Harnessing stakeholder input on Twitter: A case study of short breaks in Spanish tourist cities

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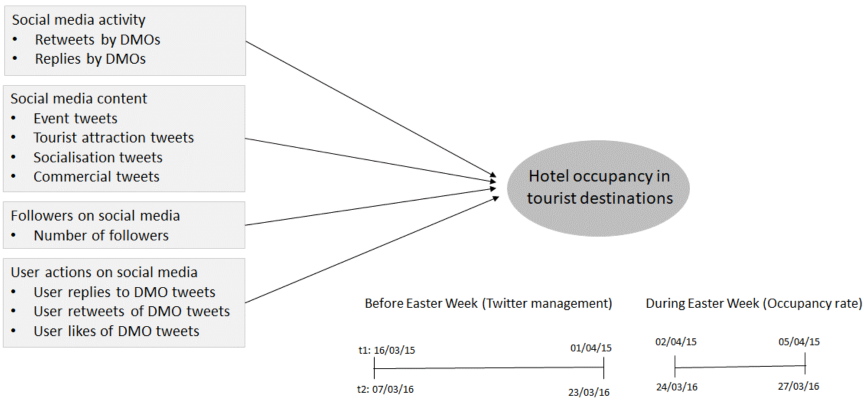
Published in Tourism Management, vol. 71, April 2019, pages 490-503. https://doi.org/10.1016/j.tourman.2018.10.013

ABSTRACT

Knowledge of how destination marketing organisations (DMOs) use Twitter is still limited. This study aimed to assess how DMOs' Twitter activity affects hotel occupancy in short-break holidays. Key dimensions of Twitter that may affect hotel occupancy in tourist destinations were first identified. A longitudinal study using data for 10 Spanish DMOs was conducted to forecast hotel occupancy. Twitter application programming interfaces were used to gather data on tweets by DMOs and retweets and likes by users. Text mining was used to analyse the tweets by DMOs, differentiating between tweets related to events, attractions, socialisation, and marketing. Data were analysed using artificial neural networks. The best fit was achieved with a multilayer perceptron artificial neural network. Findings suggest that the number of retweets and replies by users and the number of event tweets, tourist attraction tweets, and retweets by DMOs can predict the hotel occupancy rate for a given destination.

GRAPHICAL ABSTRACT



HIGHLIGHTS

- A combined method based on text mining and ANNs identified key dimensions of DMOs' Twitter activity affecting hotel occupancy in 10 tourist destinations.
- A longitudinal study was conducted to forecast hotel occupancy in tourist destinations based on dimensions of DMOs' Twitter use (activity, content, followers, and user actions).
- The dataset comprised data on different dimensions of 10 Spanish DMOs' Twitter activity and occupancy rate at two times (t1: Easter Week 2015 and t2: Easter Week 2016).
- An ANN was used to test hypotheses regarding the effects of DMOs' Twitter account management on hotel occupancy in tourist destinations.

KEYWORDS

Social media marketing, Destination marketing organisations, Twitter, Text mining, Artificial neural network, Hotel occupancy, Short-break holidays

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1. INTRODUCTION

Forecasting hotel occupancy rates is a key concern for hotel managers. Digital channels, particularly word-of-mouth channels, influence purchase decisions in different ways (Keiningham, Rust, Lariviere, Aksoy, & Williams, 2018). The significance of destination marketing organisations' (DMOs') web traffic data in predicting demand for hotel rooms reflects the crucial role of DMOs in promoting destinations and connecting travellers with local tourism and hospitality services. As suggested by Yang, Pan, and Song (2014), however, other types of online data (e.g. in the form of tweets) can also help predict tourist activities, including demand for hotel rooms.

Twitter now constitutes a part of DMOs' social media marketing strategy (Bokunewicz & Shulman, 2017; Kirilenko & Stepchenkova, 2017). DMOs are aware of Twitter's importance, and many have integrated Twitter into their own websites (Hays, Page, & Buhalis, 2013; Jabreel, Moreno & Huertas, 2017). However, research using social network analysis techniques to understand Twitter networks of DMOs is scarce (Uşaklı, Koç, & Sönmez, 2017). There is a need for further research to analyse how Twitter messages by DMOs influence hotels as key tourism stakeholders (Bokunewicz & Shulman, 2017).

DMOs use Twitter to post information about features that may attract tourists. Likewise, they use Twitter to promote destinations by retweeting posts from, for example, hotels located in the same destination (Sevin, 2013). Nevertheless, little is known about the way DMOs' social media activity affects hotels, where occupancy rate provides a key indicator of tourism-related economic activity (Crofton & Parker, 2012). A recent study of influential members of the Twitter networks of DMOs (Bokunewicz & Shulman, 2017) showed that hotels miss out on marketing opportunities because they do not use the influence of DMOs' tweets as much as other types of accounts such as media, promotional and individual accounts.

Given the need to analyse the influence of DMOs' Twitter activity, this study focused on the direct effect of DMOs' Twitter activity on hotels during short-break holidays. A short break is defined as a non-business trip lasting between one and three nights (Pike, 2003). Social media increase brand exposure and allow organisations (i.e. DMOs) to engage more with their target customers (Evans, 2010). Social media users are probably more responsive to more timely marketing efforts such as those related to short-break holidays. One of the major short-break holidays in Spain is the Easter Week holiday. This is a moveable feast. In some years, it falls entirely in March; in others, it falls in April; and in others, it straddles the two months (Park, Ok, & Chae, 2016). Our empirical study examined the effect of Twitter activity by Spanish DMOs on hotel occupancy during the short-break holiday of Easter Week.

In the context of tourist destinations, this research thus contributes to the social media marketing literature in two ways. First, the paper focuses on how tweets by DMOs can predict hotel occupancy. It provides a new perspective on analysing social media in tourist destinations by studying the effects of third-party-generated content. Second, in our case study, we examined Twitter messages by DMOs in the marketing of short-break holidays by applying data mining and artificial neural networks (ANN) to tweets by DMOs to estimate hotel occupancy. Despite limited examples of its use in the literature, this ANN technique has been successfully applied in different tourism contexts. These include forecasting demand for destinations (Law, 2000; Uysal & El Roubi, 1999), tourism expenditure (Palmer, Montaño, & Sese, 2006), guest loyalty (Tsaur, Chiu, & Huang, 2002), and occupation (Law, 1998; Pattie & Snyder, 1996; Phillips, Zigan, Silva, & Schegg, 2015).

To achieve the aims outlined above, this paper is structured as follows. The second section presents a review of the literature to provide the theoretical framework. The third section describes the study context and the method used to obtain and analyse tweets by DMOs. The fourth section sets forth and discusses the research findings. Finally, the fifth section presents the conclusions, limitations, research opportunities, and practical implications of the findings.

2. THEORETICAL FRAMEWORK

2.1. Social media in relation to destination marketing organisations as third parties

DMOs' activities are extremely helpful in developing and managing tourist destinations with the goal of enhancing the guest experience. DMOs also support local hotels by providing data to enhance local hotels' understanding of the market (Oggionni & Kwok, 2018). Accordingly, we predict that social media activity by DMOs (Twitter messages by DMOs) may affect local hotel–guest interactions, leading to changes in hotel occupancy. This type of study refers to third-party- or stakeholder-generated content. In our case, DMOs are third parties with respect to hotel–guest interactions.

Social media definitions typically emphasise user-generated content (for a review, see Zeng & Gerritsen, 2014), focusing less on firm-generated content (Kumar, Bezawada, Rishika, Janakiraman, & Kannan, 2016; Martínez-Navarro & Bigné, 2017). There is a notable lack of emphasis on third-party- or stakeholder-generated content. This type of third-party study has been conducted previously in areas such as finance to examine whether public sentiment expressed through tweets is capable of predicting changes in the stock market (Bollen, Mao, & Zeng, 2011). The study showed that changes in certain dimensions of public mood such as peace of mind or happiness expressed on Twitter seem to affect the stock market. It is therefore reasonable to expect a similar effect in the tourism context, where tweets by DMOs may act as determinants of hotel occupancy. Here, we focus on the dynamics of social media (i.e. Twitter) interactions initiated by a third party (i.e. DMOs with respect to hotel–guest interactions). These dynamics relate to the way interactions may evolve and the types of actions and reactions that may be needed.

Growing interest in social media in tourism has focused on two primary streams of research: consumer and suppliers (for a review, see Leung, Law, Hoof, & Buhalis, 2013). Studies of social networks in the context of DMOs are still scarce (Uşaklı et al., 2017). DMOs use numerous social media, but the present study focused on Twitter. Twitter is a real-time network powered by people all around the world (Nielsen, 2017; Park, Ok, & Chae, 2016; Sotiriadis & van Zyl, 2013). A limited number of studies have examined destination-level tweets to address different purposes, including building networks (Bokunewicz & Sulman, 2017), content analysis (Hays et al., 2013; Uşaklı et al., 2017), and semantic analysis (Jabreel et al., 2017). Consequently, there is a lack of understanding of social media usage by DMOs. Indeed, no study has addressed the influence of tweets by DMOs on hotel occupancy.

