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Destination engagement on Facebook: Time and seasonality

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ABSTRACT

This paper studies the influence of time frames (posting day and posting time) and seasonality (low, medium and high) on positive/negative engagement in a Destination Management Organisation (DMO) on Facebook. A content analysis was carried out on 639 posts, 178,913 audience reactions to such posts and 5,330 comments. These posts were shared 45,194 times by the audience. The data analysis (regression analyses with optimal scaling) suggests that the best times to post are at 8 AM, 10 AM, 2 PM and 5 PM; Thursday and Saturday are the best days to post, and the period before summer (from January to June) are the best months. These results have implications for DMOs and National Tourism Organisations (NTOs).

Keywords: Positive/negative engagement; time frame; seasonality; DMOs; NTOs; Facebook.

1. Introduction

Social networks are transforming the tourism industry from its traditional pattern into an acute informational pattern (Narangajavana, Fiol, Tena, Artola, & García, 2017). In this sense, the importance of social networks for the tourism industry is evident, since the search for information is a critical aspect of tourists' purchase-decision process, as per the literature (e.g., Sirakaya & Woodside, 2005; Hudson & Thal, 2013; Dos Santos, Filomena-Torres, Cunha, & Sánchez, 2016).

Before deciding to travel, most tourists look for online information and reviews using social media (Godnoy & Redek, 2016; Narangajavana et al., 2017). According to marketing research, travel decisions are influenced by social networks (Amaro, Duarte & Henriques, 2016), and the online behaviour of tourists could predict the demand for destinations (Gunter & Önder, 2016).

Social networks have radically changed the way in which tourists interact with tourism brands and make purchasing decisions (Zhang & Chen, 2017). However, the presence of tourism brands in social networks is not enough to have an impact on tourists' purchase decisions; it is necessary to generate engagement (e.g., Dos Santos et al., 2016).

Along with the rise of social networks, scholars and marketing professionals have been interested in understanding engagement, because it is an influential variable for digital marketing which influences brand loyalty, purchase intention and decisions (e.g., Kumar, Bezawada, Rishika, Janakiraman, & Kannan, 2016; Zhang, Guo, Hu, & Liu, 2017).

However, the study of engagement is a complex issue (Pitt, Plangger, Botha, Kietzmann, & Pitt, 2017). Not only because its study has recently been of interest in the marketing field (Brodie, Hollebeek, Jurić, & Ilić, 2011), but because -although there is an abundance of literature- there is no single and consistent definition of engagement (Brodie et al., 2011, Zheng, Cheung, Lee, & Liang, 2015). Currently, research on engagement still has aspects that have seldom been studied, and there are no consistent or conclusive results in many areas (Hollebeek & Chen, 2014; Zheng et al., 2015).

For example, more research is needed to understand how aspects related to time affect brand engagement (e.g., Lamberton & Stephen, 2016). In fact, variables related to time influence tourists' decision-making process (Sirakaya & Woodside, 2005), and could affect engagement (e.g., Ashley & Tuten, 2015). Time is especially relevant in the tourism industry, where seasonality directly affects the tourism market (e.g., Butler, 2001; Ridderstaat & Nijkamp, 2015; Gil-Alana & Huijbens, 2018). In addition, in professional practice, the importance of time frames in optimising brand engagement is recognised (e.g., Srinivasan, Anandhavelu, Sinha, & Revankar, 2017).

Previous studies have provided empirical evidence that variables related to time, like seasonality and time frames, are linked with engagement (e.g., Cvijikj & Michahelles, 2013; Sabate, Berbegal-Mirabent, Cañabate, & Lebherz, 2014; Parganas, Anagnostopoulos, & Chadwick, 2015; Lee et al., 2018). However, there is a need for more research, and there is no consensus among the results. This is where the central axis of this research lies. Specifically, the main objective of this investigation is to study the influence of time frames and seasonality on positive/negative engagement in a DMO in Spain. To this end, this research has two specific objectives:

a. To identify whether time frames are a predictor of positive or negative engagement on Facebook.
b. To identify whether seasonality is a predictor of positive or negative engagement on Facebook.

On the other hand, Spain is a relevant case to study for many reasons. First, it is the most competitive country in the world, according to the Global Tourism & Travel Competitiveness Index 2017 (Crotti, & Misrahi, 2017). Second, some authors have considered Spain to be a paradigm of economic development supported by a strong expansion of tourism (Mérida & Golpe, 2016). Third, according to the World Tourism Organization (UNWTO) (2018), Spain is ranked foremost in international tourist arrivals; in

2017, it was the second most visited country in the world. Lastly, Spain is a destination with higher levels of social media engagement (Uşaklı, Koç, & Sönmez, 2017).

After a review of the marketing literature, it is feasible to identify the added value of this research. First, these results help to understand engagement behaviour as a function of time. In this way, answers are offered to one of the shortcomings of marketing research according to Lamberton and Stephen (2016): factors related to time and engagement. Secondly, this research deepens the study of negative engagement. According to some researchers, more studies are needed about this construct because it has been poorly researched (e.g., Hollebeek & Chen, 2014; Dolan, Conduit, Fahy, & Goodman, 2016a; Villamediana-Pedrosa, Vila-López, & Küster-Boluda, 2018). Third, the results of this study allow us to better understand engagement behaviour in the tourism industry. This is a relevant issue to study, according to the Marketing Science Institute (2018). Finally, this research is also relevant in terms of marketing practices, because its results can be used to improve tourists' engagement and the performance of DMOs and NTOs.

2. Positive/negative engagement framework

With the publication of Algesheimer, Dholakia, and Hermann (2005), the study of engagement emerged in the field of marketing as a relevant topic (Brodie et al., 2011). Its study can be framed in the relationship between consumers and brand research, a topic that has generated significant interest during the last three decades in marketing (Hollebeek, Glynn & Brodie, 2014). Influenced by its study context (Kuvykaitė & Tarute, 2015), engagement has been defined and measured in different ways in the marketing literature (Zheng et al., 2015). Among different definitions, the construct of the brand's positively/negatively valenced engagement was created in 2014 by Hollebeek and Chen (2014). In recent years, this construct has been mentioned and studied by other scholars (e.g., Bowden et al., 2015; Dolan et al., 2016a; Bowden et al., 2017; Harrigan, Evers, Miles & Daly, 2017; Naumann, Bowden & Gabbott., 2017; Villamediana-Pedrosa et al., 2018).

