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Political conversations on Twitter in a disruptive scenario: The role of 'party evangelists' during the 2015 Spanish General Elections (*)

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Political conversations on Twitter in a disruptive scenario: The role of 'party evangelists' during the 2015 Spanish General Elections

ABSTRACT

During election campaigns, candidates, parties, and media share their relevance on Twitter with a group of especially active users, aligned with a particular party. This paper introduces the profile of 'party evangelists', and explores the activity and effects these users had on the general political conversation during the 2015 Spanish General Election. On that occasion, the electoral expectations were uncertain for the two major parties (PP and PSOE) because of the rise of two emerging parties that were disrupting the political *status quo* (Podemos and Ciudadanos). This was an ideal situation to assess the differences between the evangelists of established and emerging parties. The paper evaluates two aspects of the political conversation based on a corpus of 8.9 million tweets: the retweeting effectiveness, and the sentiment analysis of the overall conversation. We found that one of the emerging party's evangelists dominated message dissemination to a much greater extent.

KEYWORDS:

Twitter; political communication; sentiment analysis; homophily; electoral campaigns

Social media platforms are assuming important roles in the political life of modern societies. Among the main functions of social networks during electoral campaigns is the use given by political elites and parties to Twitter to achieve wider attention. Journalists and media include Twitter in their campaign coverage, whilst the general public use these platforms to gather information and share opinions about political issues and candidates (McGregor, Mourão, & Molyneux, 2017). Among the general public, there are certain users who are especially active and who may thus play a greater role in influencing other people's opinions. Researchers have analysed opinion leadership on Twitter by studying users who are remarkably politically committed (Dang-Xuan, Stieglitz, Wladarsch, & Neuberger, 2013; Park, 2013; Vaccari, Chadwick, & O'Loughlin, 2015; Xu, Sang, Blasiola, & Park, 2014). The engagement of these active users is key to understanding the processes that structures communication on Twitter, as they follow a media network logic of communication (Klinger & Svensson, 2015). Promoting engagement on social media might be a strategic move for parties during election campaigns, especially for emerging parties in need of greater visibility.

We introduce the figure of *party evangelist*. This profile corresponds to a highly involved user in the Twitter conversation, whose activity is strongly akin to a particular party. Identifying these users and mapping their activity as a whole can help understand the complex communication process in social media where so many actors interact. This research study explores the overall political conversation on Twitter during the 2015 Spanish General Election campaign, focusing on two dimensions: the retweeting effectiveness of the most active users and the interplay between sentiments expressed during the electoral campaign by the main political actors (candidates, parties, and media), those active users and the general public. Any such analysis requires an inclusion of the network structure of communication on Twitter (Klinger & Svensson, 2015).

The 2015 Spanish General Election campaign began with notable uncertainty stemming from the appearance of two new parties (Podemos and Ciudadanos). These two parties began to challenge a *status quo* dominated by the two solidly established existing political parties, the conservative Partido Popular (PP) and the social democratic Partido Socialista Obrero Español (PSOE) (López-García & Valera-Ordaz, 2017). This disruptive scenario was especially useful in comparing the different effects of the most active Twitter users.

This paper is structured as follows. First, we give an overview of the most relevant literature on political communication on Twitter by carrying out a social network analysis and a computer-assisted sentiment analysis. Following that, we detail the methodology, data, and the research instruments used. Finally, we present and discuss the results and their implications for political campaigns and research into political communication on Twitter.

LITERATURE REVIEW

Political conversation on Twitter

The relentless integration of traditional mass media and digital media has affected political communication by bringing about a hybrid communicative model in which both these types of media continuously feed off each other (Chadwick, 2013). It is noted that in such a scenario, the main political communication actors use Twitter differently during electoral campaigns. According to McGregor et al. (2017), political elites and parties post tweets that follow their electoral strategies; journalists and media usually publish content on Twitter aligned with their narrative construction, while the general public use social media to share political opinions and disseminate information. All these actors share a dynamic communication space that evokes an interpersonal communication model, in which some individuals influence the opinion of their circle of contacts (Katz & Lazarsfeld, 1955).

