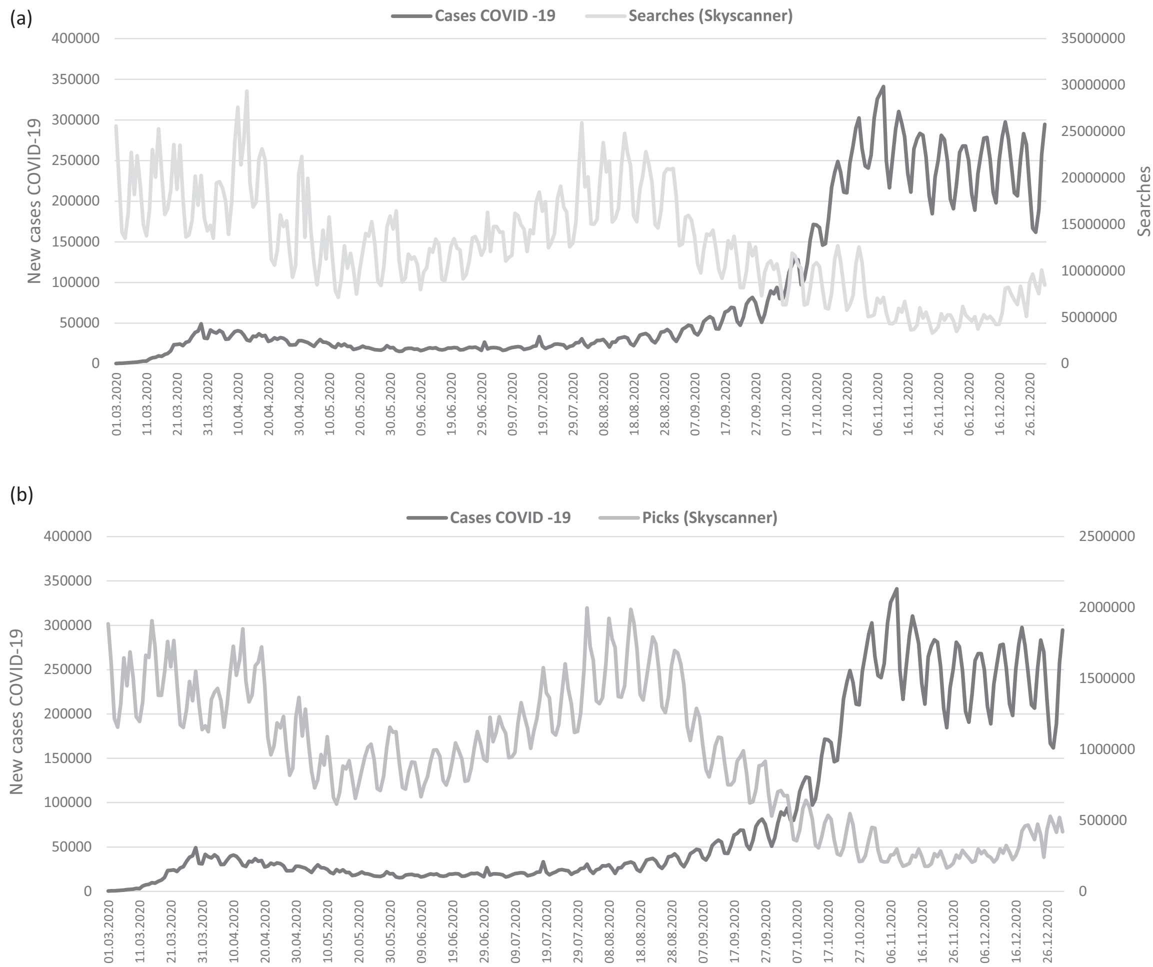
$$\mathrm{s}i = \frac{\mathrm{sit}}{\mathrm{si0}}\ \mathrm{x}\ 100\ pi = \frac{\mathrm{pit}}{\mathrm{pi0}}\ \mathrm{x}\ 100$$

Subsequently, to analyse the global behaviour of the year, a statistical measure is sought that summarises all the information while ensuring that all the months have the same weight in the average result. This decision, despite the seasonality that tourism traditionally presents, has been taken as 2020 is considered an atypical tourist year in which temporality has been subject to uncontrollable external elements. Thus, the Sauerbeck (1895) complex index is calculated as the unweighted arithmetic mean of the simple indices for search (*Si*) and picks (*Pi*):

$$Si = \frac{1}{\mathrm{t}}\sum\nolimits_{t=1}^{12} \frac{\mathrm{sit}}{\mathrm{si0}}\,\mathrm{x}\ 100\ Pi = \frac{1}{\mathrm{t}}\sum\nolimits_{t=1}^{12} \frac{\mathrm{pit}}{\mathrm{pi0}}\,\mathrm{x}\ 100$$

This complex index allows us to measure the average variation of the year in relation to the reference base period. An index higher than 100 would mean that the searches and picks made by the demand of a certain country have shown a better annual evolution than the level set for the month of January, while an index lower than 100 would imply that the average of the year has not even reached the baseline level (January). Note that we acknowledged earlier that the baseline level is already considered low for a normal year. In short, the higher the index value, the better the attitude to travel in this period of COVID-19 pandemic.