Based on Hollebeek and Chen's (2014) proposal, in addition to considering the operationalisation of Bonsón and Ratkai (2013), Villamediana-Pedrosa et al. (2018) adapted the positive/negative engagement construct and its measurement of the context of brand communities in social networks and conceptualised positive/negative engagement in the following way:

> ***"Positive engagement is considered a multidimensional construct that reveals a positive valence brand's valuation, and that is observable through virality, commitment and popularity that tourists manifest in brand communities on social networks. While negative engagement is a multidimensional construct that reveals a negative valence brand's valuation, and which is observable through the virality, commitment and popularity that tourists manifest in brand communities on social networks" (p. 5).***

While positively valenced engagement is widely recognised in the existing literature, studies on negatively valenced engagement are mainly exploratory studies revealing the need to better understand its specific manifestations (Bowden et al., 2017). Therefore, it is evident that negative engagement is beginning to emerge as a new topic and is generating interest among researchers.

The dimensions of engagement are popularity, commitment and virality (Bonsón & Ratkai, 2013). According to Villamediana et al. (2018), (a) positive/negative popularity is defined as the average positive/negative reactions to Facebook posts per thousand fans; (b) positive/negative commitment is the average positive/negative comments in Facebook posts per thousand fans; and (c) finally, positive/negative virality is the average number of times a publication has been shared per thousand fans (this is adjusted according to the average values of positive/negative popularity and commitment). Figure 1 summarises the definition of every variable of interest and its dimensions.

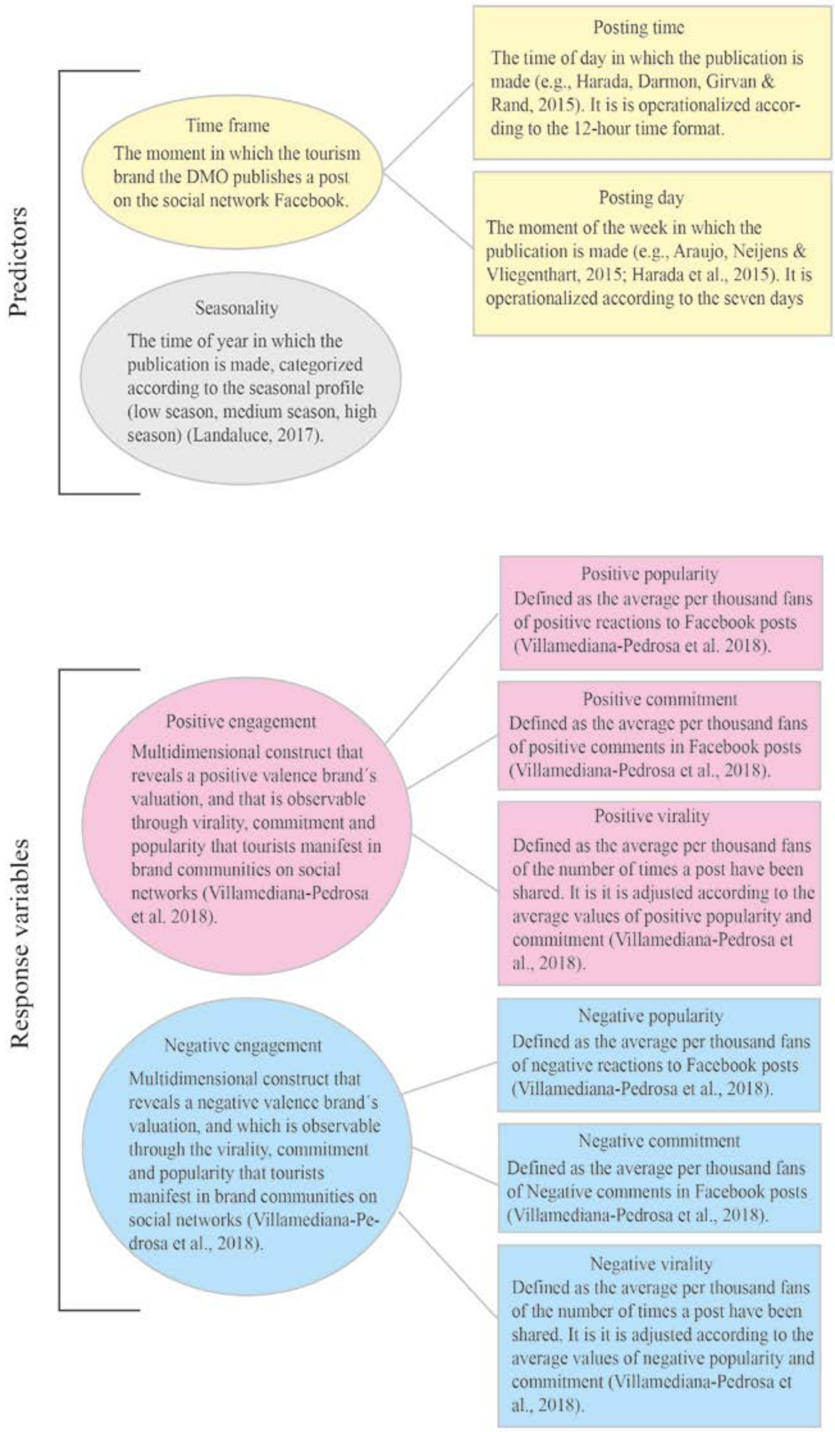

Figure 1. *Definitions of variables of interest.*

Source: own development.

2.1 Relationship between time frame, seasonality and positive/negative engagement

In this study, the time frame variable is defined as the moment in which the DMO publishes a post on Facebook. In the literature review, this could mean that time frame in the tourism industry is divided into the following dimensions: the posting time, the time of day in which the publication is made (e.g., Harada, Darmon, Girvan & Rand, 2015), the posting day and the moment of the week in which the publication is made (e.g., Araujo, Neijens & Vliegenthart, 2015; Harada et al., 2015). While seasonality is the time of year in which the publication is made, categorised according to the high seasonal profile and defined according to tourism demand in Spain (low season, medium season, high season) (Landaluce, 2017).

The time factor is essential for Facebook (Montells, 2019). According to marketers, variables related to time are relevant to Facebook's algorithm (e.g., Peters, 2018; Boyd, 2019); consequently, they are vital in increasing engagement. (Barnhart, 2018).

In previous empirical studies, there has been evidence that posting time (e.g., Sabate, Berbegal-Mirabent, Cañabate, & Lebherz, 2014), posting day (e.g., Cvijikj & Michahelles, 2013) and seasonality are related to engagement (e.g., Parganas, Anagnostopoulos, & Chadwick, 2015; e.g., Lee et al., 2018).

However, the studies that analyse the relationship between posting time, posting day and engagement show different patterns, and there is no consensus among the results (Sabate et al., 2014). The behaviour of these relationships could have different characteristics in each region and industry, an important aspect that must be considered in order to analyse the results (Sabate et al., 2014). However, few studies measure the relationship between seasonality and engagement (Lee et al., 2018). Therefore, it is important to conduct more empirical research. Considering the previous finding, a general hypothesis was formulated:
H: Time frame and seasonality influence positive/negative engagement and its dimensions.