The seminal study by Lazarsfeld, Berelson and Gaudet (1944) uncovered the role played by opinion leaders in influencing the voting decision of their friends and disseminating information published by the mass media. These leaders are usually better informed of public issues, and they comprise the base for the two-step flow of communication model. The diffusion of innovations theory highlight the critical role of certain people in disseminating new ideas through the interpersonal network of contacts (Rogers, 2003). These people are more able to influence other people and are characterised by their interest, knowledge and social activity (Katz & Lazarsfeld, 1955; Weimann, 1991). But the complexity of the relationships led some researchers to broaden the model from an initial two-step flow to a multi-step flow of communication, where multiple interrelationships conveyed the information in different ways (Robinson, 1976).

This theory was also applied to communication on social media, particularly on Twitter. For example, Park (201 found that Twitter users who self-reported being opinion leaders were more motivated to look for information, mobilise and express themselves publicly. Barberá and Rivero (2015) confirmed that a strong political view positively influenced users' participation in Twitter conversations. Interactions on political issues are more frequent during televised electoral debates, as Twitter becomes a simultaneous online discussion arena (Anstead & O'Loughlin, 2011; Gil de Zúñiga, Garcia-Perdomo, & McGregor, 2015). Twitter participants on these discussions show greater political engagement in discursive interactions as well as increased partisan and civic involvement (Vaccari et al., 2015). Twitter users' political attitudes and the dissemination shaped by a networked dynamism are two concepts that should not be dismissed. Recent research (Xu et al., 2014) has shown that users with higher connectivity and involvement are more successful in influencing information flow as a consequence of network dynamics.

The activity of these prominent users may enable new political actors to gather public online attention. In this regard, the 2008 Obama (Cogburn & Espinoza-Vasquez, 2011) and the 2016 Trump campaigns (Enli, 2017) are paradigmatic of the use of social media to gain public attention in an unfavourable or even adverse media scenario. However, activity on this social media does not guarantee that a new candidate will obtain a parallel ballot result (Vergeer & Hermans, 2013). Jungherr et al. (2012) showed that the Pirate Party would have won the 2010 German elections had the measure been simply the number of mentions on Twitter. What becomes evident with this example is that the intense conversation about this new party reflected new ways for citizens to mobilise themselves online.

One of the possible outcomes of networked interactions is homophily, the tendency of people to associate with other similar people (McPherson, Smith-Lovin, & Cook, 2001). In the same way that ideological affinities encourage conversations between people who are politically alike (Huckfeldt, Johson, & Sprague, 2004), internet users also tend to access content that is closely aligned with their political opinions (Pariser, 2011; Sunstein, 2017). Shared conversations on Twitter have been metaphorically described as an ‘echo chamber’, where opinions are reinforced by supportive commentaries and aligned information (Colleoni, Rozza, & Arvidsson, 2014). In fact, homophily on social networks allowed Barberá (2015) to infer Twitter users' ideological positions by analysing the political actors they follow. However, other researchers have highlighted that the internet may enable exposure to heterogeneous political opinions (Holt, 2004; Jennifer, 2010), due to the blurred boundaries between private and public spheres.

Thus, interactions on Twitter among the main political actors (candidates, parties and media) and active users conform a dynamic process of communication that follows a media network logic (Klinger & Svensson, 2015). In this context, social networks analyses facilitate the detection of structures of densely clustered users who interact mainly among themselves (Newman, 2010). In the case of Twitter, there are several types of interaction, and each one has the power to influence the conversation in different ways. Influence on Twitter is not an easy concept to assess. It can be interpreted and operationalised based on three dimensions: attention received, potential for information distribution, and reach (Jungherr, 2015). These dimensions may be assessed using quantitative data: as a number of followers or mentions (Dang-Xuan et al., 2013; Wu, Hofman, Mason, & Watts, 2011), network metrics such as centrality (D'heer & Verdegem, 2014), and quality of messages (Dubois & Gaffney, 2014). Since the focus of this paper is to evaluate the overall political conversation during an electoral campaign, we consider influential users to be those who are most effective at spreading information.