DMOs' social media presence differs from that of other tourism organisations such as travel agencies, hotels, or airlines in three ways. First, the number of DMO Twitter followers is much lower than the number of followers of the aforementioned organisations (see data at https://twittercounter.com/pages/100/hotel), and social media measurement is underdeveloped among European DMOs (Uşaklı et al., 2017). Second, DMOs' interests are broader. They consequently address a larger number of issues. Attractions, events, recreation facilities, local cuisine, and personal safety are the most popular issues (for details, see Uşaklı et al., 2017). Third, DMOs' target groups are much broader than those of other tourism organisations. Bokunewicz and Shulman (2017) identified the categories of influencers that have the greatest reach in relation to DMOs' Twitter accounts. To analyse network data from Twitter for a collection of DMOs that promote US cities, they used several measures of relative influence such as the number of times the accounts mentioned or retweeted others or were mentioned in posts about the DMO. The most influential accounts in the network are media, promotional, and individual accounts. Stakeholders such as hotels and restaurants occupy positions of low importance in the networks and generally fail to capitalise on opportunities created by the DMOs. Consequently, there is a need to develop our understanding of how Twitter messages by DMOs influence hotel accounts as key tourism stakeholders (Bokunewicz & Shulman, 2017).

2.2. Social media and outcome variables

Recent studies have shown social media's influence on outcome variables in different contexts such as brand building (Moro, Rita, & Vala, 2016), student recruitment (Rutter, Roper, & Lettice, 2016), the stock market (Oliveira, Cortez, & Areal, 2017), adoption of new movies (Hennig-Thurau, Wiertz, & Feldhaus, 2015), and sales (Seiler, Yao, & Wang, 2017). Two meta-analyses lend empirical support to the relationship between social media and sales. In the first, You, Vadakkepatt, and Joshi (2015) found that elasticities of volume (r = .23) and valence (r = .41) of word-of-mouth correlate with sales. Interestingly, tourism is not explicitly addressed in this meta-analysis. In the second meta-analysis, Babic, Sotgiu, De Valck, and Bijmolt (2016) systematically reviewed 96 studies. These studies spanned 15 years (1999–2013) and covered 40 platforms, 26 product categories, and 11 countries. The literature covered in this meta-analysis offers evidence of a positive overall effect of consumer-generated information on sales.

These empirical contributions may have theoretical implications (Ågerfalk, 2014). The rationale for the relationship between social media and outcome variables is based on different conceptual approaches. These approaches include information processing (Kozinets, De Valck, Wojnicki, & Wilner, 2010) and, notably, consumer socialisation theory (Ward, 1974), which explains purchase intention, as posited by Wang, Yu, and Wei (2012). These two conceptual approaches are suited to social media because of the role of social media as a promotional tool based on interactivity. First, content in any form (i.e. text, pictures, or videos) consists of pieces of information that will ultimately be processed by others. As Kozinets et al. (2010) suggest, social media analysis has adopted an information processing approach. Second, social media interactions between multiple players are affected by a socialisation process that has been explained by consumer socialisation theory (Ward, 1974). Consumer socialisation consists of different processes whereby individual consumers learn skills, knowledge, and attitudes from others through communication that leads to cognitions and behaviours (e.g. purchases). Under the traditional view, socialisation occurs within close groups such as family or friends. In online social media, socialisation is extended to potentially thousands of members of virtual communities (Wang et al., 2012).

Social media data is challenging the foundations of theorising in academia (for a detailed discussion, see Ågerfalk, 2014). The accumulation of empirical contributions in a field may lead to the detection of patterns, which in turn may help build theoretical contributions. Drawing on the information processing approach and consumer socialisation theory, the current study used active social media management and metrics (Aral & Walker, 2011; Miller & Tucker, 2013; Peters, Chen, Kaplan, Ognibeni, & Pauwels, 2013) to evaluate the influence of certain aspects of social media (e.g. activity, content, followers, and user actions) on hotel occupation in specific tourism destinations. In the next section, we formulate research hypotheses based on key dimensions of Twitter that may affect hotel occupancy in tourist destinations during short breaks.

2.3. Research hypotheses

2.3.1. Effects of social media activity

DMOs have different levels of social media activity. Hays et al. (2013) reported that the frequency with which DMOs post on social media platforms varies. Some DMOs are active in managing and expanding their use of social media, whereas other organisations join social media without sufficient support, knowledge, or interest to become truly active users (Hays et al., 2013).

Active management implies direct interactions with users of social media (Dholakia, Blazevic, Wiertz, & Algesheimer, 2009), enhancing consumer socialisation (Wang, Yu & Wei, 2012). Active management encourages user-generated content (UGC) (Miller & Tucker, 2013). User participation in response to a firm's online activity has four types of effects: (1) increasing the frequency of visits to the points of sale (Rishika, Kumar, Janakiraman, & Bezawada, 2013); (2) increasing visits to tourism websites (Milano, Baggio, & Piattelli, 2011); (3) improving the perception of corporate image through platforms such as Twitter, especially among users who are not customers (Dijkmans, Kerkhof, & Beukeboom, 2015); and (4) making users more willing to use Twitter (Smith, Fischer, & Yongjian, 2012).

Activity can be interpreted simply as number of posts, which may take the form of tweets, retweets, or replies. Rather than considering the content of the tweet itself, however, active account management entails a degree of interaction with users. In the case of Twitter, this interaction may be direct, in the form of a reply, or indirect, in the form of a retweet whereby the DMO shares content created by other users (Bokunewicz & Shulman, 2017; Jabreel, Moreno & Huertas, 2017). All these activities are expected to boost hotel bookings through more visits to websites or travel agencies and improve the reputation of tourism destinations. Hence, the following hypotheses may be proposed:

H1a. The number of retweets by DMOs will affect the hotel occupancy rate in tourist destinations during short breaks.

H1b. The number of replies by DMOs will affect the hotel occupancy rate in tourist destinations during short breaks.

2.3.2. Effects of social media content

Social media content may originate from the DMO or from other users (i.e. user-generated content), but the DMO nonetheless channels and manages this co-creation (Malthouse, Haenlein, Skiera, Wege, & Zhang, 2013). The content posted on social media affects the acceptance of products and the way users read or understand tweets. On Twitter, negative user-generated content lowers the initial acceptance of new experiential products (Hennig-Thurau et al., 2015). Users value tweets that ask questions, disseminate information, or share links (André, Bernstein, & Luther, 2012). Counts and Fisher (2011), however, suggest that users tend to pay less attention to tweets with links if the link is required to understand the tweet's main message.

Using Twitter data on the Sochi Olympics, Kirilenko and Stepchenkova (2017) conducted topical analysis of Twitter messages. This analysis yielded eight broad themes or categories: events, news, sports and sportsmen, anticipation, cheering, problems and politics, volunteering, and others. Uşaklı et al. (2017) analysed European DMOs' social media usage and observed seven categories: content, major themes, information type, engagement, interactivity, promotion, and customer service. Based on a tweet's subject (Peters et al., 2013), in the context of place marketing (Hays et al., 2013; Sevin, 2013), a tweet posted by a DMO can be categorised as relating to events, tourist attractions, socialisation, or commercial content. Similarly, in the context of tourism destinations, the number of tweets in a given category is expected to influence hotel occupancy in tourist destinations. The following hypotheses may thus be proposed:

H2a. The number of event tweets by DMOs will affect the hotel occupancy in tourist destinations during short breaks.

H2b. The number of tourist attraction tweets by DMOs will affect the hotel occupancy in tourist destinations during short breaks.

H2c. The number of socialisation tweets by DMOs will affect the hotel occupancy rate in tourist destinations during short breaks.

H2d. The number of commercial tweets by DMOs will affect the hotel occupancy rate in tourist destinations during short breaks.

2.3.3. Effects of followers on social media

Understanding links between users can help DMOs extract information about influential users and predict the likelihood that users will retweet and respond to the DMOs' tweets. On Twitter, the source of tweets and retweets is crucial for increasing the message's chances of reaching a wide audience (Zaman, Herbrich, Van Gael, & Stern, 2010).

DMOs create electronic word of mouth (eWOM) that can influence links among users and potentially make a tweet go viral. In terms of influence, having an active audience that retweets or mentions the user is preferable to having a large number of followers (Cha, Haddadi, Benevenuto, & Gummadi, 2010). Personalised, active tweeting fosters message adoption effectively and correlates with greater user participation, thereby leading to greater acceptance among users (Aral & Walker, 2011). However, in terms of its initial dissemination, the tweet may be expected to have better chances of acceptance when the number of followers who receive the tweet is greater. The following hypothesis may thus be proposed:

H3. The number of Twitter followers of DMOs will affect the hotel occupancy rate in tourist destinations during short breaks.