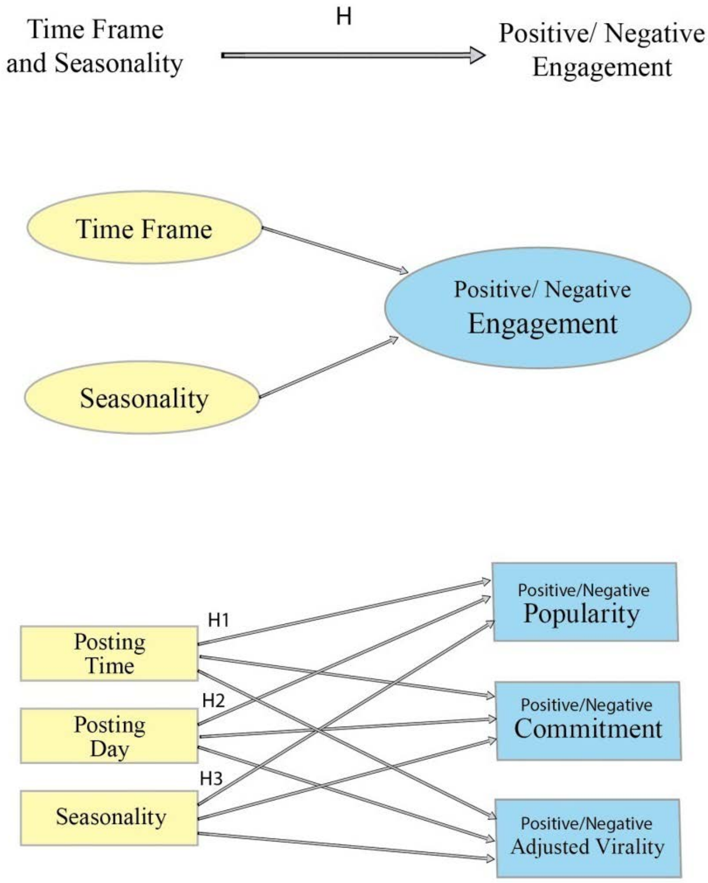

Figure 2. *Graphic representation of Hypothesis 1 and the specific hypotheses that emerge from it. Source: own development.*

2.2 Posting time, a time frame dimension

In this study, posting time is operationalised according to the 12-hour time format (AM/PM). This is a relevant variable and must be considered by marketing professionals when designing marketing strategies (Sabate et al., 2014).

As explained in this section, previous empirical research has provided clues or identified that posting time influences engagement or some of its dimensions. From professional practice, there are also signs of the influence of posting time on engagement (e.g., Patel, n.d.; Adeva, 2015).

In the marketing literature, the first clue about the importance of posting time was found in Kumar et al. (2006). These authors analysed online advertising on web pages and concluded that posting time influences its performance. A year later, Golder et al. (2007) studied the temporal patterns of Facebook activity on higher education students and found that activity in this social network usually starts around noon and peaks between 9 PM and 12 midnight. Another study within the educational context by Túñez López and Sixto García (2012) reported that activity on Facebook was greater after 8 PM. Later, Cvijikj and Michahelles (2013) studied whether the posts published during peak hours (between 4 PM and 12 midnight, and between 1 AM and 4 AM) generate more engagement in 100 mass consumer brands on Facebook. These researchers found that peak hours have a negative effect on their popularity and virality (engagement dimensions), but found no effect on the commitment dimension.

Contrary to previous results, Sabate et al. (2014) found that posts published during working hours (between 8 AM and 5 PM from Monday to Thursday, and between 8 AM and 2 PM on Fridays) positively affect the commitment dimension of engagement with travel agency brands. Recently, Dolan, Conduit, Fahy and Goodman (2016b) analysed wine brands on Facebook and observed that their popularity level is higher between 7 AM and 11 AM, their commitment level is higher between 9 AM and 11 AM, and their virality level is higher between 9 AM and 11 AM. Mariani, Di Felice and Mura (2016) explored DMOs in Italy and found that there is a relationship between posting time and engagement. According to these researchers, posts published in the evening show more engagement. Later, Mariani, Mura and Di Felice (2018) also explored posts from 10 NTOs and found that posting in the evening has a negative impact on engagement. These results affirm that findings need to be understood in the light of differences between countries and regions about the best time to post.

Table 1 summarises the findings of the previous studies and approaches that support H1.

Table 1

Empirical studies that support the specific hypothesis H1 (posting time variable)

Previous studies data		Evidence of influence of posting time			
Author (Year)	**Context of the study**	***Engagement***	**Popularity**	**Commitment**	**Virality**
Kumar et al. (2006)	Online advertising on web pages	x			
Golder et al. (2007)	Higher education students with a Facebook profile	x			
Túñez López & Sixto García (2012)	Higher education students with a Facebook profile	x			
Cvijikj & Michahelles (2013)	Mass consumer brands on Facebook		x		x
Sabate et al. (2014)	Spanish travel agencies brands on Facebook			x	
Dolan et al. (2016b)	Wine brands on Facebook		x	x	x
Mariani et al. (2016)	DMOs in Italy	x			
Mariani et al. (2018)	10 NTOs of most visited countries in World	x			

Source: own development.

Based on previous studies, the following hypothesis was formulated:

H1: There is a relationship between posting time and positive/negative engagement.

H1.1: Posts published between 12 noon and 12 midnight predict a higher level of

H1.1a) positive engagement
H1.1b) positive popularity
H1.1c) positive commitment
H1.1d) positive virality

H1.2: Posts published between 12 noon and 12 midnight predict a lower level of

H1.2a) negative engagement
H1.2b) negative popularity
H1.2c) negative commitment
H1.2d) negative virality

2.3 Posting day, a time frame dimension

In this study, posting day was operationalised according to the seven days of the week (Araujo et al., 2015; Harada et al., 2015).

In previous empirical studies, there are indications and evidence that posting day affects engagement. For example, Golder et al. (2007) found that the greatest activity on Facebook took place during business days, especially at the beginning of the week (Mondays to Wednesdays). While Túñez López and Sixto García (2012) obtained conflicting results and concluded that the highest activity on Facebook occurs on weekends, especially on Sundays. Later, Cvijikj and Michahelles (2013) found that the commitment dimension of the engagement variable is significantly higher on business days. While Sabate et al. (2014), contrary to their expectations, found no evidence that posting day influences engagement. Dolan et al. (2016b) noted that the levels of the virality dimension of engagement are lower on Mondays and higher on Fridays compared to the rest of the week. Afterwards, Mariani et al. (2018) found that posting during the weekend positively affects engagement.