The Sauerbeck complex index is the most commonly used of the unweighted, aggregate indices and is defined as a simple arithmetic mean that satisfies two properties that are optimal for this research. First, the independence of the measurement unit in which the variable is expressed allows for comparisons between the searches (*Si*) and picks (*Pi*) indexes. Second, the measurement unit fulfils the property of proportionality, which means that if the magnitude varies in a certain proportion, the index number also varies in the same proportion (Frisch, 1936). This allows us to interpret the distance between indices and to know how close or far the situation of one country is compared to another. The following section exemplifies the potential benefits of the methodology by applying it to measure the attitude to travel to Spain of the main European outbound markets during the pandemic.



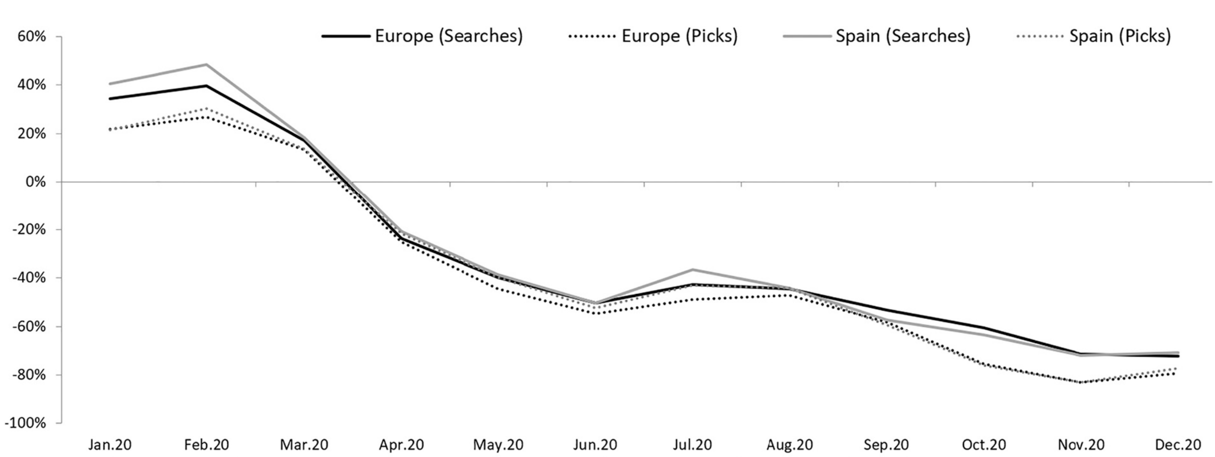
Graph 1. (a) SEARCHES | Daily evolution of cases of contagion by COVID-19 and flight searches carried out on Skyscanner for Europe (03/01/2020–31/12/2020). (b) PICKS | Daily evolution of the cases of contagion by COVID-19 and of the flight selections made on Skyscanner for Europe (03/01/2020–31/12/2020). Source: Authors, based on ForwardKeys and WHO (2020).

4. Results

4.1. Flight searches and picks' evolution 2019–2020

Flight searches and picks on Skyscanner to Europe have registered a decrease in 2020 compared to the previous year of −36.2% and − 42.6% respectively and their evolution throughout the year has progressively worsened, as can be seen in Graph 2, where in the last months of the year decline rates of over −70% for searches and − 80% for picks are achieved.

For Spain, one of the main European tourist destinations, the declines in 2020 compared to 2019 have been even more significant (−63.2% in searches and − 58.7% in picks). Despite these general declines, the desire and intention to travel to Spain have not evolved in the same way



Graph 2. Interannual variation rates in 2020 compared to 2019. Flight searches and picks to Europe and Spain. Source: Authors, based on ForwardKeys (2020).

across all the outbound markets. We believe that this information is especially interesting for tourist destination managers since it suggests that the level of marketing effort required to recover, or encourage, a market will depend on whether that market presents a high or low aversion to the risk of travelling, or whether that market is one where a Spanish destination has been part of its evoked set for possible trips during the pandemic.

This research focuses on the 17 European countries emitting the highest number of tourists to Spain, listed here in order of importance according to overnight hotel stays (INE, 2019): United Kingdom (UK), Germany (DE), France (FR), Italy (IT), Netherlands (NL),Belgium (BE), Sweden (SE), Ireland (IE), Poland (PL), Portugal (PT), Switzerland (CH), Norway (NO), Denmark (DK), Austria (AT), Finland (FI),Czech Republic (CZ) and Greece (GR). Our analysis does not include long-haul markets since the national tourist board has decided to prioritise short-haul markets as their first priority to reactive the tourism economy (Gobierno de España, 2020).

The analysis is developed in four stages to answer the four research questions. (1) For each market *i*, the complex Sauerbeck index for flight searches and picks is analysed; this measures the attitude shown towards travelling abroad, in general($S_i^{Outbound}$; $P_i^{Outbound}$) (2) The complex Sauerbeck indices for Spain are analysed,(S_i^{Spain}; P_i^{Spain}). (3) Both attitudes are compared to identify those markets that are most favourable to Spain. Then, once the most interesting target markets for Spain have been identified, (4) a competitive analysis is carried out in relation to other destinations that have also been part of the consumers' evoked sets. All stages have the year 2020 as the analysis period, since the objective is to measure the attitude to travel of consumers from different countries in the same period of uncertainty.