Some scholars have evaluated how information is conveyed in Twitter through big dataset analysis. Wu et al. (2011) evaluated a five-billion-tweet corpus along a 42 million user graph, and found that 0.05% of the users accounted for almost half the posted URLs. Cha et al. (2012) documented the significant role played by an extremely well-connected group of users in spreading information in a dataset of 54 million Twitter accounts. These users were categorised into three groups: 'evangelists', 'grassroots' - who made up 98% of users - and the 'media'. With their high number of followers and their frequent activity on Twitter, 'evangelists' spread the most news and their ability to reach groups of less connected users was especially noteworthy (Cha et al., 2012). Bigonha et al. (2012) showed the different effect ‘evangelists’ and ‘detractors’ had on two different topics on Twitter, based on the interactions and the polarity of the publications. These findings pointed to a power law structure network on Twitter where the dynamism as a whole was strongly dependent on a tiny fraction of users (Barabási & Réka, 1999).

Unfortunately, the identification of influential users on Twitter is rather problematic (Bigonha et al., 2012; Riquelme & González-Cantergiani, 2016). However, the behaviour of the network as a whole suggests that some users strongly connected with a particular party can play a critical role during an election campaign. Thus, we propose the concept of *party evangelist*, following Cha et al. (2012). We consider party evangelists to be highly active users whose activity on Twitter supports a particular party and who are intensely connected to other users strongly related to the same party. The impact of this small portion of users can be considerable if they can somehow reach the majority of users unaligned to any party. This concept might be a step forwards in the analysis of opinion leadership, as the network dynamic on Twitter offers new patterns of behaviour beyond the circle of friends. Ideological affinities of Twitter users have been identified through social network analyses in settings where two options prevailed (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015; Colleoni et al., 2014; Conover, Gonçalves, Flammini, & Menczer, 2012; Himelboim, McCreery, & Smith, 2013). In this sense, the introduction of the party evangelist profile seeks to more accurately describe users' behaviour in multi-party systems, where affinities to a particular party can be uncovered through activity on Twitter (Guerrero-Solé, 2018).

To assess the influence of these party evangelists, we used their number of followers and mapping of retweets (RT). These are useful metrics in analysing influence due to their additional metadata: the number of times the original tweet (OT) has been retweeted and the users involved in the interaction (retweeter and retweeted). As a consequence, RT-based measures become proxy variables in evaluating the dissemination of a message and the influence of a given user (Jungherr, 2015; Riquelme & González-Cantergiani, 2016).

The relationship between the number of RT and the network structure emerging from retweeting has been underexplored until now (Dubois & Gaffney, 2014). To bridge this gap, this study operationalises party evangelists as users who are very active in retweeting messages from a specific party, as well as from the cluster of users close to that same party. In this way, we introduce the effect of the network logic in the Twitter users' overall behaviour. On this basis, the following research questions are put forward:

RQ1: Do the emerging party evangelists retweet more actively than established party evangelists in an electoral campaign?

RQ2: Are OTs posted by emerging party evangelists more retweeted than those posted by established party evangelists?

Sentiment Analysis on Twitter

A relevant aspect in the dissemination of online messages is their emotional content. Berger and Milkman (2012) found evidence that the intensity of the sentiment expressed in article headlines posted on *The New York Times* website influenced the likelihood of that message going viral. Other studies have highlighted that the emotional intensity of opinions posted on social networks grows as interactions between users increase (Coviello et al., 2014; Zollo et al., 2015). Regarding Twitter, Ferrara and Young (2015) analysed the spread of intensity of sentiment during one week and concluded that the probability of transmitting an emotional valence when tweeting was influenced by overexposure to that valence.