Table 2 summarises the findings of previous studies or approaches that support H2.

Table 2

Empirical studies that support the specific hypothesis H2 (posting day variable)

Previous studies data		Evidence of influence of posting day			
Author (Year)	**Context**	***Engagement***	**Popularity**	**Commitment**	**Virality**
Kumar et al. (2006)	Online advertising on web pages	x			
Golder et al. (2007)	Higher education students with a Facebook profile	x			
Túñez López & Sixto García (2012)	Higher education students with a Facebook profile	x			
Cvijikj & Michahelles (2013)	Mass consumer brands on Facebook		x		x
Dolan et al. (2016b)	Wine brands on Facebook				x
Mariani et al. (2016)	DMOs in Italy	x			

Source: own development.

Based on previous studies, the following hypothesis was formulated:

H2: There is a relationship between posting day and positive/negative engagement.

H2.1: Posts published on weekends predict a higher level of

H2.1a) positive engagement
H2.1b) positive popularity
H2.1c) positive commitment
H2.1d) positive virality

H2.2: Posts published on weekends predict a lower level of

H2.2a) negative engagement

H2.2b) negative popularity
H2.2c) negative commitment
H2.2d) negative virality

2.5 Seasonality

In the tourism field, seasonality refers to variations in the level of tourism demand over a year, which can be grouped and categorised according to their behaviour (Landaluce, 2017). In general, seasonality has been recognised as one of the most distinctive characteristics of the tourism industry (Butler, 2001). Therefore, the study of the seasonal profile of tourism demand is a topic of interest for the scientific community (Landaluce, 2017).

This seasonality may vary depending on the region or country in question (e.g., Juganaru, Aivaz & Juganaru, 2017; Landaluce, 2017). In the case of Spain, the context of this study, tourist flows are disaggregated, temporary and mainly concentrated in the summer months (Landaluce, 2017).

After studying tourists' entry to Spain over a 10-year period (January 2006 - September 2015), Landaluce (2017) concluded that the seasonality of the Spanish tourism industry is divided into three seasons: (1) during November, December, January, February and March the influx of tourists is lower; (2) during April, May, June, September and October there is an average influx; and (3) July and August see the highest influx of tourists. Figure 3 shows how seasonality is classified in Spain.

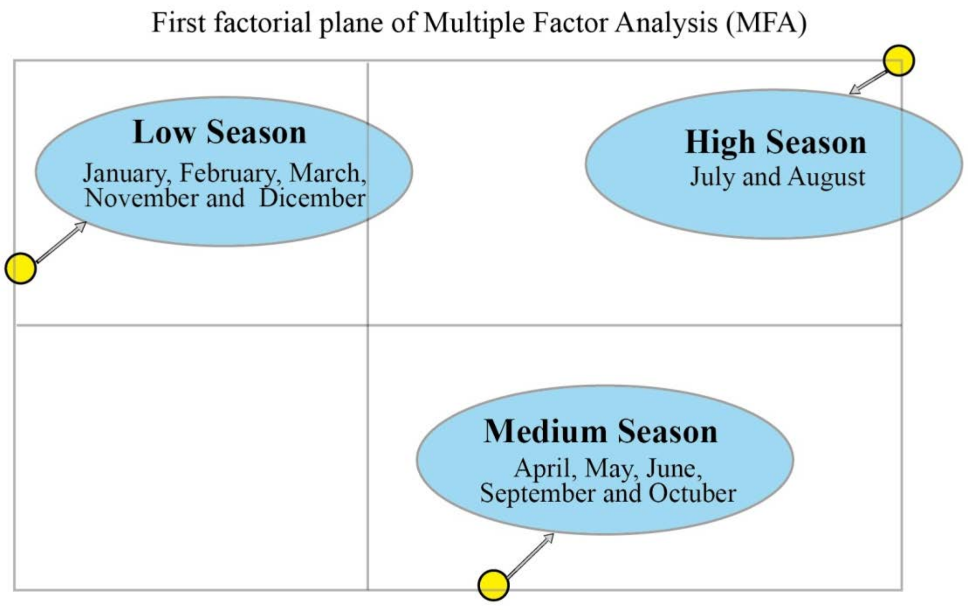

Figure 3. *First factorial plane of the Multiple Factorial Analysis of Landaluce (2017, p.484), which shows how the seasonality in Spain is classified according to the tourist flows of a period of 10 years (January 2006 - September 2015).*

According to the marketing literature, there is evidence that temporal factors can influence engagement (e.g., Harada et al., 2015; Parganas et al., 2015; Lee et al., 2018). However, even seasonality is a highly relevant variable in the tourism industry; there is a shortage of studies that assess this relationship in high impact academic journals.

The first indication in favour of the relationship between seasonality and engagement can be found in Golder et al. (2007). These researchers found that, in the educational context, the holiday season has a negative influence on Facebook activity.

One of the most relevant antecedents for this research was the study carried out by Parganas et al. (2015) in the sports marketing context. They analysed engagement on Twitter towards a professional football club brand in Europe (Liverpool Football Club). Significant differences were found in engagement levels according to the moment in which the messages were published: before, during and after the football season of 2013. Specifically, engagement was more significant during the soccer season.

Mariani et al. (2016) explained that descriptive data from DMOs showed that engagement is highest in January and reached a relative peak in July. Later, Lee et al. (2018) studied the relationship between seasonality and one of the dimensions of negative engagement (negative commitment). They analysed online consumers' complaints made over one year on the complaints.com website. The results revealed that seasonality influences negative commitment. Specifically, differences were found in the frequency and type of complaint regarding the holiday and non-holiday seasons; negative commitment was greater during the holiday period.

Table 3 summarises the findings of previous studies supporting H3.

Table 3
Empirical studies that support the specific hypothesis H3 (seasonality variable)

Previous studies data		Evidence of influence of seasonality			
Author (Year)	**Context**	***Engagement***	**Popularity**	**Commitmant**	**Virality**
Golder et al. (2007)	Higher education students with a Facebook profile	x			
Parganas et al. (2015)	Sports club brand on Twitter	x	x	x	x
Lee et al. (2018)	Retailers brands, which received criticism on the complaints.com website			x	
Mariani et al. (2016)	10 NTOs of most visited countries in World	x			

Source: own development.

Based on previous studies, the following specific hypothesis was formulated:

H3: There is a relationship between seasonality and positive/negative engagement.