4.2. RQ1: Which markets are more likely to travel abroad in 2020 (during the COVID-19 pandemic) in terms of their consumers' desires and intentions to travel?

In the first of the four stages, the source markets under study are analysed and then ordered from best to worst in terms of their predisposition to travel abroad during 2020 (Table 1). In this analysis, it is detected that three countries lead this ranking: United Kingdom, Belgium and Germany with $S_i^{Outbound} > 100$.This means that these countries have shown a favourable attitude to travelling abroad because, on average, every month in 2020 registers flight search levels greater than those of the month of January 2020, which is taken as a reference for having a low level of searches in a normal period (without pandemic).

However, while all three countries exceed the base 100 in searches, only Germany does so in flight picks. If we compare both annual average indices ($S_i^{Outbound}$and$P_i^{Outbound}$) we observe that the most common behaviour is that potential tourists from all source markets have shown a greater desire (searches) to travel abroad during the pandemic than their real intentions (picks). Only German consumers, and to a lesser extent Poles, show a more decisive attitude when it comes to travelling abroad, as their flight picks index exceeds the search index ($P_i^{Outbound} > S_i^{Outbound}$).

4.3. RQ2: To what extent does the predisposition to travel change in 2020, in terms of desire (evoked set) and intention to travel (late consideration set) when analysing a specific tourist destination?

In the second stage of the analysis, the predisposition of the markets to travel to Spain is analysed. Table 2 shows that the first eight countries in the ranking exceed the 100 indices, both in searches and in flight selection. These countries show a favourable attitude to travelling to Spain because on average every month in 2020 registers levels higher than the month of January (base period of reference) both in searches and flight picks. In addition, a higher value of the index means a better attitude towards travelling to Spain.

In the case of Spain, there is also a greater number of countries ($P_i^{Spain} > S_i^{Spain}$) where the evolution in flights picks is better than flight searches, which implies that there is a greater intention to travel and that consumers have a greater likelihood to consider Spain as their travel destination compared to the average. This occurs for Finland, Sweden, Norway, Poland, Germany and Ireland; the latter market standing out especially for registering a difference of more than 30 points and placing it first in the ranking according to flight picks.

From the previous research questions, and as mentioned in introduction, other analyses are derived: i) the most interesting source markets for Spain, based on Spain belonging to the evoked and late consideration sets of those markets; and ii) the destinations that compete with Spain (in that they also belong to both the evoked and late consideration sets) for specific, important source markets such as Germany and UK. These analyses are pertinent to guidance on the design of marketing recovery strategies in tourism and are developed in the following sections.

Table 1
Ranking (from best to worst outbound markets) according to the flight search and pick indices abroad during 2020.

	Searches ($S_i^{Outbound}$)		Picks ($P_i^{Outbound}$)	
1	United Kingdom	104.06	Germany	104.13
2	Belgium	100.80	United Kingdom	97.95
3	Germany	100.04	Belgium	94.12
4	Netherlands	95.46	Netherlands	88.54
5	Switzerland	95.34	Switzerland	88.22
6	France	87.67	Ireland	81.42
7	Ireland	82.19	France	71.33
8	Norway	77.72	Norway	71.15
9	Denmark	76.62	Sweden	68.37
10	Sweden	75.79	Denmark	67.93
11	Austria	69.64	Austria	66.29
12	Portugal	69.38	Portugal	64.08
13	Greece	68.12	Italy	61.12
14	Czech Republic	65.43	Greece	60.81
15	Italy	64.01	Czech Republic	60.29
16	Poland	59.35	Poland	59.94
17	Finland	57.57	Finland	54.76

Source: Authors.

Table 2
Ranking (from best to worst outbound market) according to the flight search and pick indices to Spain during 2020.

	Searches (S_i^{Spain})		Picks (P_i^{Spain})	
1	United Kingdom	141.49	Ireland	151.29
2	Belgium	123.84	United Kingdom	138.78
3	Netherlands	123.75	Germany	137.86
4	Germany	121.95	Netherlands	118.55
5	Ireland	119.63	Belgium	109.08
6	Switzerland	107.78	Norway	107.96
7	France	103.02	Switzerland	107.20
8	Denmark	102.05	Sweden	102.98
9	Sweden	98.43	Denmark	98.87
10	Norway	93.42	Poland	81.33
11	Czech Republic	84.32	Austria	79.95
12	Austria	83.28	Czech Republic	79.48
13	Greece	77.25	France	78.07
14	Italy	71.17	Italy	68.04
15	Portugal	66.16	Finland	65.16
16	Poland	66.11	Greece	61.13
17	Finland	63.58	Portugal	48.63

Source: Authors.