2.3.4. Effects of user actions on social media

The motivation–opportunity–ability (MOA) model proposed by MacInnis, Moorman, and Jaworski (1991) has been used as a reference to explain the action and reaction of users on social media (Leung & Bai, 2013; Peters et al., 2013; Tang, Fang, & Wang, 2014), where motivations seem particularly effective at explaining the actions of tourists. Leung and Bai (2013) argue that motivation is positively related to tourists' participation and intention to revisit hotels' social media profiles. Munar and Jacobsen (2014) suggest that altruistic motivations are relevant for sharing experiences through social media. Users can react in several ways to tweets by DMOs. Users can respond, retweet, or like.[4] With responses, the user expressly mentions the publisher of the tweet to which he or she is responding. Motivations that lead users to retweet include agreeing with someone, validating someone else's thoughts, and informing a specific audience (Boyd, Golder, & Lotan, 2010). Finally, to like a tweet, the user, motivated by pleasure or the topical relevance or utility of the tweet's content (Meier, Elsweiler, & Wilson, 2014), clicks on the heart next to the tweet, which saves the tweet and makes it easily accessible at a later date. The following hypotheses may thus be proposed:

H4a. The number of user replies to tweets by DMOs will affect the hotel occupancy rate in tourist destinations during short breaks.

H4b. The number of user retweets of tweets by DMOs will affect the hotel occupancy rate in tourist destinations during short breaks.

H4c. The number of user likes of tweets by DMOs will affect the hotel occupancy rate in tourist destinations during short breaks.

3. METHOD

3.1. Study context

Social media have changed many aspects of individual and organisational life, making such platforms as Facebook and Twitter common topics for research in the social sciences (Kwok & Yu, 2013; Park, Ok, & Chae, 2016). Social media (or Web 2.0) cover a broad range of technology platforms that allow users to share information and connect with one another. The social media platform Twitter has attracted the attention of researchers in diverse fields who have addressed topics such as social networking, information diffusion, customer engagement, and product promotion (Park, Ok, & Chae, 2016). Twitter can be understood as a platform or tool for marketing, information dissemination, and personal communication (see, for example, Boyd & Ellison, 2007; Kaplan & Haenlein, 2010; Soboleva et al., 2017; Sotiriadis & van Zyl, 2013). Chan and Guillet (2011) studied the use of social media by hotels in Hong Kong. Of the 23 social media sites under study, Twitter (56.7%) and Facebook (53.7%) were the most widely

[4] https://blog.twitter.com/es/2015/corazones-en-twitter. On 3 November 2015, Twitter replaced the 'favourite' option with the 'like' option. As with the previous configuration, a liked tweet still gets saved in the user's profile, making it easy to consult later.

used. Sotiriadis and van Zyl (2013) focused on how users of Twitter decide on tourism service purchases and which factors influence the use of the information that is retrieved from Twitter. As noted by Park, Ok, and Chae (2016, p. 893), 'companies and organizations can use social media to find out who their potential customers (and stakeholders) are and what they want'. Also, this new type of data allows researchers to address important questions in ways that were simply not possible even a decade ago.

In the context of our study, to test the research hypotheses, Spanish tourist destinations were selected at the town level. We chose inland and coastal destinations with different levels of underlying tourism demand. This choice enabled us to control for the effect of the popularity of the destinations. Furthermore, the period under analysis was not the peak summer-break season. Instead, this study focused on tourism during the Easter Week holidays, examining the effect of DMOs' Twitter activity on the hotel occupancy rate in tourist destinations. A longitudinal study was conducted in 2015 and 2016, examining the influence of Twitter (activity, content, followers, and user actions) on hotel occupancy (outcome variable) in tourist destinations during the short holiday period of Easter Week 2015 and 2016. This break was chosen for the following reasons: (1) it is the second most important period of holiday breaks in Spain; (2) it is time-limited, so long-term effects on any stimuli are avoided; and (3) typical events, social events, and activities related to tourist resources and traditions enrich the options for tweet content.

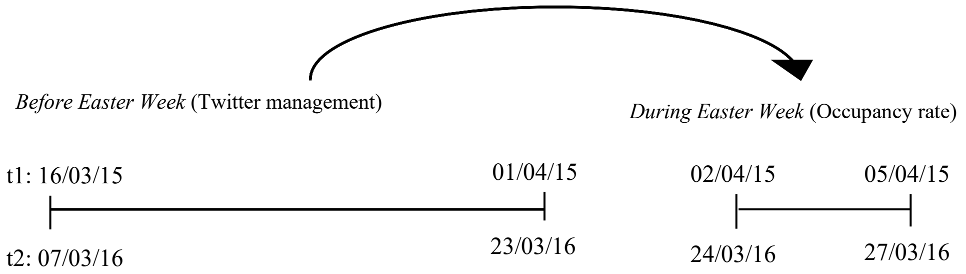
Easter Week is a bank holiday event with Christian roots. In most Spanish towns, Easter Week is celebrated with processions and other religious acts that are deeply rooted in the inhabitants' local culture (Barke & Towner, 1996; Lafuente, Devesa, & Sanz, 2017). Easter Week has evolved into a bank holiday break for all, regardless of religious roots. It is commonly known as spring break. Easter Week has a major effect on tourist activity in Spain for hotels in urban and coastal destinations (Castellanos-Verdugo, Oviedo-García, Roldán, & Veerapermal, 2009). Lafuente et al. (2017) found that the mean hotel occupancy rate in April 2012 in the city of Palencia (Castilla-León) was 59.49% at weekends and 38.93% the rest of the week, rising to 60.70% for the most important days of Easter. In the city of Malaga (Andalucía), a study of the impact of Easter Week on tourism and the economy (Malaga Tourism Observatory, 2014) showed that the main information sources used by tourists who travelled to Malaga for Easter Week 2014 were websites, social media, and blogs. During this week, the average hotel occupancy rate in Malaga was 89.8%.

3.2. Dataset and time frame

Studies have shown the direct effect of social media activity and valence on sales elasticity (You et al., 2015). To avoid a systematic effect of the underlying tourism demand in the same month, we studied data from a short period (i.e. Easter Week), which some years falls in March, other years falls in April, and other years falls in both months (Park et al., 2016). Data from 10 destinations reflected two types of tourism destinations (urban and coastal) that might be affected differently by underlying demand. Given the deliberate choice of a short study period and the immediate effect of Twitter (Uşaklı et al., 2017), Twitter content may affect short-term decisions such as where to visit during the short Easter break.

Yang et al. (2014, p. 436) analysed web traffic data from a DMO to predict demand for hotel rooms in a tourist area and reported the following: ‘the value of online data lies in the fact that they can provide time-sensitive leading indicators of visitor behavior, which cannot be otherwise captured’. Yang et al. (2014) found that because of the short planning horizon of most visitors, local hotels could use the data for short-term forecasts of demand for their hotel rooms. It is thus reasonable to expect that the period leading up to the Easter Week holiday should offer a suitable period for studying how Twitter account management by DMOs potentially affects hotel occupancy during Easter Week (Fig. 1). Furthermore, as Easter Week is a short holiday period, holidays during this time require less planning, so tweets are more likely to influence users’ decision processes.

Fig. 1. Time frame



To build a valid dataset, the volume of tweets was analysed for 22 Spanish town destinations that receive a large number of tourists and that have Twitter accounts managed by DMOs (Table 2). Next, 10 destinations were selected based on the following three criteria: (1) the volume of Twitter activity between 16 March and 1 April 2015 (the days leading up to Easter Week), (2) type of destination (inland vs. coastal tourism), and (3) geographic location (north, south, east, and west), reflecting diversity. The volume of activity was calculated as the total number of tweets, retweets, and replies. First, the 10 destinations with the highest volume of Twitter activity were selected. Next, 10 destinations were chosen, ensuring that they represented both inland and coastal tourism, reflecting different levels of tourism demand. Thus, five destinations of each type were chosen. Selecting both inland and coastal destinations was important because location influences, for example, the types of tourist attractions available at the destination and therefore the type of information the DMOs tweet to attract potential visitors. Of the 10 most active destinations, 6 were inland and 4 were coastal. The least active of these six inland destinations (i.e. Madrid) was therefore replaced by the next most active coastal destination (i.e.

Cartagena). The final sample comprised the following destinations (appearing in italics in Table 1): Zaragoza, Cadiz, Granada, Malaga, Pamplona, Santiago, Alicante, Gijon, Toledo, and Cartagena. At the time of the study, cities with high volumes of tourism such as Barcelona, Madrid, and Valencia were less active on Twitter than other less visited cities such as Zaragoza.