H3.1: Posts published in the summer months (high season) predict a higher level of

H3.1a) positive engagement
H3.1b) positive popularity
H3.1c) positive commitment
H3.1d) positive virality

H3.2: Posts published in the summer months (high season) predict a lower level of
H3.1a) negative engagement
H3.2b) negative popularity
H3.2c) negative commitment
H3.2d) negative virality

3. Method

This is a non-experimental and ex-post-facto field research study (Kerlinger, 1973), which seeks to find an explanatory relationship between the variables. Due to the objective pursued by this research, and to the scales of the variables studied, the data were analysed with regression analyses with optimal scaling (CATREG).

3. 1 Population

As mentioned previously, Spain is a relevant case to study. For this reason, a Spanish DMO's official Facebook page was selected to be studied. The fan page selected is called Spain.info, and it is managed by the National Tourist Office in Spain.

Facebook was the social network selected to pursue the research objectives for many reasons. Generally, leading social networks with a high number of user accounts or metrics demonstrate strong user engagement (Statista, 2019). According to this criterion, Facebook is classified as the most popular social network in the world. As Statista (2019) has shown, Facebook had more than 2 billion active monthly users in 2018.

According to some practitioners, if one wants to reach a mass audience, being on Facebook is a must (Card, 2019). Roque and Raposo (2016) affirmed that Facebook is one of the social media sites most used by DMOs to engage with their audiences, and it is also the one that generates increased interactions with users. Based on empirical data from DMOs, Uşaklı et al. (2017) explained that Facebook creates higher levels of engagement than other social networks.

3.2 Data collection

According to some researchers, there are some criteria to be considered when collecting data from Facebook. For example, the posts should be organic (e.g., Pronschinske, Groza, & Walker, 2012) and engagement indicators should be collected when there is no possibility of changing them with new interactions (at least a month after the publication date) (e.g., Sabate et al., 2014). These criteria were taken into account in the study. Finally, all posts published in 2017 (from January 1st to December 31st) were collected, along with all of their engagement indicators. As with previous researchers (e.g., Sabate et al., 2014), data was gathered manually in the second quarter of 2018.

3.2.1 Content analysis

Text and visual content (reactions and emoticons) from the data collected were evaluated using an analysis content. To guarantee the accuracy of the study, the data was classified following the standard rules of procedure and devised into content analytical units (e.g., Neuendorf, 2016). Each post was deemed a codable unit, as well as each comment on the post. To classify each analytical unit, there were defined coded categories based on the literature review and methodology proposed by previous researchers (see Appendix A).

For the coded comments, each unit was classified according to its valence (positive or negative) following the methodology proposed by Villamediana et al. (2018). Neutral valence was considered as an exclusion criterion. Before coding the comments, a codebook was developed based on a test sample of comments. Using the methodology of previous research (e.g., Shen & Bissell, 2013), this codebook was tested and considered to be suitable for the study. Cohen's kappa was calculated to measure inter-coder reliability (Kappa= .919, 95% confidence interval: from .890 to .948). Next, the definitive data was coded by only one trained member of the research team to avoid coding mistakes (e.g., Neuendorf, 2016).

3.3 Variables

Based on the findings of recent literature, time frame and seasonality were considered as independent variables, while the dependent variables would be the positive/negative engagement and its dimensions (positive/negative popularity, positive/negative commitment, positive/negative virality). Appendix A shows the measurement metrics for each variable and its scales of measurement.

4. Results and discussion

To achieve the study's aim, a content analysis was carried out. In total, 639 posts were analysed; in addition to 178,913 audience reactions on those posts and 5,330 audience comments. The posts were viralised 45,194 times.

Appendix B presents the frequencies of all the independent variables (coded as nominal) and the means and standard deviations for all the dependent variables (coded as interval-ratio). The posts were published more frequently in the months leading up to the high season, and they were mainly published at two schedules (at 8 AM and at 5 PM).

A descriptive analyses of the data indicate that the positive engagement average is around .2034 per thousand fans. Positive engagement is much higher ($\overline{\chi}$ =.2034) than negative engagement ($\overline{\chi}$ =.0012). Specifically, positive popularity is the dimension that contributes most to positive engagement ($\overline{\chi}$ =.1596), followed by positive adjusted virality ($\overline{\chi}$ =.0389). Positive commitment is in last place ($\overline{\chi}$ =.0048).

The level of positive/negative engagement is consistent with previous findings. In general, the reactions of the audience on social networks remains limited to a relatively small segment of available tourists (e.g., Amaro et al., 2016; e.g., Bronner & Hoog, 2016). The results support the notion that there are more people consuming tourism information than people reacting or creating content (e.g., Amaro et al., 2016).

The regression analysis with optimal scaling (CATREG) was used to test the general and specific hypotheses. The CATREG algorithm was developed by the Data Theory Scaling System Group (DTSS) (Kircher & Lutzhoft, 2011); this methodology has been used efficiently in previous studies in the tourism industry (e.g., Correia, Oliveira, & Butler, 2008; Almeida & Garrod, 2016).

The CATREG algorithm extends the standard linear regression approach by simultaneously scaling nominal, ordinal and numerical variables (Gifi, 1990). Additionally, it does not need to assume a linear relationship between variables or have normality of residuals (Correia et al., 2008).

Statistical assumptions were checked before the analyses were performed (n=639; predictors=3). Subsequently, the statistical analyses were conducted using SPSS, v.18. However, before interpreting the data, the intercorrelations among the predictors were observed, for both the untransformed and transformed predictors. According to the literature, multi-collinearity could be a problem in the regression analysis, and these intercorrelations are useful for identifying whether there were highly correlated variables (Kooij, 2007). As expected, all the values were near 0, indicating that multi-collinearity between individual variables was not a concern for this study (see Appendix C).

Finally, eight regression models were constructed, one for each dependent variable. The results were statistically significant in every regression (considering *p-value <.05*). During the analyses, the three stated hypotheses were considered.

In order to increase the model fitting, the backward Stepwise method was used (Villamediana-Pedrosa et al., 2018). This means that irrelevant predictors were excluded from the final model (Almeida & Garrod, 2016). This procedure was not available in SPSS and so it was applied manually. Below, the resulting eight models are presented. In total, all models are statistically significant in explaining the aforementioned dependent variables (see Table 6). A statistical significance level of *p-value* <.05 (α) and a 95% confidence interval were used to test the hypotheses.

In the first model, the dependent variable was **positive engagement**. As Table 6 shows, the results have shown a highly significant and moderate correlation (R=.340) between the response variable and the best predictor variables combination (posting time, posting day and seasonality). In the model, approximately 8.10% of the variance in positive engagement is explained by the predictor variables ((R2 adjusted=.081), F(.885)=3.335, *p-value*=.000). These results are highly and statistically significant, indicating adequate performance and suggesting that the three combined predictive variables explain positive engagement on Facebook.