The possibilities of the internet for mobilisation and deliberation have justified scholars' growing interest in the affective content of online political discourse. Worth noting from among many qualitative studies is Castells' (2009) analysis of the 2008 Obama Presidential campaign which found that the ability to express positive emotions (enthusiasm, confidence, hope) and the use of new media were key to Obama's success. Conversely, the impact of negative campaigning has controversial effects on individuals' participatory intentions and vote choice (Min, 2004).

When it comes to analysing sentiment expressions, the volume of content posted on Twitter requires a computer-assisted approach (Ceron, Curini, Iacus, & Porro, 2014; Vilares & Alonso, 2016). This type of analysis can discern among sentiment polarity (positive or negative), emotional expressions (such as joy or sadness) and intensity (Medhat, Hassan, & Korashy, 2014). Such analyses provide useful insights into the subjective information contained in great amounts of data, which in turn helps to better clarify users' online behaviour (Bravo-Marquez, Mendoza, & Poblete, 2014).

Considering the networked dynamism of Twitter and the central position of the main traditional actors (candidates, parties and media) and of 'party evangelists', it would be of great interest to explore the impact these groups have on all other users. We will refer to the latter group as 'general users'. This paper evaluates the impact of influential groups in terms of association of sentiment by way of correlation. This relationship will not provide a causality evaluation, but it will provide an image of how the variations on sentiment intensity expression will be interdependent. Thus, we propose the following question:

RQ3: How is the sentiment expressed by the general users associated with the sentiment expressed by (a) emergent and (b) established party evangelists?

Background: the 2015 Spanish General Election

The event under study is the campaign for the Spanish Parliament in 2015, which was marked by the appearance of two parties to the Spanish political stage. In the past, the ballot box in this country was traditionally dominated by the two major parties, PP and PSOE. However, in 2015, these parties had two other serious contenders: Podemos and Ciudadanos (Orriols & Cordero, 2016). On one hand, Podemos is a political movement that emerged at the Faculty of Political Science of the Complutense University of Madrid. After the 15M movement in 2011 and in line with the social protests of the so-called

Indignados (Anduiza, Cristancho, & Sabucedo, 2014; Díaz-Parra & Jover-Báez, 2016), it became a political force with the aim of winning the 2014 European Elections. It tried to channel the general discontent in Spain resulting from the economic crisis and based mainly on the fight against corruption and refinancing the national debt. In this last point we can find elements common to other parties that were witnessing similar growth in southern Europe, such as Syriza in Greece. On the other hand, Ciudadanos emerged in 2006 from the civic platform Ciutadans de Catalunya. Motivated mainly by the struggle against the Catalan nationalist conflict, the party moved from Catalonia regional politics to the rest of Spain having achieved good results in the 2014 European Elections. The party defines itself as constitutionalist, post-nationalist, liberal and progressive.

The European and Regional polls of 2014 and 2015, respectively, showed growing social support for both emerging parties. Their results predicted the end of political bipartisanship in Spain after more than 30 years (Boix & López-García, 2014). This supposed a huge shift in the way in which the domestic politics was framed in public opinion, and citizens consequently gave political issues more attention. All these circumstances, in addition to the consolidation of a hybrid media system in the political communication strategies (Chadwick, 2013), outlined a highly disruptive scenario for the December 2015 General Election. On this occasion the Spanish electorate faced an unusual situation, where four political parties would compete to attract voters with very uncertain expectations. The candidates of these parties were: for PP, Mariano Rajoy; for PSOE, Pedro Sánchez; for Podemos, Pablo Iglesias and for Ciudadanos, Albert Rivera. The expansion of the political spectrum led to a considerable increase in communicative activity (López-García & Valera-Ordaz, 2017). Thus, it seemed appropriate to focus our RQs on this electoral setting, as we saw that the two established parties, who continued to have a strong hold on the traditional media, were being challenged by two emerging parties mobilising their supporters on social media.