Table 1. Sample: DMO Twitter profiles, activity, and location of destinations

DMO	*TWITTER USER*	*DESTINATION*	*LOCATION*	*ACTIVITY*
Zaragoza Turismo	@ZaragozaTurismo	*Zaragoza*	Inland	359
Turismo Cadiz	@VisitCadiz	*Cadiz*	Coast	250
Granada Turismo	@granadaturismo	*Granada*	Inland	169
Malaga Ciudad Genial	@turismodemalaga	*Malaga*	Coast	153
Pamplona me gusta!	@Pamplonamegusta	*Pamplona*	Inland	152
Turismo de Santiago	@santiagoturismo	*Santiago*	Inland	147
Turismo Alicante	@Alicante_City	*Alicante*	Coast	106
Turismo Gijon	@GijonTurismo	*Gijon*	Coast	104
Toledo Turismo	@toledoturismo	*Toledo*	Inland	100
Visita Madrid	@Visita_Madrid	Madrid	Inland	86
Turismo de Murcia	@TurismodeMurcia	Murcia	Inland	79
Sevilla Turismo	@sevillaciudad	Sevilla	Inland	76
Turismo de Cartagena	@TurisCartagena	*Cartagena*	Coast	55
Turismo Valencia	@Valenciaturismo	Valencia	Coast	53
Enamorados Almería	@almerialovers	Almeria	Coast	48
Turismo de Benidorm	@turismobenidorm	Benidorm	Coast	45
Marbella Turismo	@Marbellaturismo	Marbella	Coast	40
Turismo de Cordoba	@CordobaESP	Cordoba	Inland	35
Barcelona Turisme	@BarcelonaInfoES	Barcelona	Coast	30
Palma de Mallorca	@palmademallorca	Mallorca	Coast	29
Bilbao Turismo	@TurismoBilbao	Bilbao	Inland	23
San Sebastián Turismo	@SSTurismo	San Sebastian	Coast	1

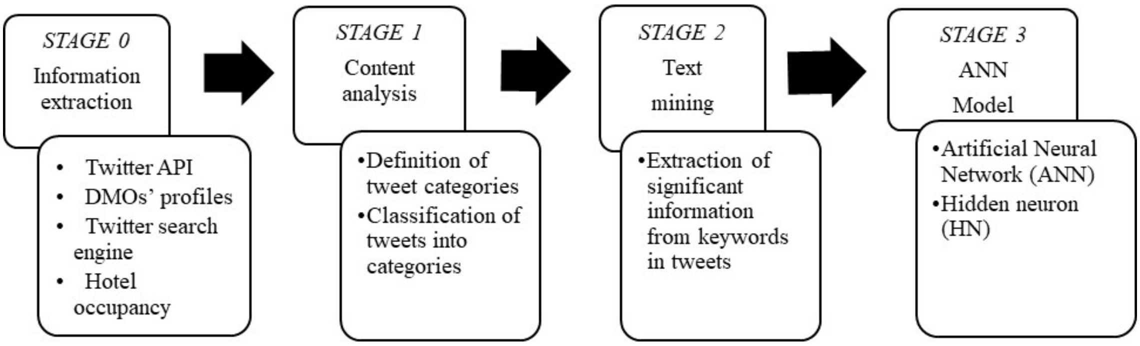
This was a longitudinal study, so the hotel occupancy was considered at two times (t1 and t2). Fig. 1 shows the study period for Easter Week 2015 (2 to 5 April) and 2016 (24 to 27 March) for the destinations in the final sample. Accordingly, the DMOs' Twitter activity for the 17-day period prior to Easter Week 2016 (i.e. 7 to 23 March 2016) was also analysed.

Regardless of the period, every tourist destination has an occupancy rate, which fluctuates daily throughout the year. Therefore, to achieve greater accuracy in the estimate of Twitter's influence on the occupancy rate, the outcome variable for occupancy rate was calculated as the difference between the occupancy rate during Easter Week and the mean weekend occupancy rate for the month prior to Easter Week. For instance, in 2015, the outcome variable (occupancy rate) for Zaragoza was 44.3%. This value is the difference between the occupancy rate for the Easter Week of 2 to 5 April 2015 (86.7%) and the mean weekend occupancy rate for March 2015 (42.4%).

3.3. Procedure

Fig. 2 graphically represents the procedure followed in this study. First, the necessary information was gathered from different sources (Stage 0). Next, content analysis (Stage 1) and text mining (Stage 2) were carried out. Finally, an ANN model was developed to study the relationship between Twitter posts by DMOs and occupancy rate in the tourist destinations represented by these DMOs (Stage 3).

Fig. 2. Study procedure



3.3.1. Stage 0: Information extraction

The information required for this study came from the following sources: Twitter, hotel associations, and the Spanish Institute of Statistics. The Twitter application programming interface (API) was used to extract tweets by DMOs and users. The API yielded (1) original tweets by DMOs, (2) retweets by DMOs, (3) replies by DMOs, (4) retweets by users, and (5) likes by users. To identify the followers of DMOs and replies by users, the first step was to examine DMOs' profiles and then study the results of a search using the Twitter search engine. Hotel associations of the tourist destinations provided the occupancy rates for Easter Week 2015 and 2016. Finally, the Hotel Occupancy Survey by the Spanish Institute of Statistics yielded the mean weekend occupancy rates for March 2015 and February 2016.

3.3.2. Stage 1: Content analysis

To determine the categories used to classify tweets by the DMOs, content analysis was performed. This method allowed for codification of the meaning of words, phrases, or subjects (Weber, 1990). Two independent experts (Twitter users not involved in the study yet with extensive professional tourism experience) separately classified the content of a random sample of 100 tweets by the DMOs of the 10 selected destinations in the days leading up to Easter Week. Based on the literature (Hays et al., 2013; He, Zha, & Li, 2013; Sevin, 2013), tweets were classified into four categories: event, tourist attraction, socialisation, and commercial. Each tweet was placed in the category that best matched the main subject of the tweet. The experts' classifications coincided in 94% of tweets. Discrepancies were discussed to reach a consensus on how the tweets should be classified. Table 2 shows an example tweet for each category.

Table 2. Classification of tweets

Tweet category	*Description*	*Example in Spanish (English)*
Event	Tweets on events in the destination.	El sábado próximo #Alicante #SpringFestival2015 @alicantelivem @A_Spring_Fest (Next Saturday #Alicante #SpringFestival2015 @alicantelivem @A_Spring_Fest)
Tourist attraction	Tweets on tourism resources/tourist attractions in the destination.	¿Conoces el Monasterio de Piedra? Un lugar único que no te puedes perder. @MondePiedra #Naturaleza #Historia #Relax (Have you seen the Stone Monastery? A unique site you can't afford to miss. @MondePiedra #Nature #History #Relax)
Socialisation	Tweets that create a friendly online rapport between DMO and user.	Cuidado si vienes d vacaciones en coche. Queremos q repitas muchas veces y tu presencia es lo más valioso #Alicante (Take care if travelling by car. We want you to come back again and again. The most important thing is for you to be here #Alicante)
Commercial	Tweets related to commercial offers posted by the DMO.	Haz un doblete de diversión y compra ya tu ticket promo de Megabús+Acuario por sólo 13€. #ZgzEnFamilia (Have double the fun and buy your ticket for the Megabus+Aquarium for just 13€. #ZgzWithFamily)

3.3.3. Stage 2: Text mining

Social media sites generate huge amounts of information in text format. Text mining is an extension of data mining, and it consists of extracting useful, significant, non-trivial information from unstructured text (Feldman & Sanger, 2006). This technique has been used for different aims in different subsectors of the tourism industry: analysis of consumer sentiment towards airlines (Mostafa, 2013); competitive analysis of fast-food chains (He et al., 2013); estimates of hotel demand (Ghose, Ipeirotis & Li, 2012); extraction of destination brand image and identity (Költringer & Dickinger, 2015); and tourist satisfaction (Guo, Barnes & Jia, 2017). Unlike prior research, this study applied text mining to improve the speed of the classification of tweets into pre-defined categories. It was thus possible to avoid manual case-by-case classification, which is time consuming when working with social media (He at al., 2013). WordStat software and, more specifically, QDA Miner were used to perform the data mining (Pollach, 2010). QDA Miner yields the word count of keywords in tweets, thereby indicating the category into which the tweet should be classified (Mostafa, 2013). In the case of @Alicante_City, for example, the software yielded the keywords contained in the tweets, including Alicantesanta15 (Alicanteeaster15): *Este fin de semana pasión por #Alicantesanta15 no te pierdas nada (This weekend passion for #Alicanteeasterweek15 don't miss anything)*. This tweet was thus classified as an event. If, however, the tweet contained a keyword that raised doubts, the software made it possible to search for that word within the tweet, thereby enabling classification of the tweet.

Table 3 provides the results of descriptive analysis for each DMO and input variable. This analysis was based on data extraction, content analysis, and text mining. QDA Miner was applied to 952 tweets from 2015 and 815 tweets from 2016. Figure 2 depicts this procedure (stages 0, 1, and 2).