As has been observed (see Table 4), the regression analysis with optimal scaling also reports Pratt's measures of relative importance, a coefficient that reflects the relative importance of the different independent variables (Pratt, 1987; Almeida & Garrot, 2017). In this case, posting time is the most important predictor in the regression model (Relative Importance=.608), followed by seasonality (Relative Importance=.256) and posting day (Relative Importance=.137).

In the second model, the dependent variable was **positive popularity.** A highly significant and moderate correlation (R=.354) was observed between the best predictor variables combination (posting time, posting day and seasonality) and positive popularity. Approximately 9.10% of the variance in positive engagement is explained by the CATREG model incorporating all three predictor variables ((R2 adjusted=.091), F(.875)=3.671, *p-value*=.000). The most important predictor in the regression model is seasonality (Relative Importance=.493), followed by posting time (Relative Importance=.411) and posting day (Relative Importance=.097). These results are highly and statistically significant. Finally, it can be affirmed that the combined predictive variables explain positive popularity on Facebook.

In the third model, the dependent variable was **positive commitment.** The results have shown a highly significant and moderate correlation (R=.343) between the response variable and the best predictor variables combination (posting time, posting day, and seasonality). In the model, approximately 8.30% of the variance in positive commitment is explained by the predictor variables ((R2 adjusted=.083), F(.883)=3.405, *p-value*=.000). The most important predictor in the regression model is seasonality (Relative Importance=.432), followed by posting time (Relative Importance=.403) and posting day (Relative Importance=.165). These results are statistically highly significant. As a result, the combined predictive variables explain positive commitment on Facebook.

In the fourth model, the dependent variable was **positive adjusted virality.** A highly significant and low correlation (R=.282) was observed between the best predictor variables combination (posting time, posting day and seasonality) and positive adjusted virality. Approximately 4.30% of the variance in positive engagement is explained by the CATREG model incorporating all three predictor variables ((R2 adjusted=.043), F(.921)=2.208, *p-value*=.001). The Relative Importance values (Pratt's measure) emphasise the relevance of posting time (Relative Importance=.480) as the most important predictor in the model, followed by seasonality (Relative Importance=.355) and posting day (Relative Importance=.164). These results are statistically highly significant. Finally, it can be affirmed that the combined predictive variables explain positive adjusted virality on Facebook.

In the fifth model, the dependent variable was **negative engagement.** The results demonstrate a highly significant and moderate correlation (R=.316) between the response variable and the best predictor variables combination (posting time, posting day and seasonality). In the model, approximately 6.50% of the variance in negative engagement is explained by the predictor variables ((R2 adjusted=.065), F(.900)=2.840, *p-value*=.000). The most important predictor in the regression model is posting time (Relative Importance=.668), followed by seasonality (Relative Importance=.181) and posting day (Relative Importance=.152). These results are statistically highly significant. Consequently, the combined predictive variables explain negative engagement on Facebook.

In the sixth model, the dependent variable was **negative popularity.** The results reveal a highly significant and moderate correlation (R=.325) between the response variable and the best predictor variables combination (posting time, posting day and seasonality). In the model, approximately 7.10% of the variance in negative popularity is explained by the predictor variables ((R^2 adjusted=.071), F(.894)=3.023, *p-value*=.000). The most important predictor in the regression model is posting time (Relative Importance=.805), followed by seasonality (Relative Importance=.138) and posting day (Relative Importance=.057). These results are statistically highly significant. Accordingly, the combined predictive variables explain negative popularity on Facebook.

In the seventh model, the dependent variable was **negative commitment.** A highly significant and moderate correlation (R=.341) was observed between the best predictor variables combination (posting time and seasonality) and negative commitment. Approximately 9% of the variance in positive engagement is explained by the regression model incorporating all three predictor variables ((R^2 adjusted=.090), F(.884)=4.521, *p-value*=.000). The Relative Importance values emphasise the relevance of posting time (Relative Importance=.873) as the most important predictor in the model, followed by seasonality (Relative Importance=.127). Finally, it can be affirmed that the combined predictive variables explain negative commitment on Facebook.

Finally, in the eighth model, the dependent variable was **negative adjusted virality.** The results have shown a highly significant and low correlation (R=.324) between the response variable and the best predictor variables combination (posting time, posting day and seasonality). In the model, approximately 7% of the variance in negative adjusted virality is explained by the predictor variables ((R^2 adjusted=.070), F(.895)=3.001, *p-value*=.000). The most important predictor in the regression model is posting time (Relative Importance=.730), followed by seasonality (Relative Importance=.183) and posting day (Relative Importance=.087). These results are statistically highly significant, hence the combined predictive variables explain negative adjusted virality on Facebook.

In summary, there is evidence to prove that time frame and seasonality predict both positive and negative engagement, as well as its three dimensions (popularity, commitment and virality). Consequently, **the general hypothesis of the study has been accepted**.

After this initial presentation, it is necessary to move onto the evaluation of the specific hypotheses. Nevertheless, to reject or accept the specific hypotheses, further analysis of the relationship between time frame, seasonality and positive/negative engagement is needed, as well as its dimensions. It is worth mentioning that every relationship between the predictors and the response variables was nonlinear according to the CATREG results (see transformation graphs in Appendix D).

For these reasons, the graphed means of positive/negative engagement and its dimensions have been analysed. The means have been categorised according to the predictor variables. As such, they are helpful in understanding the behaviour of the relationships found; Appendix E shows these graphs (see Figure 1, Figure 2 and Figure 3). Up to this point, as can be seen in Table 4 and Appendix E, the data already analysed reveals evidence to accept or reject the specific hypotheses. Next, the results for or against the three remaining hypotheses are explained. Furthermore, Table 5 shows the hypotheses that have been accepted or rejected.

Firstly, it was found that the posts published between 12 noon and 12 midnight do not generate a higher level of positive engagement. On the contrary, this study discovered that posts published in the morning generate more positive engagement than posts published in the afternoon. Posts published at 8 AM and at 10 AM clearly show more positive engagement than other posts, whereas posts published between 12 noon and 12 midnight have a lower level of engagement. In fact, there is peak negative engagement at 10 AM.

Furthermore, it was observed that posts published in mornings generated more positive popularity. However, they produced less positive commitment and positive virality. More specifically, posts published at 10 AM reached the highest level of positive popularity. However, posts published at 2 PM displayed more positive commitment. In addition, posts published at 5 PM generated more positive virality. Finally, it was identified that posts published at 10 AM peaked in negative popularity. While negative commitment is higher both in the morning and the afternoon if posts are published at the following hours: from 10 AM until 11 AM, at 3 PM, at 8 PM and at 10 PM. Similarly, negative virality is higher at 10 AM and at 3 PM.

