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Variables of Twitter's brand activity that influence audience spreading behavior of branded content

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Abstract

This paper investigates spreading behavior of branded content, within an online brand community. A total of 41.392 pieces of content were gathered to analyze the activity of 45 Twitter brands, in the Spanish food industry, during one-year period. The study uses an Exploratory Factor Analysis (EFA) to reveal the structure of that spreading behavior, addressing two key constructs: propagation and sharing. In addition, multiple regression analysis is conducted to identity the influence of the independent variables controlled by the company, which predict that spreading action on the proposed structural model. Findings indicate the significant effect of variables such as: mentions made by the brand, posting time or volume of tweets, in predicting audience spreading behavior. Controversially, results suggest that brand use of the retweet function generates a negative influence on audience response. The research also innovates exploring the impact of sentiment expressions used by the brand on audience spreading behavior.

Keywords: Spanish economy; social media; Twitter; brand audience; online community.

JEL codes: M21, M15, M31.

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探讨在Twitter中品牌活动的变量如何影响其资讯在拥护者之间的传播行为

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文章摘要

本专题研究于在线群体中品牌资讯的传播行为。我们在一年内收集了一共41，392项资讯内容，来分析于西班牙食品产业45个品牌在Twitter的活动。研究利用探索性因子分析法（EFA）来显示在品牌传播行为中的潜在因素结构，发现有两个构成部分：传送与分享。此外，我们更进行了多元回归分析，确认企业所操控的自变量的影响，这些自变量可以在所提出的结构模型里预测其资讯传播。研究结果指出以上提及被用到的变量：品牌、发布资讯的时间及tweets的量，对预测在拥护者中的传播行为都有着重要的影响。同时，研究结果指出，拥护者对品牌使用retweet功能有着负面的回响。为了进一步研究本专题，我们更分析了品牌所使用的情感表达对上述传播行为的影响。

关键词: 西班牙产业、社交媒体、Twitter、品牌拥护者、在线群体 。

JEL 分类号: M21、M15、M31。

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1. Introduction

The Internet and the vast set of Information and Communication Technologies (ICTs), developed through the years, have changed the way brands communicate with their audiences and potential customers. The availability, openness, and reach of the Internet to gather information and spread costumer's opinion are key in the success of this phenomena (Hennig-Thurau *et al.*, 2004). Consumers, use search engines, forums, blogs, and social networking platforms to search and spread goods or services information. Traditional Word of Mouth (WOM) communication, reach a new dimension with the advent of all these digital systems, defining a new formula of WOM, known as Electronic Word of Mouth (e-WOM) (Weinberg and Davis, 2005). The interactive nature of these platforms in spreading information, provides even a more remarkable role to the concept of e-WOM (Jansen *et al.*, 2009).

This digital phenomenon has brought the appearance of multiple social media sites including Facebook, Twitter, YouTube or Instagram among others. Based on the information-sharing paradigm, the social media phenomena opens a new sphere of opportunities for consumers and brands to benefit from the comments and experiences that others post in the platform (Kim *et al.*, 2014). Thus, due to the explosion of social media sites like Facebook or Twitter, many companies create online brand communities around these platforms on the Internet (Kaplan and Haenlein, 2010). These communities enable the brand to establish a bidirectional conversation with its audience. Hence, this interactive channel allows the company to gain a higher share of audiences' attention, increasing the engagement with them (Brodie *et al.*, 2013; Hanna *et al.*, 2011).

This phenomena has modified former marketing practices to create a new and influential marketing tool for companies and brands to reach their audiences (McCarthy *et al.*, 2014). Nevertheless, critical factors to accurately engage with audiences, getting the desired impact, remain widely unknown. So, the aim of this research is shedding light on the factors that mediate between brands and audiences, on their relationship within a social media platform.

Based on the analysis of an extensive dataset across a period of time in the context of Twitter's brand communities in Spanish food industry, present paper contributes to the existing literature in two ways. Firstly, the study provides a detailed description of actions and functionalities (replies, mentions, links, hashtags, pictorial items…) that influence the spreading behavior of branded content within an online brand community. Secondly, the research considers an issue generally unexplored in previous studies; the impact that sentiments expressions, used from brand side, have on its audience.