Table 3. Descriptive data for each variable by DMO (absolute values)

VARIABLE (Code)	*DESTINATION*																							
	Alicante		Cadiz		Cartagena		Gijon		Granada		Malaga		Pamplona		Santiago		Toledo		Zaragoza		Mean		S.D.	
	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	15	16
Event tweets (ET)	19	14	127	157	23	17	26	36	104	29	89	30	79	5	77	124	23	9	78	53	64.5	47.4	38.9	51.6
Tourist attraction tweets (TA)	2	5	14	16	5	4	4	14	7	37	12	4	11	0	3	6	4	3	60	37	12.2	12.6	17.3	13.8
Commercial tweets (CT)	4	10	6	4	1	1	5	7	22	2	24	7	3	0	11	2	0	1	47	43	12.3	7.7	14.8	12.8
Socialisation tweets (ST)	7	3	16	17	4	8	5	10	6	12	7	30	1	0	2	18	4	1	10	39	6.2	13.8	4.3	12.7
DMO retweets (DRT)	68	39	85	68	19	22	58	19	19	2	18	50	52	1	45	24	69	0	152	95	58.5	32.0	40.3	31.4
DMO replies (DRE)	6	1	2	0	3	0	6	0	11	0	3	3	6	0	9	1	0	0	12	9	5.8	1.4	3.9	2.8
User replies (URE)	6	3	6	1	5	3	7	5	18	7	13	6	12	0	8	0	3	0	30	9	10.8	3.4	8.1	3.2
User likes (ULI)	98	115	167	399	45	197	151	302	279	784	445	477	349	21	247	96	37	53	333	540	215.1	298.4	137.7	249.1
User retweets (URT)	147	135	392	440	90	212	246	285	389	661	543	391	475	13	247	57	51	39	340	341	292.0	257.4	164.1	207.2
DMO followers (DFO)	10350	14449	12207	14766	10138	10766	24455	27693	26660	35823	15118	20095	7584	8733	11128	12275	4060	4588	18408	21838	14010.8	17102.6	7226.0	9408.1
Occupancy % (OCU)	44.3	21.3	33	34.3	17.4	19.2	48.3	44.4	16.1	7.8	35.2	28.5	29.1	29.5	54.5	32.8	15.3	17.1	24.8	32.6	31.8	26.8	13.9	10.5

To provide an overview of the DMOs' Twitter management and to allow for comparison, Table 4 shows the aggregate values for each variable at times t1 and t2. In terms of type of content, event tweets (ET) were the most common tweets in both 2015 and 2016, although there were far fewer event tweets in 2016 than in 2015. The number of tourist attraction tweets (TA) was practically the same in both years. The DMOs made more commercial tweets (CT) in 2015 than in 2016. In contrast, the DMOs made fewer socialisation tweets in 2015 than in 2016.

Table 4. Data aggregated across all DMOs for each variable at times t1 and t2 (absolute values)

TIME FRAME	*VARIABLE**									
	ET	TA	CT	ST	DRT	DRE	URE	ULI	URT	DFO
AGGREGATE t1 (2015)	645	122	123	62	585	58	108	2151	2920	140108
AGGREGATE t2 (2016)	474	126	77	138	320	14	34	2984	2574	171025
Dif. t2 – t1	-171	4	-46	76	-265	-44	-74	833	-346	30917

*ET (event tweets), TA (tourist attraction tweets), CT (commercial tweets), ST (socialisation tweets), DRT (DMO retweets), DRE (DMO replies), URE (user replies), ULI (user likes), URT (user retweets), DFO (DMO followers).

In terms of other types of Twitter activity, the numbers of both retweets (DRT) and replies (DRE) were higher in 2015 than in 2016 (585 DRT and 58 DRE vs. 320 DRT and 14 DRE, respectively). The difference between number of retweets in 2015 and 2016 (265) was greater for retweets than for replies. In terms of the actions of other users, the number of user replies (URE) was higher in 2015 (108) than in 2016 (34). Posts by the DMOs got fewer likes (ULI) in 2015 (2151) than in 2016 (2984). Posts by DMOs got more shares (URT) in 2015 (2920) than in 2016 (2574). It seems reasonable to expect that if the DMOs' management and use of Twitter differed between 2015 and 2016, then the effect on hotel occupancy should also differ between these two years. Once Stages 0, 1, and 2 were complete, the data were ready for empirical analysis (Stage 3).

3.3.4. Stage 3: ANN model

An artificial neural network (ANN) is an interconnection of neurons that replicates the processing mechanism of the human brain. An ANN consists of many simple processing elements. Each neuron receives a stimulus with varying intensity, which leads to different responses (Bigné, Aldas-Manzano, Küster, & Vila, 2010). The development of ANN arose from attempts to simulate biological nervous systems by combining many simple computing elements (neurons) in a highly interconnected system (Hinton, 1992; Sarle, 1994). The first major work on neural networks was published in 1943 by McCulloch and Pitts (DeTienne et al., 2003). Their research showed that human brain functionality could be modelled mathematically and that a network of artificial binary-valued neurons could perform the calculations. As described by Hinton (1992, p. 145-146), the ANN:

> …consists of three groups, or layers, of units: a layer of input units is connected to a

layer of 'hidden' units, which is connected to a layer of output units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and hidden units. Similarly, the behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

There has been increasing interest in the use of ANN methodology to analyse data in business research (DeTienne et al., 2003, 2017; Somers & Casal, 2009) and tourism studies (Moutinho et al., 2015; Phillips et al., 2015). Methodological studies have discussed the trade-offs between ANN and traditional statistical models, showing why ANNs offer an attractive alternative to regression analyses (Bansal, Kauffman, & Weitz, 1993; DeTienne et al., 2003). The growing popularity of neural networks owes to the following reasons (DeTienne et al., 2003): (i) neural networks are capable of learning using real data, (ii) they do not need a priori knowledge required by expert systems and regression, (iii) they outperform multiple regression in data analysis, (iv) they offer capabilities beyond regression, such as the ability to deal with non-linear relationships, missing data, and outliers, and (v) there is good availability of powerful neural network software packages.

The ANN, a non-parametric, data-driven technique, was preferred because of its ability to map linear or non-linear functions (Wu, Song, & Shen, 2017). ANN models offer greater predictive accuracy than other models that are based on traditional statistical methods such as multiple linear regression (Law & Au, 1999; Pattie & Snyder, 1996; West, Brockett, & Golden, 1997). Furthermore, comparisons have revealed no significant differences between machine learning techniques and ANN, although machine learning techniques are especially suitable for mid- and long-term forecasting (Claveria, Monte, & Torra, 2017). Akın (2015) compared seasonal autoregressive integrated moving average, ν-support vector regression, and the multilayer perceptron for tourism demand and concluded that there is no single best model for all cases, consistent with the 'no free lunch' theorems.

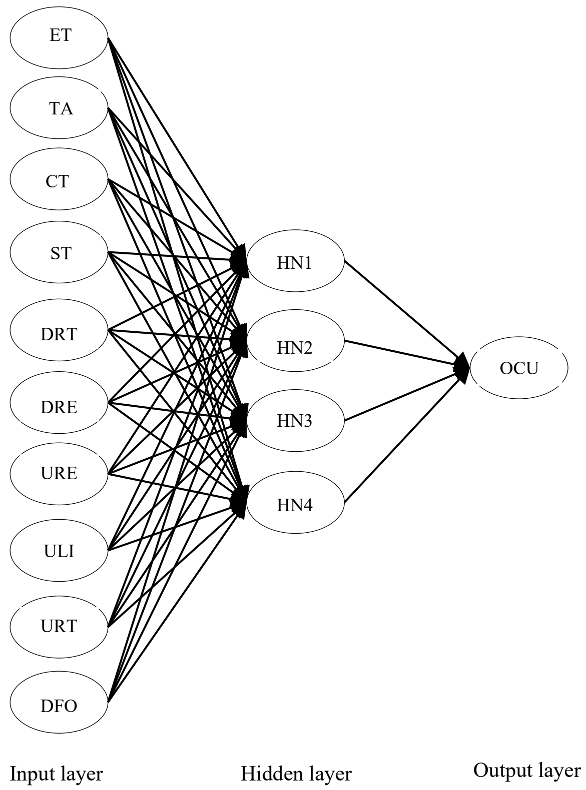
According to Law (2000, p. 332), 'it is unrealistic to assume that all the data in tourism demand can be represented by linearly separable functions'. In tourism studies, the predictive accuracy of multiple linear regression has been shown to be lower than that of ANNs in tourism (Bloom, 2004; Burger, Dohnal, Kathrada, & Law, 2001; Phillips et al., 2015). The multilayer perceptron (MLP) and radial basis function (RBF) are the most widely used ANN techniques. The MLP has been applied numerous times in tourism demand forecasting (Wu, Song, & Shen, 2017), whereas RBF networks are less common in tourism studies (Claveira, Monte, & Torra, 2017).

In this study, ANNs were preferable to multiple linear regression methods because these techniques work for non-linear, non-parametric data, do not require an explicit a priori relationship between inputs and outputs, and do not have to meet the rigorous assumptions of conventional regression analysis (DeTienne, DeTienne, & Joshi, 2003; Law, 2000). Furthermore, the R^2 values for Models t1 and t2 (using ANNs) were high (.89 and .95, respectively). As mentioned earlier, other types of ANNs also exist, so we compared the predictive accuracy of a RBF ANN against the accuracy of the MLP ANN. The errors for the RBF ANN were 0.438 in Model t1 and 0.382 in Model t2, both of which were substantially higher than the errors for the MLP ANN (0.033 and 0.024, respectively). Consequently, the MLP ANN was chosen as the predictive tool for this study.