According to these findings, posts published between 12 noon and 12 midnight predict a higher level of positive commitment (F=12.004**) and positive virality (F=20.855**). However, contrary to what is expected, posts published before this time predict a higher level of positive engagement (F=23.773**) and positive popularity (F=18.751). On the other hand, posts published between 12 noon and 12 midnight predict a lower level of negative engagement (F=18.766**) and negative popularity (F=9.031**). Despite this, they do not predict a lower level of negative commitment (F=13.501**) or negative virality (F=24.064**). In this regard, **the first specific hypothesis (H1) has been accepted, as well as its sub-hypotheses: H1.1c, H1.1d, H1.2a and H1.2b.**

Secondly, posts published on Saturday produce a higher level of positive engagement, positive commitment and positive virality. However, posts published on Thursday generate a higher level of positive popularity. In addition, posts published on Saturday obtain the highest level of negative engagement and negative virality. In contrast, posts published on Friday generate a higher level of negative popularity.

In short, posts published on weekends predict a higher level of positive engagement (F=6.402**) and some of its dimensions: positive commitment (F=8.408**) and positive virality (F=10.558**). However, contradicting what is expected, posts on weekdays predict a higher level of positive popularity (F=8.408**). Contrary to the hypotheses, posts published on weekends do not predict a lower level of negative engagement (F=13.786**) and negative virality (F=7.171**). However, they predict a lower level of negative popularity (F=2.332**). Considering this finding, **the second specific hypothesis (H2) has been accepted**, as well as **its sub-hypotheses: H2.1a, H2.1c, H2.1d and H2.2b.**

Thirdly, posts published before summer (July and August) produce more positive engagement, positive popularity, positive commitment and positive virality than other posts. Furthermore, posts published during summer generates more negative engagement, negative popularity, negative commitment and negative virality. These results oppose what is expected. It is worth mentioning that the level of positive engagement, positive popularity and positive commitment is even lower in posts published after summer.

Finally, it was found that posts published during summer (July and August) do not predict a higher level of positive engagement (F=3.986*) or its dimensions: positive popularity (F=10.890**), positive commitment (F=6.768**) and positive virality (F=3.512*). Nevertheless, posts published during summer predict a higher level of negative engagement (F=5.143**) and its dimensions: negative popularity (F=7.552**), negative commitment (F=5.701**) and negative virality (F=6.232**). In this regard, **the third specific hypothesis (H3) has been accepted. However, in this case, none of its sub-hypotheses have been accepted.**

Based on these results, the most important predictor of positive/negative engagement is posting time, while the second most important predictor is seasonality, and the least is posting day. As Sabate et al. (2014) concluded in previous research, this finding suggests that posting time is a significant variable and must be considered by marketing professionals when designing marketing strategies.

This means that posting at suitable times is heavily relevant to engagement. According to the data, the most favourable and advantageous times for positive engagement are 8 AM, 10 AM, 2 PM and 5 PM. These results are quite similar to those reported by other researchers (e.g., Sabate et al., 2014; e.g., Dolan et al., 2016b), who found that engagement increases from 8 AM to 5 PM, especially at 9 and 11 AM. However, these findings are contradictory to the results reported by Mariani et al. (2018); as these authors have explained, the differences are likely due to the differences between countries and regions.

Furthermore, it has been identified that Thursday and Saturday are the best days to post on Facebook. These findings are slightly similar to those of Túñez López and Sixto García (2012) and Mariani et al. (2018), who concluded that engagement is higher on weekends; Dolan et al. (2016b) also found that engagement increases at the end of the week. Nevertheless, they oppose those results described in some previous studies (Golder et al., 2007; Cvijikj & Michahelles, 2013; Sabate et al., 2014).

Based on the data, it could be affirmed that the months before summer (from January to June) are the best period in which to post. Posting before the high tourism season is favourable to increased positive engagement in the context studied. These results are similar to Mariani et al. (2016), but they contradict Parganas et al. (2015). These findings are also consistent with the stages of the consumer decision journey (e.g., Sumi & Kabir, 2010; Hudson & Thal, 2013). According to research, social media has a great impact on purchasing decisions in tourism because it intervenes during the most relevant moments of the purchase decision process: the evaluation of alternatives; at this stage, consumers are evaluating the alternatives of a purchase (Hudson & Thal, 2013).

These results support that conclusion. Positive engagement is potentially higher before summer because consumers more actively seek information about tourist destinations from January to June (i.e., consumers evaluate the alternatives to deciding on tourism purchases during the period before the high season). It is worth mentioning that, according to the results, the audience behaves similarly to the Consuming Enthusiast and Apathetic Creator groups defined by Amaro et al. (2016). As can be seen, the audience is very active before the higher season, but is less so during the summer (likely travelling time), and is almost absent after summer.

Contrary to results in positive engagement, negative engagement is higher during the summer. These results are similar to those revealed by Lee et al. (2018), who found that negative commitment is higher during the holiday period. The differences between positive and negative engagement support the idea that these variables behave differently (e.g., Hollebeek & Chen, 2014). For this reason, we suggest that they should be analysed separately in research.

Table 4

Regression analyses

	Regression 1				Regression 2				Regression 3				Regression 4			
	Positive Engagement				**Positive Popularity**				**Positive Commitment**				**Positive Adjusted Virality**			
	β	**e**	**F**	**I**	**β**	**e**	**F**	**I**	**β**	**e**	**F**	**I**	**β**	**e**	**F**	**I**
Time frame/ H1, H2: They were accepted																
Posting Time	.254	.052	**23.773****	**.608**[1]	.219	.051	**18.751****	.411	.210	.061	**12.004****	.403	.195	.043	**20.855****	**.480**[1]
Posting Day	.124	.049	**6.402****	.137	.105	.048	**4.826****	.097	.137	.047	**8.408****	.164	.166	.051	**10.558****	.355
Seasonality/ H3: It was accepted																
Seasonality	.158	.079	**3,986***	.256	.245	.074	**10.89****	**.493**[1]	.216	.083	**6.768****	**.432**[1]	.117	.062	**3.512***	.164
R	.340				.354				.343				.282			
R2	.115				.125				.117				.079			
R2 ajusted	.081				.091				.083				.043			
Predicction error	.885				.875				.883				.921			
F (ANOVA)	**3,335****				**3,671****				**3,405****				**2,208****			