2. Theoretical Framework

Literature in the field of digital media is divided in two main lines of research: one is e-WOM; the other is customer-brand engagement on brand communities. Within e-WOM literature, researches have focused in a wide range of subjects. Park *et al.* (2009) study the positive-negative impact of e-WOM on website's reputation, Gupta *et al.* (2010) analyze the influence of e-WOM recommendations in product decision making, Gruen *et al.* (2006) explore e-WOM as form of know-how exchange among consumers, or Chevalier and Mayzlin (2006) analyze the direct impact of e-WOM on sales. The stream of customer-brand engagement is focused on engagement consequences; including: consumer empowerment (Cova and Pace, 2006), satisfaction (Bowden, 2009), commitment and sensitive connection with the brand (Chan and Li, 2010), value creation (Schau *et al.*, 2009), brand loyalty (Hollebeek, 2011; Jahn and Kunz, 2012), or growth of trust (Habibi *et al.*, 2014) among others.

Present work, focused on the study of audience behavior in an online brand community, is grounded in Uses & Gratification (U&G) Theory. U&G Theory, defines a conceptual framework that examines how mass media is used to satisfy needs and wants of individual users with different objectives (Katz *et al.*, 1974; Katz *et al.*, 1973; Ruggiero, 2000). This stream contemplates the next five assumptions: 1) Media choice and use, is motivated and objective directed; 2) User takes the first step in selecting and using the media to gratify needs; 3) Social factors intercede on audience's communication behavior; 4) Media strive with other options of mass communication in terms of selection, use, and needs gratification; 5) Audience is considered influential in its relationship with the media (Rubin, 1994).

Researchers have used this approach to describe how and why audiences engage with a wide spectrum of mass media forms through the years: Herzog (1941) with the gratification of quiz programs on the radio, Berelson (1949) in reading motivations on newspapers, or Rubin (1983) in the viewing patterns on television. More recently, other authors have found U&G Theory to be a suitable frame to develop their works on the Internet media in general (Hollenbaugh, 2010; Ko *et al.*, 2005; Wu *et al.*, 2010), and in online brand communities in particular. So, U&G approach is used to explore social networking sites such as Facebook, MySpace (Raacke and Bonds-Raacke, 2008; Smock *et al.*, 2011) or Twitter (Chen, 2011; Johnson and Yang, 2009).

The potential of social media platforms to spread information reaching big audiences, as it happens with other mass media instruments (newspapers, radio or television), makes U&G approach especially appropriate for this research. In addition, the nature of the media meets the basic assumptions on the U&G Theory: Users having other possibilities chose freely the media; enter on the site with the objective of obtaining a gratification; communicate influenced by social aspects and have an empowerment position on the platform.

Additionally, in terms of mass media gratification, Cutler and Danowski (1980) conceptualize two main categories: Content gratifications and mean gratification. While in the first one, the user obtains the gratification on the intrinsic value the message has for him or her; on the second one, user gains that gratification by the mere act of participating on the communicational experience inside the media. Within the theoretical frame of the U&G approach the author draws the study on the use of Twitter as mean of gratification itself.

Finally, user's need to be satisfied through the process of using and participating in the platform, has to be delimited. In Twitter's case, different studies reveal the potential of the microblogging site in gratifying user's need to connect and share information with others, over a group of topics, no matter they are brands or other users (Chen, 2011; Jansen *et al.*, 2009; Kim *et al.*, 2014; Morales *et al.*, 2014; Rudat and Buder, 2015). In the context of an online brand community, audience need to connect with others can be satisfied thought the use of platform functionalities. Functionalities that allow the user to spread the content published by the brand among other users. In Twitter the mechanisms to do so are essentially two. The first one Retweeting, which means to forward brand-related content to other users, named, followers. The second one, the Favorite marker (Now called 'Like'.), which implies recognizing the Tweet as valued portion of content.

Thus, the study is focused on: The audience spreading behavior of branded content and the brand actions that influence that response within the Spanish food industry. Based on the preceding discussion, the following research questions are posed:

RQ1: Which are the constructs that represent audience spreading behavior of branded content within an online brand community?

RQ2: Among brand controlled variables, which are the key indicators on predicting spreading behavior of branded content within an online brand community?

3. Research Methodology

3.1. Research design and data collection

A group of Twitter brands is selected from the population of companies in the Spanish food industry. The selection of food industry is based on the results of the Industrial Companies Survey carried out by the Spanish National Statistics Institute. That survey reports, that food sector makes the greatest contribution to the total turnover of the industrial activity in Spanish economy (15.6%), in the previous year. With the objective of delimiting the universe of study; a selection of companies with turnover above 100 million euros is extracted from list of companies with CNAE 2009- Manufacture of Food Products under the National Classification of Economic Activities (National Statistics Institute, 2009). The amount of 100 million euros is fixed to extract the companies that have enough economic resources to make a strong investment on marketing and communication actions. Therefore, the ones that manage their social media presence in a professional way.