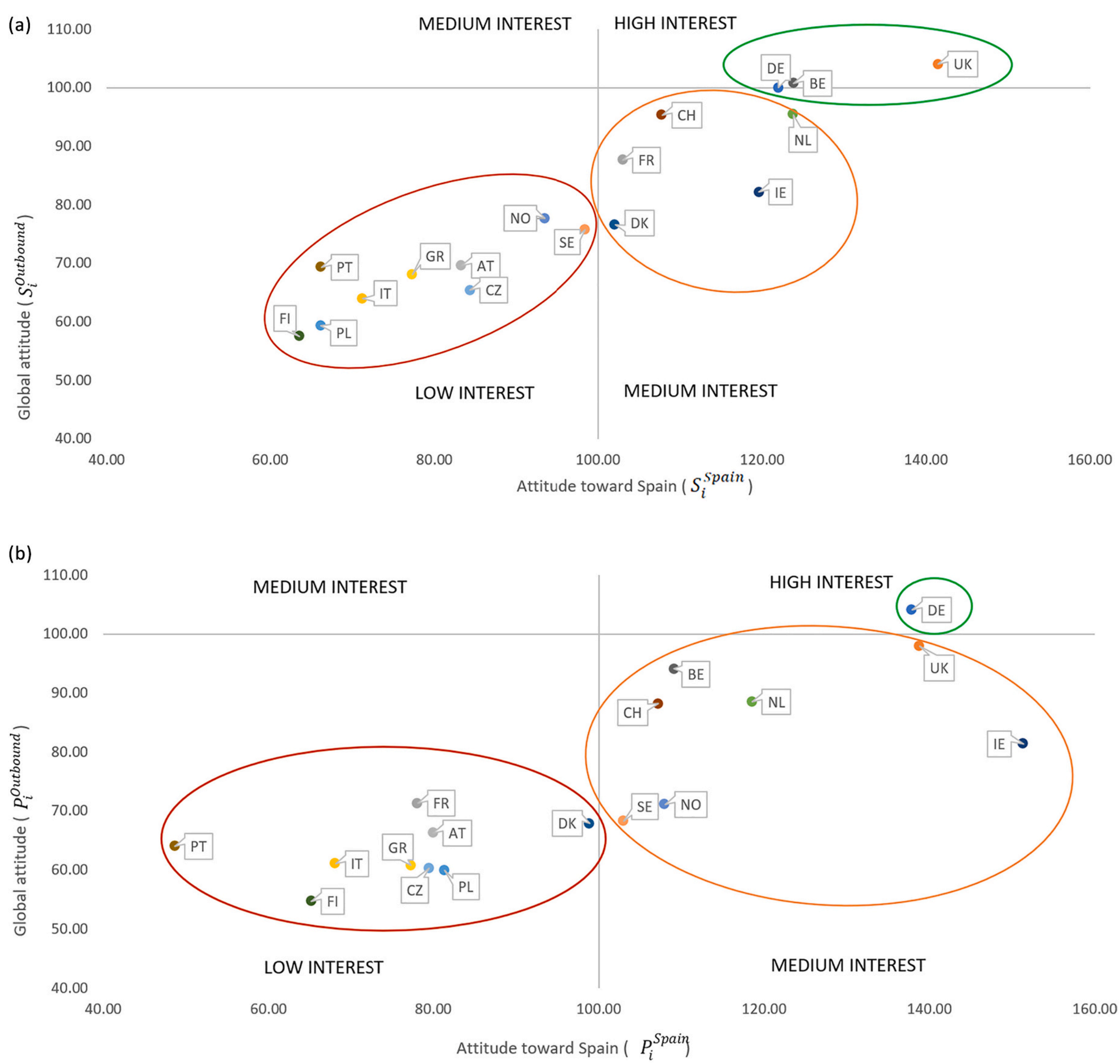
4.4. Identification of the most interesting markets for Spain

The third stage determines which markets are the most interesting by combining both attitudes (searches and picks). The analysis contrasts the values that the markets reach in their attitudes towards Spain (Table 2) with their attitudes towards travel abroad (Table 1). We observe that, for both variables, all the outbound markets show a more favourable attitude towards Spain except Portugal, which is highly influenced by being a local market where road transport to access Spain is common [in 2019, 82% of Portuguese tourists who accessed Spain did so by road (INE, 2020)].

To facilitate analysis and decision-making by managers, two matrices are constructed (one for each variable (searches and picks), where the X axis is defined by the index that measures the attitude of the different markets towards Spain (S_i^{Spain}; P_i^{Spain}), seen in Table 2, and the Y axis represents attitude to travel abroad ($S_i^{Outbound}$; $P_i^{Outbound}$) as seen in Table 1; the axes cut-off points are defined by the reference base level (100). In these matrices, the outbound markets can be positioned in the HIGH INTEREST quadrant (>100 attitude to travel both globally and towards Spain). This is the best possible situation since it indicates that the average evolution during 2020 has been above the reference base value both at a global level as well as towards Spain. In this quadrant, we find countries with a *positive attitude to travel in risk situations*. At the other extreme, we find those countries placed in the LOW INTEREST quadrant (<100 attitude to travel globally and towards Spain), this is the worst situation as these markets display the *most apprehensive attitudes towards travel in risk situations*.

In between, we find two intermediate MEDIUM INTEREST situations that occur when the attitude is favourable (>100) for only one of the two indices. This can take place when a country has a better attitude to travel globally than to travel to Spain, which means a *lost opportunity* for Spain, or, instead, that there is a better attitude towards Spain than to travel abroad more generally, which would indicate a *competitive advantage* for Spain. The matrices are a useful analytical tool when it comes to tourist destination managers making decisions about the most interesting markets to direct their marketing efforts to, based on the markets' behaviours or attitudes during the pandemic. This information can be decisive in terms of economic recovery.