	Regression 5				Regression 6				Regression 7				Regression 8			
	Negative Engagement				**Negative Popularity**				**Negative Commitment**				**Negative Adjusted Virality**			
	β	**e**	**F**	**I**	**β**	**e**	**F**	**I**	**β**	**e**	**F**	**I**	**β**	**e**	**F**	**I**
Time frame/ H1, H2: They were accepted																
Posting Time	.269	.062	**18.766****	**.668**[1]	.291	.097	**9.031****	**.805**[1]	.320	.087	**13.501****	**.873**[1]	.290	.045	**24.064****	**.730**[1]
Posting Day	.130	.035	**13.786****	.152	.069	.045	**2.332****	.057	--	--	--	--	.099	.054	**7.171****	.087
Seasonality/ H3: It was accepted																
Seasonality	.146	.064	**5.143****	.181	.126	.046	**7.552****	.138	.127	.053	**5,701****	.127	.117	.160	**6.232****	.183
R	.316				.325				.341				.324			
R2	.100				.106				.116				.105			
R2 ajusted	.065				.071				.090				.070			
Predicction error	.900				.894				.884				.895			
F (ANOVA)	**2,840****				**3,023****				**4.521****				**3,001****			

** p-value<0,01; *p-value<0.05;
For Positive Engagement and its dimensions, liberty grades are 24/614 at the Anova models, and 16, 6, and 2 at the coefficient results.
For Negative Engagement and Negative Popularity, liberty grades are 24/614 at the Anova models, and 16, 6, and 2 at the coefficient results.
For Negative Commitment, liberty grades are 18/620 at the Anova models, and 16 and 2 at the coefficient results.
β = Beta coefficients
e = Estimation Typical error
F = F-statistic value
I = Relative Importance (Pratt's measures)
-- = In order to improve fit models, these variables were extracted during the *Stepwise* technique.
1= Indicate which is the most importance predictor in the model.

Table 5

Hypothesis tests

			Sub- hypotheses							
			Positive Engagement				**Negative Engagement**			
Predictors		**Specific hypothesis**	**Positive engagement**	**Positive popularity**	**Positive commitment**	**Positive Virality**	**Negative Engagement**	**Negative popularity**	**Negative commitment**	**Negative Virality**
Posting time	H1.	Accepted	1a) Rejected	1b) Rejected	1c) Accepted	1d) Accepted	2a) Accepted	2b) Accepted	2c) Rejected	2d) Rejected
Posting day	H2.	Accepted	1a) Accepted	1b) Rejected	1c) Accepted	1d) Accepted	2a) Rejected	2b) Accepted	2c) Rejected	2d) Rejected
Seasonality	H3.	Accepted	1a) Rejected	1b) Rejected	1c) Rejected	1d) Rejected	2a) Rejected	2b) Rejected	2c) Rejected	2d) Rejected

5. Conclusions, implications, limitations and future lines of research

The aim of this research was to study the influence of time frame and seasonality on positive/negative engagement in a DMO in Spain. It was expected that the time frame and seasonality could affect positive/negative engagement and its dimensions. According to the data analysed, the general hypothesis was confirmed, as well as the three specific hypotheses. Nevertheless, many sub-hypotheses were rejected. The main findings of the study are summarised in this section. Consequently, the contribution of the work to the marketing field, the limitations of the study and future lines of research are outlined.

Firstly, posting time is the most potent predictor of positive/negative engagement in the study. It was found that posting at 8 am, 10 am, 2 pm and 5 pm increases positive engagement. Therefore, we recommend DMO managers consider posting time in their marketing strategies. Secondly, we have concluded that posting on Thursdays and Saturdays increases positive engagement. Although the posting day is less important than the posting time, it should also be considered in designing marketing strategies. Thirdly, it could be affirmed that posting before the high tourism season increases positive engagement. According to the data analysed, posting from January to June is very relevant to positive engagement. This conclusion supports the idea that social media influences consumers' purchase decision journeys.

We think that tourists are more active on DMOs' Facebook pages before the high season because they are evaluating tourism destinations and deciding about their next tourism purchase. By way of an explanation, they may be seeking information about tourism destinations for holidays (summer). These results suggest that social networks are an appropriate destination marketing tool that must be effectively managed by DMOs to create a competitive advantage for their destinations (Pike & Page, 2014).

According to Ksiazek, Peer and Lessard (2014), while it is one thing to simply read or see a post, deciding to react, to share or to comment is a sign that an individual is more involved, conscious and attentive; evidently, this individual shows more engagement. In general, the reactions of customers in the social networks of a brand can be considered as manifestations of engagement (Ashley & Tuten, 2015). This research has measured those indicators of engagement and found that, in certain contexts, it behaves differently if its valence is positive or negative. For example, the empirical analysis has shown contradictions in the relationship between seasonality and positive or negative engagement. Contrary to positive engagement, negative engagement is higher during the high season. These results provide empirical support for preview researchers who propose that it is not just positive engagement that should be studied (e.g., Hollebeek & Chen, 2014; Dolan et al., 2016a). In this regard, these findings have contributed to deepening the notion of engagement. Therefore, marketing managers should monitor not only positive engagement but also negative engagement.

The difference between positive and negative engagement during summer could be explained by the possible differences between tourists' expectations and actual experiences. Some tourists could have been disappointed with the destination's provided experience. However, to obtain a comprehensive answer, it would be necessary to carry out new studies.

These findings are valid and can be replicated in other contexts. The data from this research have been carefully processed and analysed. Alterations and unnecessary errors that could generate biases were avoided; this is important for the scientific field and professional practice. The data analysed have facilitated a better understanding of positive/negative engagement behaviour in a DMO context. The results have implications for DMOs and NTOs; taking them into account would improve relationships with tourists. They also provide valuable decision-making input for Spanish tourism management (e.g., Godnoy & Redek, 2016) and can contribute to the development of a methodology for the smart harvesting of big data (e.g., Dolnicar & Ring, 2014).

However, there are some limitations to the study. First, the models studied have shown low percentages of explained variance. This could be explained by the fact that engagement is a multivariable phenomenon, meaning that engagement could be explained by other variables, in addition to those identified in this research. For example, it is possible that variables related to tourists' characteristics and individual differences influence positive/negative engagement (e.g., Strekalova, 2016), as well as post characteristics and content (e.g., Villamediana-Pedrosa et al., 2018).

Second, because this was an ex-post-facto research study with a non-probabilistic sample, in addition to being a content analysis study, the obtained findings should not be generalised to populations with different characteristics from the one studied. The presented results should not be taken as conclusive data, but are a new step in the understanding of the complex relationships between time frame, seasonality and engagement. Consequently, more studies are required to confirm the conclusions of the current study. Additionally, longitudinal investigations are suggested, during which the variations of positive/negative engagement over time could be analysed, as well as the influence of change in Facebook's algorithm. In the future, other methodologies to measure engagement in real-life contexts should also be created. For example, experimental studies can be carried out. On the other hand, future research could explore whether there are different segments among the DMO's Spanish audience.

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