The extraction is made using Sabi Database system (Bureau van Dijk Electronic Publishing, 2016).That query results in a number of 147 companies; from these companies, 50 exhibit brand presence on Twitter. After removing the inactive profiles on the last year, the final population has a total amount of 45 active brand accounts.

In this population of 45 Twitter accounts, the researcher gathers all the content posted by the brands (Original Tweets, Genuine Replies and Retweets done), in a one-year period, from the 4th of February of 2015 till the 4th of February of 2016. The data collection for the research is performed using Twitter's service provider Twittonomy (Diginomy Pty Ltd, 2013). A total number of 41.392 pieces of brand-related content were retrieved, besides the effect caused by every single post on brand audience, in terms of Retweets or Favorites. The dataset gathered from the service provider, is exported and stored in a database for further examination in next steps of the study.

The author uses a two-steps analytical approach to address the research questions. Firstly, an exploratory factor analysis (EFA) is conducted to cluster the dependent measures (expressed by Retweets and Favorites), generating the constructs of the structural model. Secondly a multiple regression analysis is performed, to identity the influence of the independent variables (those controlled by the brand) as predictors of brand audience response.

3.2. Measures

According to previous literature (Godes and Mayzlin, 2009), variables are classified distinguishing between brand created content under company's control to arrange independent measures, and user generated communication to represent dependent measures. The study presents independent variables considering five different categories: Interactivity, vividness, sentiment, posting time, and type of action. Dependent variables are represented through Retweets and Favorites.

Draw on simple pattern matching inside the database; the author extracts in each piece of content the indicators of: links, mentions, pictorial items, hashtags, and emoticons. Afterwards, due to the descriptive perspective of the study, all the metrics are added as frequencies of occurrence (De Vries, Gensler and Leeflang, 2012), to form the variables the researcher uses to arrange independent and dependent measures. Finally, indicators are standardized as z-scores (μ =0, σ =1), in order to make different coefficients easily comparable across stages in the study.

3.2.1. Independent Measures

3.2.1.1. Interactivity

The author addresses the concept of interactivity as the capacity of creating a two-way communication, between brand and audience (Goldfarb and Tucker, 2011). The measure is operationalized through the adaptation of brand post characteristics from De Vries *et al.* (2012). Brand-related content composed simply by text, do not stimulate the audience to start a bidirectional communication, on the contrary, those posts that include a link are considered as interactive, since the followers can click on it (De Vries et al., 2012; Fortin and Dholakia, 2005). Additionally, and founded in the same conceptual idea, mentions (posts referring another user by using his or her username, preceded by the '@'character) are considered also as measure of interactivity, ever since they proceed as a call to action that invite the individual to participate on the conversation. Although, the researcher could assess different levels of interactivity, the study builds this measure as a dichotomous indicator, assuming that any trait of prospective interaction on the content implies interactivity.

3.2.1.2. Vividness

Vividness measure, considers those features oriented to stimulate the sensorial dimension on the audience, covering: pictures, animations or colors (Fortin and Dholakia, 2005; Goldfarb and Tucker, 2011). Concepts of interactivity and vividness often appear partly overlapped; however they differ in their bidirectional communicational power. So, some content can show great vividness, without being interactive (Fortin and Dholakia, 2005).

To assess this measure, the author adopts the vividness operationalization from De Vries *et al.* (2012), taking pictorial items as indicators. In addition, since vividness is also addressed on the literature as any form of media enrichment that extends the standard appearance of the content (Daft and Lengel, 1986), the author introduces in this measure a characteristic feature from Twitter known as hashtag. Hashtags are keywords preceded by the sign '#'. This mechanism makes content more visible and reachable within the media (Bruns and Stieglitz, 2013). As it happens in the interactivity measure; even though vividness can contemplate different degrees of stimulus, the research takes this indicator dichotomously.

3.2.1.3. Posting Time

The study assess posting time in accordance with previous research (Moro *et al.*, 2016; Cvijikj *et al.*, 2013), defining different slots along the day. The frame of time that concentrates most of the posting activity (86.38%) is sub-divided in four space slots of three hours each, from 8:00 a.m. to 7:00 p.m. The remaining part of the activity, the one experimented during evening and night, is separated in two periods of six hours each, from 8:00 p.m. to 1:00 p.m. and from 2 a.m. to 7 a.m.