DATA AND METHOD

RQ1 needed to discriminate, on one hand, among different kinds of users, and, on the other, between OTs and RTs. Users were firstly classified according to five group categories: candidates, parties, media, clusters of party evangelists and general users. The criterion for the classification of users in the clusters category was their homophilic tendency when retweeting. It was assumed that users who shared clusters with a political party were evangelists for that party, given that this cluster would consistently disseminate messages posted by that party or by users closely related to it. Furthermore, we distinguished among the candidates, the parties and the party evangelists for each one of the four parties, and we made a selection of the mainstream media that was most prominent in the corpus. In total, 21 user groups were retrieved. The user classification is presented in detail below.

RQ2 was approached through a multivariate regression analysis, using the number of RTs as a dependent variable and OTs as the unit of analysis. Two models were suggested: the first included basic aspects of the tweet, while the second added belonging to the clusters of party evangelists. RQ1 and the RQ2 were evaluated by differentiating the retweet activity carried out during the electoral campaign and on the election night.

We expected different behaviour among the clusters, given their expectations during the campaign and the results on election night. PP took the most votes but did not obtain an absolute majority (123 seats); PSOE came second (90 seats), its worst result ever. New parties Podemos (69 seats) and Ciudadanos (40 seats) obtained remarkably good results.

The software SentiStrength (Thelwall, Buckley, Paltoglou, & Cai, 2010) was used for RQ3. This program was designed to analyse the intensity of sentiment in social media texts and has been used for research into political communication (Alvarez, Garcia, Moreno, & Schweitzer, 2015; Dang-Xuan et al., 2013; Guo & Vargo, 2015). The software assigns two scores to the texts: one evaluates the intensity of positive sentiments with a score ranging between 1 and 5, and the other evaluates negative sentiments with a score ranging between -1 and -5

For each group of users, the aggregated score per hour of the sentiment indices provided by SentiStrength for each tweet was calculated. Carrying out an analysis of interdependence among all the 21 user groups was considered opportune as the emotional reactions expressed in the tweets may depend on the context and the action of other users. For this reason, and given the high number of variables, a Principal Component Analysis (PCA) was performed to address RQ3. This analysis grouped the strongly correlated variables through an orthogonal transformation. The resulting components grouped the variables linearly, such that each variable stood out because of its coefficient in only one component while its coefficients in other components were more discrete. These coefficients are known as ‘load factors’. Thus, the variables that stood out because of their load factor in the same component as general users did would be the variables that most correlated with them.

Data Collection

The election took place on 20 December 2015. Two periods were chosen: first, the electoral campaign, which ranged from the first day of the campaign, 4 December, until the day before the election (19 December), when electoral silence is enforced; second, election day, which included 20 and 21 December, to closely monitor the conversation on election night.

Tweets were obtained directly from Twitter API using Python. The API allows the developer to collect data through one of two ways: retrieving tweets posted by particular users and retrieving tweets containing a specific keyword. We used the second method, as we were interested in the whole conversation. However, Twitter does not guarantee that this method collects all the tweets with the search terms selected (Felt, 2016). Consequently, the social researcher must work only with a sample of the conversation.

Three criteria for filtering tweets were established: two general terms related to the elections (#20D; 20-D); the names and Twitter handles of the four major political parties and the names and Twitter handles of the four prime ministerial candidates. The name of the political party Podemos was not included as a filter, because *podemos* means ‘we can’ in Spanish, and it is used in many other contexts. We also filtered out messages written in languages other than Spanish. These filters resulted in limiting the study's results, given that tweets in Spain's regional languages were excluded from the corpus, but was a necessary step to carry out a computer-assisted content analysis. The final corpus consisted of 8,943,134 tweets written by 915,049 different users.

User classification

The category ‘candidates’ included the four candidates, and the category ‘parties’ the four parties’ main Twitter account. Regarding the category ‘media’, the 20 most linked to websites in the Twitter corpus were listed. They corresponded to eight media outlets. Table 1 contains the eight media outlets selected and their media type.