In recent years, ANNs have been used in tourism to predict firm failures among accommodation firms (Youn & Gu, 2010), competitive revenue management in hotels (Padhi & Aggarwal, 2011), and the impact of group package tour dimensions on customer satisfaction (Moutinho, Caber, Silva, & Albayrak, 2015). In the social media context, Phillips et al. (2015) used ANNs to study the relationships linking user-generated content, hotel characteristics, and revenue per available room (RevPAR). Our aim here was to adopt a third approach based on third-party-generated content to analyse the relationship between DMOs' Twitter activity and the hotel occupancy rate of the corresponding destinations. The study sought the best ANN model to predict relationships between the 10 explanatory or predictive variables appearing in Table 3 and the outcome variable (i.e. occupancy rate). To build this model, several MLP ANNs (Kuan & White, 1994) were developed and trained by varying the number of hidden layers and neurons. A MLP ANN with feedforward architecture, represented visually in Fig. 3, yielded the optimal fit between inputs and output for both Model t1 (2015) and Model t2 (2016). This ANN comprised an input layer with 10 predictors, a hidden layer with 4 neurons generated by the program, and an output layer with 1 outcome variable.

The Sigmoid function was used to model the hidden and output layers. The Sigmoid function is capable of scaling the dataset between 0 and 1, thereby allowing the use of all variables as inputs (Phillips et al., 2015). The dataset was divided into a training set of seven DMOs and a test set of three DMOs to validate the model. During the training phase, the backpropagation and gradient descent algorithms were used. This type of supervised learning gives the researcher a wide choice of ways to configure the ANN parameters through the momentum term and the learning rate.

Fig. 3. ANN architecture*



*ET (event tweets), TA (tourist attraction tweets), CT (commercial tweets), ST (socialisation tweets), DRT (DMO retweets), DRE (DMO replies), URE (user replies), ULI (user likes), URT (user retweets), DFO (DMO followers), Occupancy (OCU)

In the empirical study, we analysed the effects of Twitter management of the same 10 DMOs for two consecutive years: 2015 (t1) and 2016 (t2). As Table 5 shows, the root mean square error (RMSE) was 0.033 and 0.024, respectively. The momentum term is used to accelerate network training. It adds a proportion of the previous weight changes to the current weight change (Attoh-Okine, 1999). The momentum factor usually has a value close to 1 (Rumelhart, McClelland, & PDP Research Group, 1986), as was the case in this study. The learning rate determines the size of the weight adjustment each time the weights are changed during training. Small values for the learning rate cause small weight changes, and large values cause large changes. The optimal learning rate is unclear. If the learning rate is 0, the network will not learn. In a social media study using ANN, Phillips et al. (2015) reported a learning rate of 0.5. In our study, the learning rates for the models were 0.7 and 0.8 for Models t1 and t2, respectively. To evaluate the performance of the network, a goodness-of-fit coefficient was used. The R^2 values for the models were 0.89 and 0.95, so the neural network models explained 89% and 95% of the output variable.

Table 5. Goodness-of-fit coefficients for ANN models

Parameter	*Model t1 (2015)*	*Model t2 (2016)*
Learning rate	0.7	0.8
Momentum term	0.9	0.9
Root mean square error (RMSE)	0.033	0.024
R^2	0.89	0.95

4. DATA ANALYSIS AND DISCUSSION

In this section, the results yielded by the two models are first analysed and discussed. The results of the hypothesis testing based on the importance of each predictor in Models t1 and t2 are then presented.

4.1.1. Artificial neural network models: Inputs to hidden layers and hidden layers to outputs

The results for the hidden layer (see Table 6) show how and to what extent the weights of the input layers affected the four neurons making up the hidden layer, thereby indicating which attributes should be used to name the hidden neurons (Phillips et al., 2015). Naming the hidden neurons involves an element of subjectivity, although this subjectivity is a common characteristic of causal models that seek to explain attitudes or behaviours in terms of latent variables (Moutinho et al., 2015).

For hidden neuron 1 (HN1) in Model t1, the weights were high and positive for user replies (1.556), user retweets (1.285), user likes (1.108), and DMO followers (0.408). The pattern was similar in Model t2, with large weights for user retweets (1.640), user replies (1.306), user likes (1.213), and DMO followers (0.824). HN1 was thus named ‘User interaction’. These results suggest that although having many followers is important (tweets by these DMOs during the period under study may have reached more than 170,000 people if the 10 DMOs are considered together), it is not enough on its own because user participation is fundamental. Thus, the DMO’s ability to encourage interaction – be it in the form of retweets, replies, or likes – may lead to an increase in the number of visits to the destination, which may then translate into hotel bookings by users. Encouraging interaction is therefore important because it is crucial for attracting and retaining users (Hays et al., 2013).

For hidden neuron 2 (HN2) in both Models t1 and t2, the weights for event tweets (1.581 and 1.308), socialisation tweets (0.977 and 1.439), and user retweets (1.247 and 0.786) were high and positive. HN2 was thus named ‘News and socialisation tweets for users’. Although DMOs predominantly tweeted about events (see Table 4), an observation consistent with findings reported by Sevin (2013), the weights of socialisation tweets also suggest that it is important to create a friendly online rapport between DMO and user (He et al., 2013). In addition, the number of user retweets achieved by DMOs also seems to be a predictor that positively influences the occupancy rate. This finding indicates that achieving a greater number of retweets means a broader dissemination of information and therefore a greater likelihood of influencing the user to visit and stay overnight in the destination.

Table 6. Impact (weights) of the input layer on hidden layer, and impact (weights) of the hidden layer on the output layer

From the input layer	*To the hidden layer*									
	Hidden neuron 1		Hidden neuron 2		Hidden neuron 3		Hidden neuron 4		Total contribution	
	Model									
	t1	t2	t1	t2	t1	t2	t1	t2	t1	t2
(Bias)	0.344	0.250	-0.307	0.245	-0.302	-0.212	-0.106	0.283	-	-
ET	-0.256	0.124	1.581	1.308	-0.235	-0.113	1.368	1.196	3.440	2.741
TA	-0.158	-0.158	0.425	0.027	-0.378	-0.500	1.104	1.308	2.065	1.993
CT	0.273	0.506	-0.366	-0.253	-0.429	-0.224	-0.207	-0.072	1.275	1.055
ST	0.368	0.171	0.977	1.439	-0.089	-0.150	-0.199	-0.258	1.633	2.018
DRT	-0.399	-0.128	-0.506	-0.301	1.734	1.456	0.318	0.465	2.957	2.35
DRE	-0.270	0.277	-0.317	-0.127	-0.187	0.046	0.171	0.416	0.945	0.866
URE	1.556	1.306	0.092	0.009	-0.135	-0.312	0.932	0.826	2.715	2.453
ULI	1.108	1.213	0.121	-0.203	-0.383	-0.453	0.178	0.138	1.790	2.007
URT	1.285	1.640	1.247	0.786	-0.110	-0.189	0.437	-0.319	3.079	2.934
DFO	0.408	0.824	0.118	0.436	-0.238	0.012	0.319	0.537	1.083	1.809

To the output layer	*From the hidden layer*									
	(Bias)		Hidden neuron 1		Hidden neuron 2		Hidden neuron 3		Hidden neuron 4	
	Model									
	t1	t2	t1	t2	t	t2	t1	t2	t1	t2
OCU	-1.180	-.463	1.001	1.422	-0.64	-0.292	-1.191	-1.226	1.943	0.414

*ET (event tweets), TA (tourist attraction tweets), CT (commercial tweets), ST (socialisation tweets), DRT (DMO retweets), DRE (DMO replies), URE (user replies), ULI (user likes), URT (user retweets), DFO (DMO followers), Occupancy (OCU)

In Model t1, the most notable characteristic of hidden neuron 3 (HN3) was that with just one exception, namely DMO retweets (1.734), all input variables had a negative impact on HN3. A similar pattern was observed for Model t2. The greatest weight was for DMO retweets (1.456), although, unlike in Model t1, DMO replies (0.046) and DMO followers (0.012) were also weighted positively, albeit weakly, with all other inputs weighted negatively. HN3 was thus named 'Origin of shared tweets'. DMOs retweet information from a range of organisations operating in the same destination, such as hotel associations and specific hotels. Results suggest that interactions among DMOs and hotel stakeholders create an online community with the power to positively contribute to room bookings by users, who are exposed to a greater amount of information about the destination derived from numerous sources.