3.2.1.4. Sentiment

While much is written on consumer sentiment analysis, and its influence on eWOM; the existing literature is generally soundless regarding how can the sentiment expressions produced from the brand side affect consumer's behavior. Previous research (Berger and Milkman, 2012; Huffaker, 2010) provides evidence of content containing sentiment expressions, is more likely to obtain a response, or to be shared in an online context. Sentiment measure on the present study, focus on the effect caused by brand controlled sentiment expressions. Jansen *et al.* (2009) state, that more than a half of the Tweets expressing brand sentiment have positive valence; therefore considering that brand's intention is creating a positive atmosphere on the community; the indicator contemplates only content with positive sentiment expressions. The researcher assess this measure by two means: firstly evaluating lexicon on the collected Tweets, secondly analyzing the frequency of occurrence in emoticons.

In the first place, the author undertakes lexicon analysis with a machine-based sentiment scoring system. Through natural language processing, the system analyzes basic parts of speech that are evaluated with the corresponding sentiment weight. Lexalytics (Lexalytics Inc., 2003), with a 200 points scale (from -1.00 to +1.00) appears as a representative engine of this analysis technique (Ghiassi *et al.*, 2013). Using Lexalytics as service provider and its solution for spreadsheets, the researcher examines Tweets in the dataset, obtaining for each one of them a hit count that determines the score of the overall sentiment for the given content. After that, the author gathers frequencies from those with positive valence to form the indicators, separating positive sentiment on original tweets, from sentiment on genuine replies.

In the second place, the researcher performs the analysis of frequencies over emoticons. The use of emoticons (alphanumerical characters, e.g., XD) in Twitter to convey emotions have demonstrated to provide a huge explanatory potential, especially in food industry (Ghiassi *et al.*, 2013; Vidal *et al.*, 2016). The researcher builds the indicators, using emoticons as markers to identify positive sentiment expressions in the dataset, retrieving the observed frequency of usage. In addition, as the researcher did before on lexicon analysis, the author differentiates, between frequencies of emoticons in original tweets, and frequencies in genuine replies.

Vidal *et al.* (2016) observes, that in most of the cases (76.4%), food-related emotional expressions in Twitter include one unique emotional symbol. Hence, consistent with Pak and Paroubek (2010) the author assumes that the positive sentiment marker represents the sentimient of the branded content in that post as a whole. The list of emoticons retrieved from the dataset is designed according to Vidal *et al.* (2016). Since providing more exhaustive sentiment analysis is beyond the scope of the study, for data simplification purposes, the author takes the ten positive emoticons with the highest frequency of occurrence on the referenced study. By pattern matching, the author searches for emoticons on the dataset, using its representation in alphanumerical characters (e.g., XD).

3.2.1.5. Type of Action

Finally, the researcher addresses the type of action, considering the basic metrics identified in Twitter to generate content listing: original tweets sent, genuine replies sent, and retweets done (Bruns and Stieglitz, 2013). Original tweets, comprises content created by the brand which is not a direct reply to a previous user interpellation. Genuine replies cover the feedback provided by the brand, to a prior solicitude made by the user by means of the reply native function. Regarding retweets, although different protocols are used to identify retweeting activity (e.g., RT, @username, via @username), the retweet variable is operationalized through the use of the native retweet button. These retweets made by the company contemplate retweets over content previously created by the brand, and those made over other user's content.

3.2.2. Dependent Measures

To build dependent measures, the researcher uses retweet and favorite activity triggered around each piece of content posted by the brand. Retweets are widely recognized as mechanism to spread information among users on Twitter (Bruns and Stieglitz, 2013; Rudat and Buder, 2015). Besides, adapted from other studies (Oviedo-García *et al*., 2014; Cvijikj *et al*., 2013), research comprises also favorite function. Favorite marker enables the user to indicate interest on the content, providing a sign of recognition as it happens with the 'Like' functionality on Facebook or Instagram. Tweets flagged as favorites do not appear on users' wall or timeline, but they are highlighted inside the platform as a valuable piece of content, with spreading potential.

The author assess, in terms of frequencies, original tweets, besides retweets and favorites retweeted by brand audience. In addition, the study complements those indicators with brand original tweets marked as favorites by other users. Finally, the researcher takes also in consideration the number of times a single piece of branded content is retweeted. To do so, the author aggregates the number of times brand followers retweeted a given post, and the number of subsequent independent propagators that retweet that post, retransmitting the message to new audiences (Oviedo-García et al., 2014). So, the researcher extracts the top 5 of retweets and favorites most retweeted in each brand, collecting the number of times that content is propagated by successive retweets of different users.