Insert Table 1 here

Retweeting activity was predominant in the corpus: 69% of tweets were RTs. We performed a cluster analysis based on modularity optimisation (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Four main clusters emerged, each containing one of the main parties. Thus, the users grouped into the cluster of a particular party were deemed ‘party evangelists of that party’. The remaining users were classified as ‘general users’. Table 2 shows the size of the 21 user groups and the tweet volume.

Insert Table 2 here

Variables for the regression analysis

‘Number of RTs’. When retweeting an OT, the aggregate number of RTs is included in the metadata. To obtain the value of this variable, the highest RT value for each OT registered in the corpus was selected.

‘Basic features of each tweet’. Several variables were calculated for each OT. The first was time: the two time variables were: ‘time of posting’, in 24-hour format, and ‘days remaining until the election’. The latter was removed for the second period. The second was the number of followers the author had when tweet was posted. Finally, the number of hashtags was assessed, while the presence of images and URLs in the tweet were analysed as dichotomous variables.

‘Posting user’s cluster’. Each OT had four dummy variables corresponding to the four parties. When the author belonged to a party cluster, the variable corresponding to that party would be activated.

Computer-assisted sentiment analysis

Vilares et al. (2015) validated the Spanish version of SentiStrength to analyse perceptions on Twitter of the main Spanish political leaders. Their archives were a starting point to adjust to the context of the 2015 General Election. All the hashtags and emoticons found in the corpus were extracted and added to the dictionaries. Furthermore, the 3,500 most frequent words in the corpus not included in the SentiStrenght's dictionary were also incorporated. The final volume was 35,549 words, 1,075 idioms and 329 emoticons.

The software facilitated adjusting the weight associated with each term from a corpus of manually annotated tweets with positive and negative sentiment values. To carry out this process, 2,000 tweets were randomly extracted and distributed into three subsamples whose sizes were chosen following the indications provided by the software. The first one served as a pilot for the coders (300 tweets), the second was used to optimise weights (1,200 tweets) and the third was used as a test (500 tweets). Two of the authors manually coded each of the three subsamples. Any discrepancies were discussed and resolved with the third author. The results of the test gave an 81% accuracy rate with a margin of error of ±1 for positive sentiment, and 84.8% accuracy rate with a margin of error of ±1 for negative sentiment. Given that the results exceeded 80%, the dictionary weights recalculated by the SentiStrength were considered valid.

Variables for the PCA

As SentiStrength provides two separate indices for the intensity of positive and negative sentiments, there were a total of 42 variables available, two for each of the 21 user groups. The units of analysis were the hours of the period under study (N = 432). For each unit of analysis, the aggregate intensity of the positive and negative sentiment with which each group posted tweets was calculated.

RESULTS

Table 3 shows each cluster's activity in the dissemination of messages. The units of analysis were the OTs. For each of them, we identified the party evangelists who retweeted them. Table 3 distinguishes between the OTs retweeted by party evangelists, and the cumulative retweet activity by users of each cluster. Both aspects were evaluated for the two stages of the study period.

Insert Table 3 here

The regression analysis for the two stages is shown in Table 4. All coefficients were significant, with the exception of the variable 'days until the election' in model 2 of the campaign period. The only negative coefficient among all the analysed models was the one corresponding to URL: the tendency to retweet was greater if the original tweet had no link. The larger coefficients corresponded to the presence of images.

Insert Table 4 here

A PCA was applied to a total of 42 variables resulting from assessing the sentiment intensity of each group during each hour. The number of selected components followed the Kaiser (1960) criteria, by which components with an eigenvalue greater than 1 were taken into account. In this case, 12 components emerged, and they explained 85.48% of the variance. Table 5 shows the results of the PCA after applying the Varimax rotation. The highest load factors in each component have been highlighted. The variables highlighted in each component can be considered as strongly correlating with each other.