In the case of Spain, both the matrices in Graph 3 show that no outbound market is in the upper left quadrant (medium interest) since the attitudes towards travelling to Spain, of all of the 17 European outbound markets analysed, show better results than their attitudes to travel globally. The most interesting market for Spain is Germany (DE), located in the quadrant of high interest both in flight searches (Graph



Graph 3. (a) SEARCHES - market positioning matrix according to flight search indices in 2020. Source: Authors. (b) PICKS - market positioning matrix according to flight pick indices in 2020. Source: Authors

3a) and picks (Graph 3b). In relation to flight searches, Germany is also joined by the United Kingdom (UK) and Belgium (BE), however the consumers from these countries move to the medium interest quadrant in relation to flight picks. In the intermediate quadrant for both variables, we find Switzerland (CH), Netherlands (NL) and Ireland (IE), with the latter country standing out especially for registering the highest value towards Spain in intention to travel. The remaining markets present more unstable situations. We find quadrant changes according to the analysis variable for France (FR), Denmark (DK), Norway (NO) and Sweden (SE). Finally, we find that the less interesting markets, i.e. those that have<100 indexes in both searches and flight picks, are: Portugal (PT), Finland (FI), Italy (IT), Greece (GR), Poland (PL), Czech Republic (CZ) and Austria (AT).

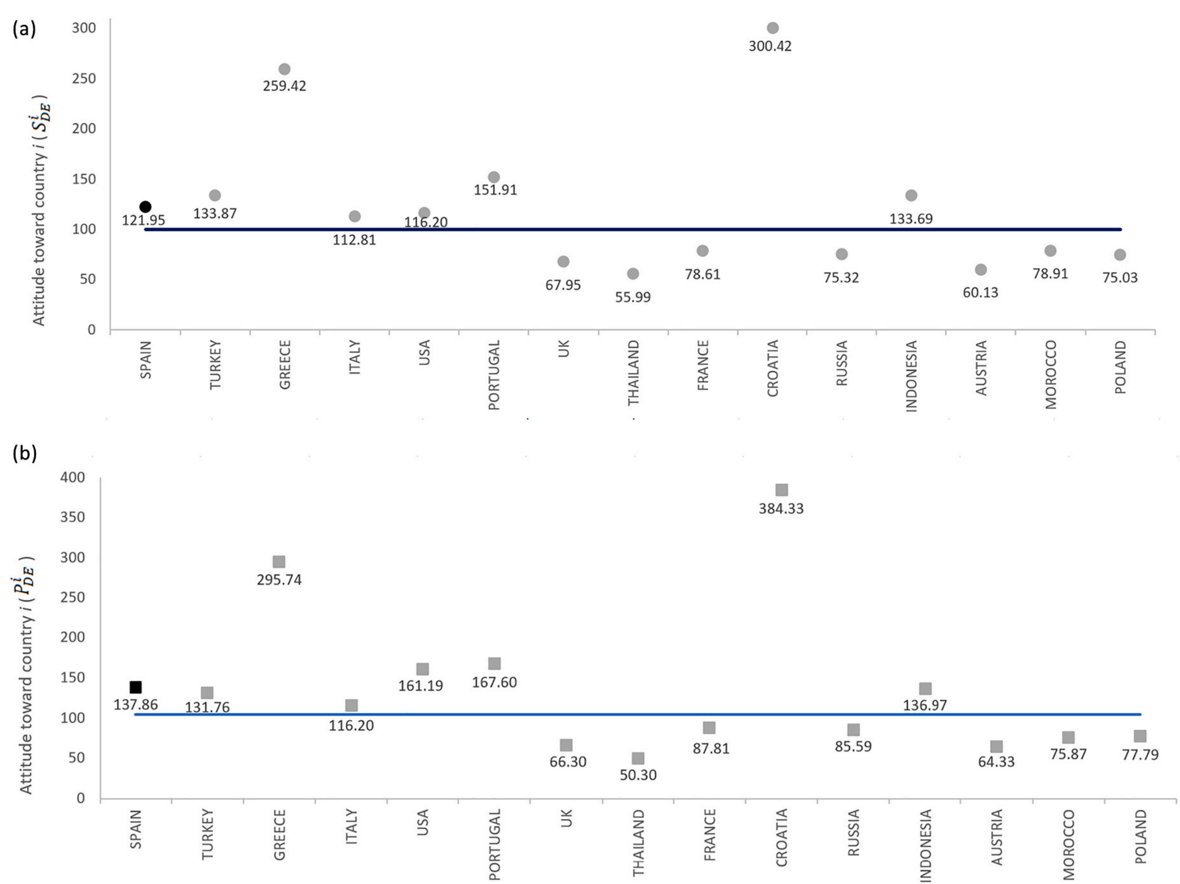
4.5. Identification of destinations that compete with Spain for the Germany and UK source markets

The last stage of the analysis (4) compares Spain's indices with its main competing destinations in the evoked sets. We select the best target markets for Spain, namely Germany (high degree of interest in both searches and picks) and the United Kingdom (high degree of interest in searches and the best of the cases in the medium range of picks). To compare these two markets, the Sauerbeck complex index is calculated for 14 tourist destinations' competitors in relation to the German ($S_{DE}{}^{i}$ & $P_{DE}{}^{i}$) and British ($S_{UK}{}^{i}$ & $P_{UK}{}^{i}$) markets. This analysis provides the destination managers with complementary data about the alternative destinations that their potential consumers are considering, and how near or far their own market is to each of the alternatives.