4. Results

4.1. Research Question 1

An exploratory factor analysis (EFA) was conducted to answer the first research question. This EFA indentifies the underlying constructs on the group of studied dependent measures. EFA is substantiated as a suitable method, instead of confirmatory factor analysis (CFA), due to the scale development purposes on this study stage, and the lack of a prior conclusive model on the research context (Hurley *et al*., 1997). EFA is performed to detect underlying factors among the dependent variables, using principal components technique with varimax rotation to produce orthogonal factors (Conway and Huffcutt, 2003). An initial EFA with eigenvalues over 1 was conducted, generating 4 components. Since, previous studies show that eigenvalues greater than 1 criteria, tends to provide overmuch factors, a multiple criteria technique was adopted (Fabrigar *et al*., 1999; Gorsuch, 1997). Observation of the scree plot and loadings, suggested retaining only 2 factors explaining 68.38% of the total variance. Afterwards, EFA was relaunched to save the scores of these two components as variables, for the future regression analysis.

The ten items loaded onto factor 1, represent the aggregate number of times a single retweet or favorite post is retweeted and subsequently propagated by brand audience. This first construct, is labeled as 'Propagation' and explains 42.10% of the variance.

The four items loaded onto factor 2, indicate if the post is generating a response or not. The dependent variables on this second factor display: number of tweets and replies or retweets that are retweeted. Complementary, this second factor also retains the number of favorites. This second construct, labeled as 'Sharing' explains 26.28% of total variance. Table 1 shows the empirical results.

Table 1. Components Loadings

Construct and reliability		Factor 1	Factor 2
Factor 1: Propagation	Nº of Times 4º Top most Retweeted Tweet is Retweeted	.873	
Cronbach α = .914	Nº of Times 5º Top most Favorited Tweet is Retweeted	.820	
AVE = .552	Nº of Times 3º Top most Favorited Tweet is Retweeted	.815	
	Nº of Times 2º Top most Retweeted Tweet is Retweeted	.809	
	Nº of Times 5º Top most Retweeted Tweet is Retweeted	.808	
	Nº of Times 2º Top most Favorited Tweet is Retweeted	.726	
	Nº of Times 4º Top most Favorited Tweet is Retweeted	.720	
	Nº of Times 1º Top most Retweeted Tweet is Retweeted	.617	
	Nº of Times 1º Top most Favorited Tweet is Retweeted	.589	
	Nº of Times 3º Top most Retweeted Tweet is Retweeted	.584	
Factor 2: Sharing	Nº of Favorited Tweets Retweeted by the Audience		.983
Cronbach α = .953	Nº of Original Tweets Retweeted by the Audience		.972
AVE = .815	Nº of Original Tweets marked as Favorite by the Audience		.966
	Nº of Retweeted Tweets Retweeted by the Audience		.644

Source: Self Elaboration.

The EFA accounted a Kaiser-Meyer-Olkin (KMO) statistic of .704, suggesting the construct underlies the dataset (Kaiser, 1970). Bartlett's test of sphericity of: χ^2 (df: 91) = 1004.493 (sig =.000), indicated the presence of important correlations amongst the variables of each factor (Bartlett, 1950). Additionally, no sign of cross-loadings among items was observed in the components. To evaluate the internal consistency of the factors, the study considered Cronbach alphas coefficients for the two components. The Cronbach alpha values obtained for these constructs were over .70 in both cases (Propagation: .914 – Sharing: .953). This supports measures' reliability, indicating that the scales were suitable to develop further analyses (Hair *et al.*, 2010). Moreover, the average variance extracted (AVE) above .50 (Propagation: .552 – Sharing: .815) underlines the validity of the constructs (Bagozzi and Yi, 1988).