Insert Table 5 here

DISCUSSION

Data from Table 3 indicate that the most active evangelists were from Podemos, both regarding retweeted messages and the total number of retweet actions: 8.08% of the OTs posted during the campaign and 5.89% of the OTs posted on the electoral evening were retweeted by a user in this cluster. These are significant percentages. Conversely, the party evangelists who disseminated the fewest messages were from the other emerging party, Ciudadanos. However, their mean number of RTs per message posted was the highest for the campaign and almost the highest for the electoral evening, confirming these users' commitment to the dissemination of messages. Thus, a nuanced answer to

RQ1 can be given. Data show that emerging-party evangelists contributed more, as their mean number of RTs per OT is higher. Regarding the dissemination of messages, the volume of users in the cluster is quite significant. Given that there are more evangelists in the PP cluster than in the Ciudadanos' cluster, we might conclude that this difference in size may have influenced the volume of RTs.

RQ2 points to the dependence of the number of RTs regarding the user posting the OT. Table 4 shows that the tweets posted by Podemos evangelists had a huge advantage in their dissemination compared to those posted by users from other clusters. In addition, they had very similar standardised coefficients. During the campaign, the order of difference between the Podemos and the other parties evangelists' coefficients was 3 to 1, and on election evening, 6 to 1. These data show the strength of this cluster in the conversation.

The objective of RQ3 was to explore patterns of sentiment association among the actors who dominate the political conversation on Twitter, with particular attention to party evangelists. The PCA included the general users' variables in the first component. This result was not surprising given the volume of users assigned to this group. Regarding the remaining actors associated with this component, three corresponded to party evangelists (PP, PSOE and Podemos) and the fourth corresponded to a media company (A3Media). Among them, one of the Podemos clusters had the greatest load factor. It is possible that these party evangelists outlined the pattern of the majority of users' sentiment reactions, especially in its negative valence, even though this cluster included only 1% of all the users in the corpus.

It should be noted that the variables of the Ciudadanos cluster were found in a different component to the first one: both of them were associated with the clusters related to their own party. Therefore, from the perspective of sentiment, we might assume that the tweets posted by these emerging party evangelists did not really engage with the general sentiment of the conversation.

The assessment of these RQs in the context of this case study allows us to qualify the role of emerging parties on Twitter. The analyses have confirmed the central position on Twitter of the evangelists of one of the emerging parties, Podemos. This leading role arises from the cluster's retweeting activity and the strong association of their messages with the sentiments of general users. The other emerging party, Ciudadanos, actively retweets, but lags behind in other aspects. These dissimilarities can be traced back to different reasons that eventually shaped the online engagement of the party evangelists of these two emerging parties. Podemos' origin was strongly related to the social movement of 15M. The activists who most articulated the popular mobilisations in 2011 had been interconnected through the Democracia Real Ya platform (Real Democracy Now) where an increasing discontent for the current party system was conveyed via social media (Anduiza et al., 2014). One of the most demanded issues was direct democracy, as well as the vindication of a better future for young people (Robles, Castromil, Rodríguez, Cruz, & Díez, 2015). This street and online activism nurtured the creation of Podemos, the party that would demand these requirements with an integrated communication strategy. Along with the intense use of social media by its supporters, their leaders promoted an engaging presence on TV programmes, and developed a conscious appeal to emotions (Casero-Ripollés, Feenstra, & Tormey, 2016; Sampietro & Valera Ordaz, 2015). The impact of this strategy grabbed the attention of the electorate, despite its recent creation. The other main alternative to the established parties, Ciudadanos, focused on a more moderate strategy. In fact, the voter profile of both parties in 2015 was very different (Orriols & Cordero, 2016). Whilst Podemos was born as a participatory party and stimulates internal debate, Ciudadanos seeks to reform democratic procedures without calling for a highly intense citizen participation (Lavezzolo & Ramiro, 2019). The different discourses and supporter profiles of these emerging parties might explain the different impact of their party evangelists in Twitter on the general users group.