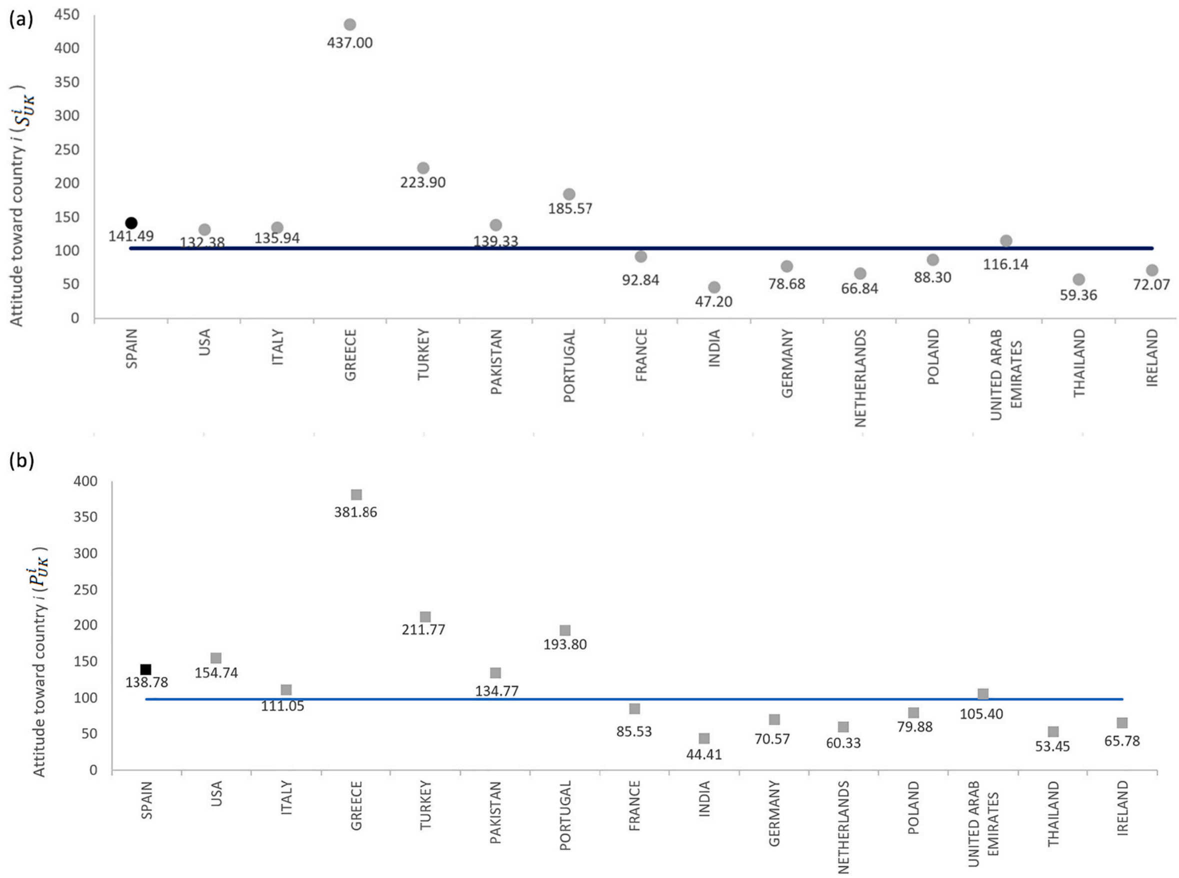
In the subsequent graphics, the destinations are shown on the X axis, ordered from left to right according to relevance by volume of flight searches during 2020, for the German (Graphs 4a and 4b) and British (Graphs 5a and 5b) markets. Spain appears in first place on the X axis in all four graphs because it is the most sought after, and selected, destination for both markets. The Y axis displays the attitude that the Germans and British show towards each potential destination they are considering travelling to. This axis shows that the index for German searches to travel to Spain was 121.95 (as seen in Table 2 and the X axis of Graph 4a) and picks 137.86 (Table 2 and the X axis of Graph 4b), while the British searches to travel to Spain was 141.49 (as seen in Table 2 and the X axis of Graph 3a) and picks 138.78 (Table 2 and the X axis of Graph 3b). Similarly, it also shows the indices for all other outbound destinations considered by both outbound markets, indicating whether they are above or below the average value of your trips abroad (based on data from Table 1); the average value is shown by the horizontal line.

The higher this index, the better the market's attitude towards the destination during 2020. Hence, despite the favourable attitude shown by German and British consumers towards Spain, whose indices are substantially above the horizontal axis, it should be noted that during 2020 other destinations have had more favourable attitudes from both outbound markets. For the German market (Graphs 4a and 4b), Croatia and Greece show flight search and pick values much higher than other destinations, with both variables registering indexes above 250, while in the case of the British market (Graphs 5a and 5b) we find flight searches and picks above those for Spain particularly for Greece, and to a lesser extent for Turkey and Portugal.