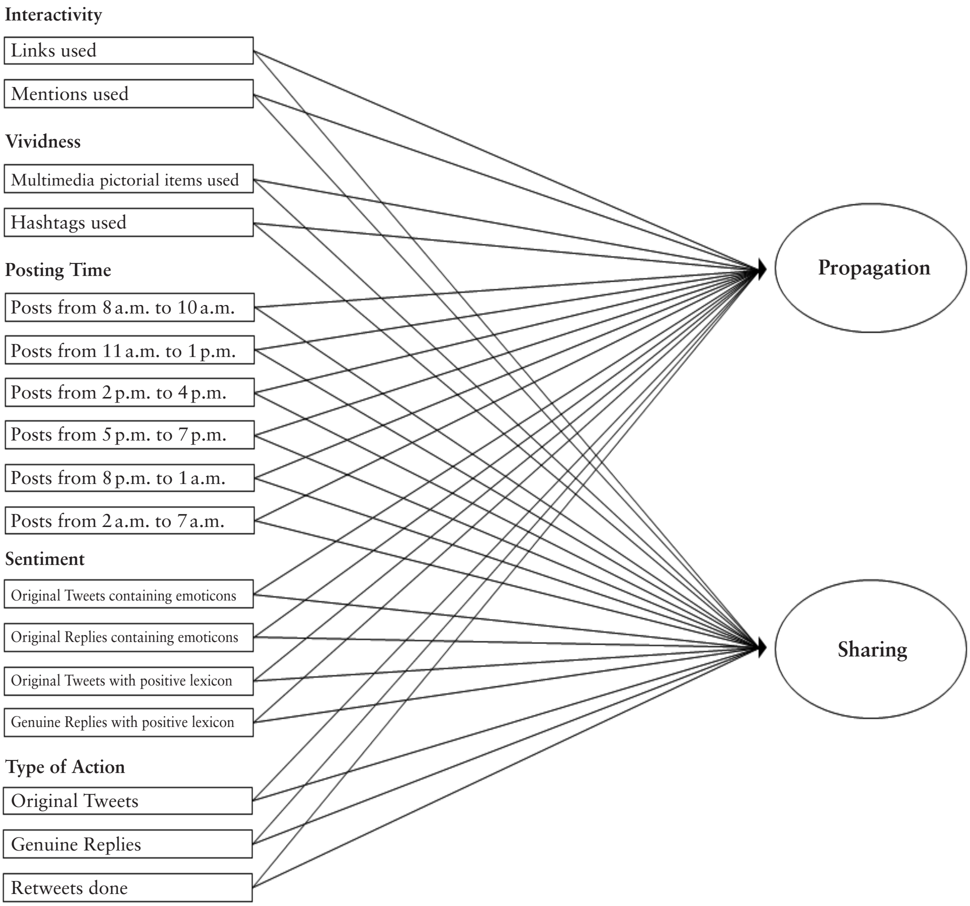
4.2. Research Question 2

Path analysis approach was used to evaluate the impact and contribution of the independent variables on the variability of dependent scales on the model. Multiple linear regressions were applied to describe correlations among the set of variables defined in the research model (Olobatuyi, 2006). Even though, models using item parcels as indicators of the constructs, can increase the percentage of the variance explained (Coffman and MacCallum, 2005; Rodriguez Ayan *et al.*, 2010) the study conserves the independent variables as individual disaggregated indicators during the analysis. The objective of keeping the independent variables as individual indicators was maintaining the explanatory power of these items on the structural model. Structural model presented on Fig. 1.

Two separate multiple linear regression analyses were conducted to answer the second research question. Scores of propagation and sharing factors of the EFA served as dependent variables, for the two regressions. The 17 items arranged in the interactivity, vividness, posting time, sentiment and type of action measurement categories, entered on the regression as predictors to assess their contribution on the overall model (Fig. 1). Initially, with the objective of revealing potential missing cases on the analysis, two regressions were performed with case wise diagnostic to detect outliers outside the range of 3 standard deviations (Tabachnick and Fidell, 2001). This preliminary process, identified two clear outliers in the population (cases 8 and 31). These outliers were removed from the dataset following the related literature (Weston and Gore, 2006).

On the multiple linear regression conducted for the propagation scale, the item nº of original tweets containing text emoticons ($\beta = .501$, p-value $< .001$) entered on the first step of the process. The variable nº of genuine replies containing text emoticons ($\beta = .281$, p-value $< .05$) was added on the second one. The model for the propagation factor results significant as a whole ($F = 11.614$, p-value $< .001$) explaining reasonably well the variance of the dependent variable ($R = .606$, $R^2 = .367$). Thus, the finding of these two predictors on the model indicates that sentiment on brand produced content has an impact on propagation construct. See Table 2.

Figure 1. Structural model



Source: Self Elaboration.

Identical multiple regression procedure was performed for the sharing construct. The analysis for this scale yields six variables in six subsequent stages. The item tweets posted from 2:00 p.m. to 4:00 p.m. ($\beta = .411$, p-value $< .01$) entered in the first step of the process. Mentions made by the brand item ($\beta = .520$, p-value $< .001$) was added on a second stage. Original tweets created by the brand ($\beta = .214$, p-value $< .05$) and retweets made by the brand ($\beta = -.137$, p-value $< .05$) entered as predictors on the steps third and fourth. The complexity of models 5 and 6, influence in a way that not all the independent variables added on the equation reach the necessary level of significance to explain the variability on the construct. Therefore, in order to improve the final structural model, stages 5 and 6 were rejected. So, the model is simplified, maintaining those indicators that provide the highest experimental and theoretical support in explaining the studied scale. See Table 2.