Hidden neuron 4 (HN4) was named 'News and tourist attraction tweets for users' because the input factors with the greatest weights in Model t1 were event tweets (1.368), tourist attraction tweets (1.104), and user replies (0.932). Results were similar for Model t2, with large weights for tourist attraction tweets (1.196), event tweets (1.308), user replies (0.826), and DMO followers (0.537). These results suggest that, as with HN2, event tweets contain content related to issues with the potential to attract tourists to the destination. The weights of tourist attraction tweets also suggest that DMOs should tweet information about tourist attractions in the destination. Notably, although the number of user replies to tweets by DMOs was low (see Table 4), the weight of such tweets indicate that they are important. DMOs should therefore seek to evaluate the comments and replies they receive (Hays et al., 2013).

In terms of the results for the output layer, in both models, these neurons had inhibitory weights, thereby exerting a negative effect on occupancy, albeit to a greater extent in HN3 (-1.191 and -1.226 in Models t1 and t2, respectively) than in HN2 (-0.640 and -0.292 in Models t1 and t2, respectively). These results may be based on negative patterns. In other words, nearly all the input neurons had negative weights in HN2 and HN3. In contrast, in both models, HN1 (1.001 and 1.422 in Models t1 and t2, respectively) and HN4 (1.943 and 0.414 in Models t1 and t2, respectively) had positive weights, thereby exerting a positive effect on occupancy. These results may owe to the fact that most input neurons had positive impacts that outweighed the negative impacts on these hidden neurons.

4.1.2. Hypothesis testing

Following Olden and Jackson (2002), we tested the research hypotheses by analysing the magnitude and direction of weights (percentage values) between neurons. We thus identified the effects of the input variables on the output. Fielding and Bell (1997) used an arbitrary threshold value (50%) at which to accept variables as the most important predictors. Values greater than 65% in Table 7 indicate a strong influence of the predictor on the outcome variable (occupancy).

DMO retweets exerted a strong influence on occupancy in both Model t1 (importance of 75.6%) and Model t2 (importance of 71.9%), a finding that supports hypothesis H1a. Retweets contained information about organisations operating at the same destination. This finding is consistent with those of Sevin (2013). Examples of such organisations are hotels, theatres, and associations of tourism businesses. For example, @ZaragozaTurismo retweeted: *'RT @palafoxhoteles: Pasas #SemanaSanta en #Zaragoza? Hay muchas actividades para estos días en la ciudad. Consúltalas (RT @palafoxhoteles: Spending #SemanaSanta (Easter Week) in #Zaragoza? The city offers loads of activities for Easter Week. Check for details)'.* The presence of these stakeholders seemed to improve occupancy because users were exposed to more information about the destination, thereby making their acceptance of the destination more likely. Replies, however, had a low influence on occupancy. This result holds for Model t1 (importance of 29.3%) and Model t2 (25.3%), leading to the rejection of hypothesis H1b.

Table 7. Normalised importance (percentage values) of the explanatory variables and results of hypothesis testing

Variable	*Model t1*	*Model t2*	*Hypothesis*	*Test result*
DRT	75.6	71.9	H1a	Supported
DRE	29.3	25.3	H1b	Rejected
ET	93.2	82.7	H2a	Supported
TA	55.4	51.9	H2b	Supported
ST	49.6	57.3	H2c	Partially supported
CT	46.6	40.3	H2d	Rejected
DFO	33.3	39.9	H3	Rejected
URE	71.9	68.2	H4a	Supported
URT	81.4	79.2	H4b	Supported
ULI	35.0	46.0	H4c	Rejected

* DRT (DMO retweets), DRE (DMO replies), ET (event tweets), TA (tourist attraction tweets), ST (socialisation tweets), CT (commercial tweets), DFO (DMO followers), URE (user replies), URT (user retweets), ULI (user likes)

The tweet categories were event, tourist attraction, socialisation, and commercial tweets. The category that most affected hotel occupancy, with values greater than 80%, was event tweets. Event tweets strongly influenced occupancy in Models t1 and t2, with an importance of 93.2% and 82.7%, respectively. Hypothesis H2a was therefore supported. DMOs tended to make event tweets, a tendency also reported by Sevin (2013). These tweets were concise and informative – two characteristics that are highly valued by users (André et al., 2012) – and hence conducive to generating interest in destinations. These findings suggest that tweets such as *'La magia del #JuevesSanto tendrá lugar en el #Albaicín esta #SSantaGr15 ¡Consulta el horario de las procesiones! (The magic of #JuevesSanto (Maundy Thursday) will take place in #Albaicín this #SSantaGr15 (2015 Easter Week in Granada). Check the times of processions!)'* might have been a big enough motivation to stir interest among users who felt a greater affinity with Easter Week.

Tourist attraction tweets in Models t1 and t2 had an influence of 55.4% and 51.9%, respectively. According to Fielding and Bell (1997), values greater than 50% can be used to accept variables as predictors. Therefore, although their influence was weaker than the influence of event tweets, tourist attraction tweets also exerted an important influence on the outcome variable. This result supports H2b. For socialisation tweets, the percentage values were 49.6% and 57.3%. Therefore, H2c was partially supported. Finally, commercial tweets scarcely influenced occupancy in Models t1 and t2 (importance of 46.6% and 40.3%, respectively), thereby leading to the rejection of H2d. It seems that users pay no attention to the commercial use of social networks. This original and insightful finding implies that the commercial use of social media should not be explicit.

Although the number of followers had some relationship with occupancy (importance of 33.3% and 39.9% in Models t1 and t2, respectively), it was ultimately unimportant in both models, thereby leading to the rejection of hypothesis H3. This finding implies that quality is better than quantity; in other words, active users are better than a large number of non-active followers.

Replies by users exerted a strong influence on occupancy in both models (importance of 71.9% and 68.2% in Models t1 and t2, respectively), thereby lending support to hypothesis H4a. User replies such as *'@VisitCadiz cuál será el itinerario? (@VisitCadiz what's on?)'* and *'@granadaturismo hoy todavía sirven las tapas? (@granadaturismo are they still serving tapas today?)'* reveal a certain interest among users in processing information that may lead to making a visit. Retweets by users affected occupancy in Models t1 and t2 (importance of 81.4% and 79.2%, respectively), lending support to hypothesis H4b. This finding suggests that retweets might be crucial for boosting the dissemination of information (Zaman et al., 2010) by DMOs, thereby increasing the chances that visitors stay overnight in the destination. Finally, although the number of likes exerted a considerable influence on occupancy in both models (importance of 35% and 46% in Models t1 and t2, respectively), it was insufficient to accept the hypothesis, thereby leading to the rejection of H4c.

5. CONCLUSIONS AND IMPLICATIONS

Data gathered from online sources creates opportunities that until recently had remained undiscovered (Bigné, 2016). For instance, data from sources such as search engines and social networks offer a host of advantages (Park, Ok, & Chae, 2016). These data are high frequency, high volume, and real time, and the information they provide is sensitive to changes in consumer behaviour. These data therefore have the potential to yield accurate socioeconomic forecasts (Yang et al., 2014). Accordingly, from a methodological perspective in an online environment, data mining tools such as text mining and ANNs are valuable because such tools yield information that is both useful and meaningful. In the context of transportation research, Karlaftis and Vlahogianni (2011) provide an in-depth discussion of statistical methods versus artificial neural networks. These approaches differ in their underlying philosophies. Neural networks emphasise implementation, whereas statistics largely emphasise inference and estimation (Hand, 2000). As Breiman (2001) indicates, statistics treat data as having been generated from a stochastic process, whereas neural networks assume data to have been generated by a mechanism of unknown dynamics.

This paper presents a model of the links between predictors of Twitter with respect to accounts managed by DMOs (i.e. activity, content, followers, and actions of users) and the outcome (i.e. occupancy rates in tourist destinations). Results from hypothesis testing using ANNs suggest that social media usage might influence occupancy. Results thereby provide evidence of the impact of social media, an area that requires greater attention from scholars (Anderson, 2012; Leung et al., 2013; Zeng & Gerritsen, 2014). DMOs differ in terms of how they use Twitter over time (Hays et al., 2013; Milwood, Marchiori, & Zach, 2013; Sevin, 2013), as shown in Tables 3 and 4. These different uses of Twitter led to different occupancy rates across destinations. Nevertheless, four predictors made the greatest contribution to explaining the occupancy rate. These predictors were event tweets and retweets by DMOs and replies and retweets by users in response to the DMOs' tweets. Furthermore, the results suggest that four hidden neurons are responsible for transferring the impacts from the input variables to the output variable. These hidden neurons are 'User interaction' (HN1), 'News and socialisation tweets for users' (HN2), 'Origin of shared tweets' (HN3), and 'News and tourist attraction tweets for users' (HN4).

Our results indicate that the number of followers of DMOs does not affect the hotel occupancy rate in tourist destinations during short breaks. This finding confirms that user interactivity is preferable to having a large number of followers (Cha, Haddadi, Benevuto, & Gummadi, 2010). Intuitively, this means that having a large number of followers does not guarantee interactions. Therefore, non-active followers may not lead to hotel occupancy. Further research could replicate this study for different types of social media. For instance, Twitter and Facebook employ somewhat different mechanisms for aggregating social connections. A Facebook friend represents a bi-directional connection between two people (i.e. both individuals in the relationship must give their consent before they become friends). However, on Twitter, one may choose to follow whomever one wishes, whether the person being followed is aware of it or not. Furthermore, although Twitter users may choose to remove a follower, they need do nothing more than generate timely micro-blogging message content to attract a follower (Westerman, Spence, & Van Der Heide, 2012).