From the data and analysis, we can deduct that although Spain remains the main outbound market for both Germany and the UK in total numbers, and is still the destination most searched for during 2020 (the reason why it is positioned on the far left of the horizontal axis),



Graph 4. (a) SEARCHES ($S_{DE}{}^{i}$)- Attitude of the German market in 2020 according to searches for flights to Spain and to its 14 competing destinations.Source: Authors. (b) PICKS ($P_{DE}{}^{i}$)- Attitude of the German market during 2020 according to flight selections to Spain and to its 14 competing destinations. Source: Authors.



Graph 5. (a) SEARCHES (S_{UK}^{i})- Attitude of the British market during 2020 according to searches for flights to Spain and its 14 competing destinations. Source: Authors. (b) PICKS (P_{UK}^{i})- Attitude of the British market during 2020 according to flight selections to Spain and to its 14 competing destinations. Source: Authors.

consumers from Germany and the UK are conducting considerably more flight searches for other competing destinations, compared to the number of flight searches in previous years (index in the vertical axis), because they consider these other countries more attractive during a period of pandemic risk. The combination of both figures, i.e. volume and change over time in searches and picks, provides valuable marketing intelligence for Spain to determine its competitors amongst the evoked sets of tourist destinations for both markets.

5. Discussion

The data demonstrates how the increasing awareness of the risk of COVID-19 resulting from the infodemic (Williams, Wassler, & Ferdinand, 2020), in line with the growing number of cases globally, significantly affects the desire and intention to travel (responding to research questions 1 and 2). Travel risk perception of COVID-19 has increased over time, partly explained by the increasing number of cases, geographical spread, government responses and media coverage (Neuburger & Egger, 2020). We argue that an acceptably low level of perceived risk when travelling is a hygiene factor that in normal circumstances is assumed to be a pre-condition (Herzberg et al., 1957), but that when consumers believe this risk to vary across their options, they will use their perception of risk to reject higher risk destinations from their early choices to form the evoked set (and the available set) (Abougomaah, Schlacter, & Gaidis, 1987; Perdue & Meng, 2006), as observed from the literature review.

However, once we delve deeper into national level data, we see significantly different patterns across source markets that demonstrate the need to understand better: i) the contextual conditions that affect risk attitude, ii) the perceived health risks of travel, and iii) travel anxiety impact on travel intention (Chua et al., 2020; Luo & Lam, 2020). Also, new opportunities exist to advance this line of analysis to incorporate the elasticity of demand due to economic factors, where risk is one of those factors.

Perceived risk of a disease is informed by the subjective perception of susceptibility and severity (Floyd, Prentice-Dunn, & Rogers, 2000), hence it is important to understand consumers' levels of self-efficacy to protect themselves during a pandemic (Liao, Cowling, Lam, Ng, & Fielding, 2010). We know that the acceptable level of perceived risk depends on one's cultural orientation and psychographic factors (Reisinger & Mavondo, 2005; Sjöberg et al., 2004). However, belonging to a high/low uncertainty culture (Hofstede, 2001) alone is not a strong explanatory variable for desire to travel. Although some of the countries with the greatest desire to travel have a low uncertainty culture (UK, Ireland, Netherlands, Belgium), the country with the greatest desire to travel, Germany, is a risk avoiding culture. Moreover, evidence shows that frequency and experience in travel reduce risk perception (Neuburger & Egger, 2020; Pennington-Gray, Schroeder, & Kaplanidou, 2011). Those countries with the highest travel propensity in Europe, such as Germany and the UK, show the greatest desire and intention to travel during the pandemic.

The selection of destinations that travellers are already familiar with can be explained by the anxiety/uncertainty management theory (Gudykunst & Hammer, 1988). Emotional, affective and tacit knowledge of tourist destinations influences consumer choices in conditions of risk and uncertainty (Williams & Baláž, 2015). Knowledge, such as familiarity, reduces the perception of risk (Sönmez & Graefe, 1998). In the case of Spain, being a well-known destination for these markets and, therefore, being part of the evoked markets, the country offers greater confidence in times of uncertainty. The desire to travel to familiar places in times of uncertainty can also be explained by the emotional attachment and place bond, derived from a sense of identity and need for belonging to restore their sense of safety (Majeed & Ramkissoon, 2020; Ramkissoon, Smith, & Weiler, 2013). In addition, second-home ownership overseas may also explain some of the flight searches and picks, as the need to quarantine both at the destination and at home is less likely to deter travellers that own a second home at the destination, and that are travelling for longer periods, such as is the case for the over-65 market (Graham et al., 2020).

Finally, focusing on the destinations that compete with Spain for UK and German markets, results can be explained because threat severity (Floyd et al., 2000; Rogers & Prentice-Dunn, 1997) may also help to explain the choice of Greece for the UK outbound market, or Croatia for the German market. This may be because uncertainty resulting from fast changing contexts reduces the currency and validity of knowledge (Williams & Baláž, 2015). Tourists might avoid destinations that they perceive might be overcrowded as a risk mitigation mechanism (Zenker & Kock, 2020). Further research is required in this area to identify whether travellers are adopting other mechanisms that would confirm such argument, such as avoiding city breaks in favour of rural locations, opting for smaller airports and direct routes; some of these may be possible to determine through granular analysis of flight patterns with ForwardKeys.