Consequently, the regression analysis on the sharing scale produces an overall significant equation (F = 142.583, *p*-value < .001) with four predictors. This four variables model explains 94% of the variance in the dependent measure (R = .968, R^2 = .938). Predictors from posting time, interactivity and type of action categories loaded on the model, indicate that these items have an effect on the sharing behavior. On the contrary, no influence was found from the independent variables arranged within the vividness category.

Table 2. Regression coefficients over analyzed constructs

	Propagation			**Sharing**		
Categories / Predictors	Coefficient β	Standard Error	*t*-value	Coefficient β	Standard Error	*t*-value
Interactivity						
Links used	-.164	.125	-1.31	.012	.075	.160
Mentions used	-.118	.174	-.677	.520***	.065	7.94
Vividness						
Multimedia pictorial items used	-.038	.138	-.275	.085	.051	1.66
Hashtags used	-.035	.128	-.273	-.004	.058	-.068
Posting Time						
Posts from 8 a.m. to 10 a.m.	-.264	.154	-1.71	.246	.102	2.40
Posts from 11 a.m. to 1 p.m.	-.224	.150	-1,49	-.073	.088	-.83
Posts from 2 p.m. to 4 p.m.	-.010	.131	-.076	.411**	.117	3.48
Posts from 5 p.m. to 7 p.m.	-.087	.130	-.666	.288	.104	2.77
Posts from 8 p.m. to 1 a.m.	.061	.132	.460	.018	.070	.253
Posts from 2 a.m. to 7 a.m.	.058	.128	.457	-.023	.041	-.566
Sentiment						
Original Tweets containing emoticons	.501***	.126	3.95	-.002	.037	-.054
Replies containing emoticons	.281*	.127	2.21	-.011	.068	-.160
Original Tweets with positive lexicon	-.198	.132	-1.48	-.010	.121	-.082
Replies with positive lexicon	-.402	.314	-1.27	.069	.091	.753
Type of Action						
Original Tweets	-.132	.128	-1.02	.214*	.079	2.68
Genuine Replies	-.202	.227	-.888	.203	.114	1.78
Retweets done	.013	.130	.100	-.137*	.056	-2.44
R	.606			.968		
R^2	.367			.938		

**p*-value < .05 ***p*-value < .01 ****p*-value < .0001. *Source:* Self Elaboration.

To assess the validity of the linear regressions; normality test over residuals and collinearity diagnosis were conducted. Shapiro-Wilk test was calculated (Propagation: .086 – Sharing: .149) to test that the residual values were normally distributed with *p*-values over .05 (Razali and Wah, 2011). The observation of tolerance and variance inflation factors on the coefficients on the model suggests the required non collinearity on the regression (Bryman and Cramer, 1994).

5. Conclusions

Inducted on U&G Theory, paper's main objective is to throw light on the actions that influence brand audience spreading behavior, in the context of an online brand community within the Spanish food industry. The study, contributes to previous literature, offering a view of the concrete actions developed for a Twitter brand, which trigger the spreading behavior of branded content. Among these actions, present paper covers a topic which is poorly explored in previous research: the influence of sentiment expressions used by the brand.

The findings, suggest that, mentions, posting time, use of emoticons in original tweets and replies, brand produced tweets, and retweets are key indicators on predicting the analyzed spreading behavior.

To begin with, the research indicates that amongst interactivity features, mentions have strong impact on sharing actions. Previous studies (Boyd *et al.*, 2010; Smith *et al.*, 2012), indicate that user's ego determines its response within an online community. Consistent with this, ever since a mention is a direct call, in which the brand provides the individual a sing of credit that can reinforce user's ego, mentions made by the brand are considered a significant predictor of brand audience behavior. The recognition conferred by the brand to the mentioned user, serves as incentive to trigger user's response in form of retweet or favorite, to display that acknowledgement in front of its followers.

On the contrary, although links are clearly identified as pattern of interactivity; its use is not significantly related to either sharing or propagation constructs. This, might be explained by the fact that link functionality in the analyzed dataset, is overexploited in comparison with other features. While only 28.88% of the original tweets examined on the study contain a mention, 85.06% of them include a link. So links can be perceived by brand audience as a non-distinctive element on the content; failing on their purpose of capturing audience's attention, to stimulate interactions.

In accordance with previous research from Cvijikj *et al.* (2013), results show that posting time is a significant predictor within an online brand community. Specifically, the study shows that branded content posted from 2 pm to 4 pm has a positive influence on sharing construct. This is consistent with the findings of Cvijikj *et al.* (2013), who suggest that publishing branded content out of peak hours, improves sharing activity. Further exploration of the dataset, reveals that the time slot from 11:00 a.m. to 1:00 p.m. concentrates most of the posting activity (33.28%); so content posted out of that peak timeframe enhance the share ability of the analyzed content. Additionally, the nature of brands and content in food industry, and the lunch time from 2:00 p.m. set up in the territory where the study is geographically located also provide support for the findings.