Regarding the effects of social media content in terms of commercial tweets, users seemingly do not feel comfortable with the promotional use of social media. Socialisation and tourist attraction tweets exerted less of an influence than event tweets. In our study applied to Easter Week, tweets on events in the destination were the most popular types of tweets. Further studies are needed to analyse the effects of social media content in different contexts.

Our findings show that the number of retweets by DMOs affects the hotel occupancy rate. Therefore, when DMOs interact with potential tourists by retweeting posts from, for example, hotels located in the same destination (Sevin, 2013), the actions of these DMOs affect hotel occupancy. However, when DMOs interact directly by replying, it does not affect hotel occupancy. These findings underline the role of DMOs as third parties that retweet content created by other users (Bokunewick & Shulman, 2017).

User actions such as ‘user replies to tweets by DMOs’ and ‘user retweets of tweets by DMOs’ affect the hotel occupancy rate in tourist destinations during short breaks. However, the action of user likes of tweets does not affect hotel occupancy. This finding can be explained by the differences in user involvement in these different actions (i.e. greater user involvement in reply and retweet actions). Future studies could replicate this study to analyse the differences among user actions on Twitter.

As discussed in the theoretical framework, the rationale for the relationship between social media and the outcome variables is based on two different approaches: consumer socialisation theory and information processing. Consumer socialisation refers to the process whereby individual consumers learn skills, knowledge, and attitudes from others through communication, and these skills, knowledge, and attitudes then help them function as consumers in the marketplace (Ward, 1974). Social media, especially social networking sites, provide a virtual space for people to communicate over the Internet, which might also be an important agent of consumer socialisation (Köhler et al., 2011; Zhang & Daugherty, 2009). Wang et al. (2012) investigated the influence of socialisation through virtual communities (e.g. peer communication through social media websites) and its impact on purchase intentions. In other words, they studied how an individual becomes socialised through positive interactions on a social media website to use some product or service. Twitter allows users to connect with peers by following them. This facilitates communication among peer groups (Chu & Sung, 2015). Drawing on the consumer socialisation framework, our research findings show that Twitter provides communication content that makes the socialisation process easy and convenient. Specifically, Twitter messages by DMOs are agents of consumer socialisation. For example, tweets about events are highly valued by users and help them make various consumption-related decisions such as hotel bookings.

With the increasing popularity of social media, Twitter has played an influential role in reaching consumers and disseminating information for marketers (Chu, Chen & Sung, 2016). In online community settings, Kozinets et al. (2010) found that positive attitudes towards social media messages (i.e. Twitter messages by DMOs):

> will be a function of the way that it [the message] (1) is consistent with the goals, context, and history of the communicator’s character narrative and the communications forum, or media; (2) acknowledges and successfully discharges commercial–communal tensions or offers a strong reason an individualistic orientation is suitable; and (3) fits with the community’s norms and is relevant to its objectives. (p. 86)

Research has shown that, of the different social media platforms, Twitter provides opportunities for marketers to facilitate consumer-to-consumer brand-related conversations because of its focus on sharing information and encouraging discussion (Soboleva et al., 2017). Brands can send tweets to followers, striving to make the messages sufficiently engaging for those followers to forward (or retweet) them to their own networks. Retweeting is an important activity on Twitter because it encourages virality and the spread of real-time information (Rudat & Buder, 2015). In our study, both retweets by DMOs and user retweets were observed to exert an influence on hotel occupancy.

Managerial implications

These findings have practical implications that could help optimise DMOs' social media marketing strategies, thereby helping destinations achieve higher occupancy rates. First, DMOs should increase their retweet activity because DMOs mainly share information about organisations (e.g. hotels) that operate at the same destination. This retweet activity would thus create a community to promote the destination (Sevin, 2013). Second, Twitter is an effective way of communicating what is happening now (Hays et al., 2013), so in a context where trust in service providers depends greatly on the quality of the information they share (Matute, Polo, & Utrillas, 2015), it is important for DMOs to tweet content on current events regularly and clearly. Third, DMOs should encourage user interactivity through retweets and replies. By getting users to retweet information, DMOs can increase the tweet's viral nature and the chances of destination acceptance within the network of users who have retweeted. In addition, replies by users indicate an interest in the destination, which may lead to a visit or overnight stay by these users. Our results also provide two interesting implications for decision making in DMOs' management of tweets: (i) the type of content is important, with event tweets exerting the highest influence and commercial tweets exerting the lowest influence; (ii) the quality of users (i.e. user replies and user retweets) is more relevant than the quantity of users (i.e. number of followers).

Study limitations and further research avenues

This study was limited by the scope of the variables provided by Twitter. Richer integrative approaches are emerging in related fields (Hewett, Rand, Rust, & van Heerde, 2016; Kumar, Choi, & Greene, 2017). Future tourism research must adopt an integrative perspective to determine the synergies that can be derived from using a mixture of tools and variables. To ensure that data were homogeneous in terms of the origin of the users, we focused on a short period (Easter Week) and tweets in one language (Spanish). This approach helped us gain a better understanding of the relationships that were under study. Future research could replicate the study at different times and in other geographical contexts to test whether the findings of this study can be generalised. Beyond the specific context examined in this study, these findings are applicable to other short holidays such as spring breaks and short winter holidays. It also creates opportunities for further studies to focus on longer periods such as summer holidays and other user locations. Future research might consider the geolocation of DMO followers as an additional variable for data analysis.

Although this study covers the majority of the formal accommodation offer (i.e. hotels), it overlooks other forms of formal accommodation. Likewise, the study omits the non-formal offer because of a lack of specific information about the occupancy rate by type of tourism offer (i.e. formal or non-formal accommodation) over a specific period (i.e. Easter Week) in the chosen destinations. Hence, it is difficult to generalise the findings of this study. This study could also be extended by including tweets by hotels. Further studies could adopt an integrative perspective that combines user-generated content, firm-generated content, and third-party-generated content.

This paper presents an ANN that uses variables to predict occupancy. A number of factors influence occupancy rates. These are both external (e.g. seasonality) and internal (e.g. influenced by marketers in the form of price, promotion, etc.). However, new sources of influence must be fully considered. More specifically, these new sources consist of eWOM generated by the users in the form of user-generated content. In this study, we analysed what type of social media content generated by DMOs (specifically, what type of Twitter content) is meaningful and affects occupancy rates of hotels. We developed a method that enables us to understand what kinds of information and interactions on social media (in this case Twitter) are meaningful and affect occupancy rates.

Because online opinions also affect the hotel sector (Ye, Law, & Gu, 2009), future research could include other explanatory variables that reflect tourists' TripAdvisor opinions regarding the hotel offer at the destinations under study. Also, social media affect tourists' perceptions and the image of destinations (Llodrà-Riera, Martínez-Ruiz, Jiménez-Zarco, & Izquierdo-Yusta, 2015). Therefore, future research could determine the extent to which tweets by DMOs affect tourists' perceptions and the image of tourist destinations.

Although this study focused on a tool that is widely used in tourism, namely the microblogging platform Twitter, DMOs also have a presence on other important social media platforms such as Facebook. Further studies could therefore examine the use of Facebook by DMOs to determine its potential impact on occupancy. Additionally, despite providing useful information to potential tourists, social media are unlikely to be the sole influencers of these tourists' decisions. Only recently has research addressed the synergistic effects of eWOM and traditional communication formats (Hewett et al., 2016; Kumar, Choi, & Greene, 2017), highlighting the positive, enhanced effects of combining both tools. Future research could analyse the joint effects of DMOs' use of both communication tools.

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Authors' contributions

Enrique Bigné conceived the idea for the study. Enrique Bigné and Enrique Oltra developed the conceptual model. Enrique Oltra took the lead in the data collection, obtaining the occupancy rate of the DMOs, developing the API, and downloading the tweets in a longitudinal study. Enrique Oltra performed the data mining and artificial neural network analysis. Enrique Bigné took the lead in writing up the context of the manuscript, theoretical framework, and conclusions. Enrique Oltra performed the interpretation of the data. Luisa Andreu supervised the description of the study context and the adequacy of artificial neural networks regarding the trade-offs with other traditional statistical models. All authors contributed to the description of the study context and interpretation of the results of the hypothesis testing. All authors read and approved the manuscript.

ACKNOWLEDGMENTS

This work was supported by the Ministry of Economy and Competitiveness (Spain) under Grant ECO2014-53837R. The authors are grateful to Juergen Gnoth (University of Otago, New Zealand) for comments on an earlier draft of this manuscript. We thank the anonymous reviewers for their comments throughout the review process. We also appreciate the support of Adam King in proofreading this article.