6. Conclusions

It is believed that consumers identify the destination that offers the most benefits for the least cost (or risk) (Sönmez & Graefe, 1998). The perceived benefits from travel can help to explain why consumers have a latent desire to travel (as manifested in their evoked set) and why they continue searching for travel options, thus, revealing their intention to travel (and therefore, constituting their late consideration set), even at times when travel corridors are closed (Champion & Skinner, 2008) and when it is evident that the COVID-19 pandemic has increased the uncertainty and, therefore, the perceived risk of travel. Instead of interpreting such desire to travel during periods of risk as a maladaptive response, we use it to make a methodological contribution by developing a tool to forecast the more profitable markets to target when striving for economic recovery of a tourist destination. We identify specific markets that have a high-risk tolerance, and we provide some details about why certain markets may have a higher desire and intention to travel than others.

Theoretical and managerial implications are derived from this research. The study contributes to the academic literature on the process of information searching and choice reduction (set theory), as a result of analysing changes in complex decisions resulting from perceived risk derived from the COVID19 pandemic. We contribute to the call for research to better understand how emotional responses to perceived risks of a pandemic determine behaviour (Taylor, 2019) and, specifically, how consumers develop strategies to cope with the impact of the pandemic in relation to their travel desires (Chua et al., 2020). To this end, a methodological framework is proposed that demonstrates the benefits of Big Data in providing granular data that is essential to the study of volatile situations (see Gallego & Font, 2020). Furthermore, the methodology employed can be applied to any situation, regardless of the degree of uncertainty. COVID-19 has become an infodemic of constantly evolving data, policy and media, that affects the risk perceptions of travel (Williams et al., 2020). Tourist destinations, therefore, require timely data as perceptions of travel risk due to COVID-19 have increased substantially over a short period of time (Neuburger & Egger, 2020). In these situations, it is necessary for managers to have indicators that quickly detect changes in the destinations evoked by potential tourists and the best or worst attitude towards a certain destination at an early stage of the purchase decision process. The methodology developed in this study ought to be used as an early warning system to identify market changes and to inform the design of more specific studies to test the middle range theories developed.

Our results show the usefulness, for destination managers, of having indicators that measure the attitudes of different markets, during the pandemic, towards both travelling abroad, in general, and to specific destinations. Thus, the study has clear management and research implications, as we show how customer tolerance to risk needs to be built into marketing decisions (Reisinger & Mavondo, 2005; Sönmez & Graefe, 1998; Williams & Baláž, 2015). It is particularly important to help tourist boards to develop strategies for market recovery, which have not been observed in the initial responses at national level (Kreiner & Ram, 2020). With our methodology, a tourist board can not only analyse how the attitude of its main markets has evolved during the pandemic, but it can also incorporate new information when it comes to identifying and prioritising markets in its marketing strategies. This new vision should be incorporated into destination management as a criterion when selecting the best target markets, at least in the short or medium term until the unstable situation disappears and, ideally, as a reference for future situations that may pose global risk situations for travel.

Our study is not without its limitations. On the one hand, we acknowledge that the use of the Skyscanner database does not allow us to carry out the study by tourist segments since we are limited to the data available in the system (flight search and picks), without the possibility of considering further variables relating to the tourist profile or travel habits, such as age, gender and motivations for travel. In addition, the data provided by ForwardKeys is more representative of the behaviour intention (flight picks) than the actual behaviour since data on the actual bookings are not provided. However, in times of high volatility, it is important to understand the process of formation of destination CSs that lead to the final choices (Decrop, 2010). Hence, academics can use the ForwardKeys dataset with other methodological approaches to identify competing destinations in situations where structural constraints and situational inhibitors exist. Moreover, the database can be used as a vehicle to develop theories to explain consumer behaviour changes. Likewise, we have discussed the findings by focusing on certain aspects of travellers that are already noted in the CS literature, namely, cultural orientation, familiarity with the destination, frequency of travel and experience in travel. Other factors (such as geographical location, flight prices and the countries' policy decisions prevailing at the time of the search) that can help to explain the formation of the evoked and available sets, have not been discussed as these factors are already implicit to any search made on the Skyscanner platform.

Of the 7-Vs currently identified as the characteristics that define Big Data (El Alaoui, Gahi, Messoussi, Todoskoff, & Kobi, 2017; Gandomi & Haider, 2015), our data is characterised by: *volume*, working with millions of data that allow a high level of representation; *velocity*, the data are updated daily, which allows us to quickly detect changes in behaviour; *variability*, referring to the variation in data flow rates; *veracity*, high degree of veracity of the information received as it is real data and not estimates or extrapolations; *visualisation,* the data is understandable and easy to read for the end user; and *value*, the data is transformed into useful information for decision making. We acknowledge that our data has limitations with respect to the characteristic "variety" that also defines Big Data. In fact, the flight information provided by ForwardKeys only refers to international flights, not accommodation searches and picks, so it offers a partial picture of tourism demand. Hence, other data sources appear to be necessary to complement the study.

Credit author statement

Dr. Inma Gallego designed the study, prepared and wrote the methodology, conducted the data analysis and wrote the results section, as well as contributed to write the manuscript overall.

Prof Xavier Font wrote the introduction, literature review, discussion and conclusions for the first submission of the manuscript.

Dr M. Rosario González-Rodríguez rewrote the introduction and improved the literature review, restructured the article, and revised the manuscript based on the referee's feedback.

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