Regarding the sentiment category, the study reports that use of emoticons is significantly related to spreading behavior of branded content. The use of positive text emoticons, in original tweets and genuine replies, has a direct influence on the propagation scale of the model. In contrast, the use of positive lexicon in branded content is not significantly related with audience spreading behavior. While emoticons reflect in a clear and synthesized form company's aim to encourage user's participation; lexicon, probably conditioned by Twitter's 140 characters limitation, fall through in the same objective. These findings support the theorizing of Dodoo and Wu (2015) who present the use of emotional content and emoticons in particular, as a suitable way to engage with food industry audiences in Twitter. In addition, text emoticons (unlike other pictographical characters such as emoji's) can be displayed by any smartphone or tablet increasing probability of these symbols to be seeing by any audience.

The findings, provide also evidence that the type of action developed by the brand has a moderate effect on its audience response. The volume of original tweets produced by the brand is positive related with the sharing construct. This result corroborates the findings of Chen (2011), who indicates that posting frequency and total tweets serve as motivator for users to connect, and interact with others on Twitter. Moreover, the higher the posting frequency, the longer the brand-related content is displayed on followers' time lime, boosting the likelihood of that content to be shared.

While the amount of original tweets has a positive impact on the sharing scale; conversely retweeting activity is negatively related to the same construct. This might be explained by a number of reasons. Firstly, could be an excess of posts (Sashittal *et al.*, 2015) or what is even worst, an overload of non-valuable posts. Secondly, considering the source of the retweet, the researcher can differentiate between own branded content and third party content. In case the company retweets its own content that can be perceived as an act of narcissism. On the other hand when the brand retweets too much others' content, it transmits weakness or lack of originality. In both cases connotations are negative. In conclusion, although retweets can be initially viewed as a system to provide acknowledgement to the audience, encouraging them to participate in the platform; it is a sensitive variable that deserves great attention.

To conclude, concerning the variables pictorial items and hashtags, considered within vividness category, none of them presents significant correlations with the constructs of the model. The empirical approach of the study, focus on usage of pictorial items, but currently Twitter's timeline of any user appears full of illustrations, no matter the accounts the user follows. Therefore, the author can infer that the crucial aspect on this issue is not the mere fact of using the feature itself, but the accuracy of the pictorial element in terms of quality (e.g., contrast, saturation, resolution, dimensions…). That quality can be also affected by the dashboard used to publish the content. Further examination of the dataset shows that only 24.32% of all the original tweets analyzed were posted using Twitter Web Client, while rest of them were published using different social media dashboards (e.g., Hootsuite, Buffer, Spredfast, Radian6, Sprout Social…). Twitters native platform guarantee the brand a set of functionalities and quality standards that can vary depending on the social media dashboard used. For instance, while Twitter's Web Client allows the user to post up to 4 images on the same Tweet, some social media dashboards have limitations in this sense. All these peculiarities are lastly reflected in the way Tweet is displayed on brand's timeline conditioning the impact of the content in its propagation and share ability. Finally, with regard to the second item considered in the vividness measure, hashtags; its use enhance the content with new functionalities; increasing Tweet visibility, enabling content monitoring or even facilitating users participation on brand-related conversations. Nevertheless, the findings provide evidence that hashtags do not predict audience spreading behavior.

The present study has also a number of limitations. Firstly, the research is limited to the empirical exploration of content during one-year period. Increasing the temporal range of analysis to two or three years could improve the solidness of the proposed model. Secondly, the paper considers one single industry. Since variances in the audience behavior may exist depending on the market or product category, greater insights can be gained by comparing a number of sectors.

Despite these limitations, the present research is able to contribute to the existing literature in various ways. The study, in consonance with previous research (Brodie *et al*., 2013; Chen, 2011; Johnson and Yang 2009; Hanna *et al*., 2011), confirms the importance of the interactions between company and audience in terms of brand engagement. Additionally, in line with McCarthy *et al.* (2014) the paper also ratifies the relevance of Twitter as marketing tool to share and propagate content with the brand's audience.

To finish, the study provides clarification on the key factors that affect audience gratification behavior, within an online brand community. However, since academics and marketers need an in-depth understanding on the implications of those factors over different scenarios, more research is needed to undertake with guaranties the challenges of this new communicational paradigm on the digital sphere.

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