The dynamisms underlying the resulting components from the PCA point to the important role played by party evangelists. Table 3 highlights the relevance of the dissemination of messages from the Podemos, PP and PSOE clusters, and is further confirmed by Table 5, as these clusters are present in the same component as general users are. Candidates, parties and party evangelists not included in the first component occupy components with an ideological alignment. The media are also distributed into four components in which there are no-party evangelists. An objective text style might have contributed to positioning the media into an orthogonal component with regard to non-aligned users. The only exception is A3Media, whose negative sentiment variable was included in the first component and the positive sentiment variable was associated with 'Mariano Rajoy' and the PP political party in the same component.

A3Media's peculiar position could be largely explained by the prominence that the media had during the campaign through this communication group, specifically the political talk shows televised on La Sexta and the four-party debate broadcast on the TV channel Antena 3. This analysis shows that its influence was also reflected in the digital sphere, at least in the sentimental aspect of the Twitter conversation as a whole. This result might support the hybridisation of media as proposed by Chadwick (2013), where different logics act in an interrelated manner.

This research study has some limitations that condition the reach of our discussion. First, the identification of party evangelists suggested here is based on their retweeting activity. This characterisation ignores other evangelist features emerging from the original content they posted. However, such a content analysis would imply using more complex techniques based on natural language processing. Studying the clusters emerging from retweeting activity has turned out to be more feasible and has allowed us to evaluate a specific feature of active party supporters, message dissemination. Second, the association between sentiment and the overall conversation has been carried out by a PCA. The effects of sentiments of the political conversations, even more so when it comes to 'hot topics', require a refined analysis to trace the multiple conversation threads. Similarly, the sentiment analysis was restricted to text content, and this excludes images. Finally, the sample of tweets for this study is inevitably limited. The corpus was extracted by filtering terms associated with candidates and parties, but these criteria ignore tweets in the political conversation about other issues. Future research would benefit from removing these limitations.

CONCLUSION

The networked dynamism of Twitter structures the dissemination of messages similarly to interpersonal communication, where attention is paid to users who are especially active in disseminating messages to their contacts. This profile is of special interest for political communication. These users have been labelled as 'party evangelists', as they become an involved player in political conversations. This study was limited to just one aspect of their endeavour, retweeting. This grassroots support can be of great relevance for any party, and especially for new parties that might not yet have attracted mass media attention. The present study focused on the disruptive scenario of the 2015 Spanish General Election. This campaign was very suitable to this study as there were two new emerging parties challenging the traditional bipartisanship and the ballot outcome was presented as being very uncertain from the beginning. Another important aspect of the network logic described by Klinger and Svensson (2015) is the association between message dissemination and sentiment expressed. This study analysed the interdependence of the intensity of sentiments conveyed by the main actors in the political conversation on Twitter: the candidates, the parties, media and party evangelists. PCA unveiled which of the tweets written by these main political actors were more associated with the general group of users.

The analysis has shown the important role that the most committed users play in Twitter's political conversation. One relevant finding that may be drawn from this study is that attracting as many active users as possible is very beneficial for emerging parties. As a first implication, the research study has allowed us to delve into key aspects of the multi-step communication model applied to Twitter, and more specifically the dissemination of messages by active users strongly involved with a party, as well as the influence the sentiment expressed has on the overall conversation.

Another relevant implication of this research study is outlining the importance party evangelists play for new parties' electoral strategy. This study proved to be very useful in this regard, as we tested the effects of two different approaches to this communication arena. One of the new parties, Podemos, benefited from a very active cluster of users, which impacted the dissemination of messages and the sentiment intensity of the conversation, while the evangelists of the other new party, Ciudadanos, had a weaker incidence. This is likely a sign of a strong tendency to homophily among these users. In any case, this difference shows the benefits of fostering evangelists' activity and properly aligning with the network logic of this communication space.

This research study has sought to move forward the understanding of the dynamics of political discussions on Twitter, focusing on features of network structure and sentiment expression. As digital media are in continuous transformation, this small step might help respond to the challenges Twitter poses for political communication researchers.

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Media	Type of media	Number of references to the media website in the corpus
eldiario.es	Digital	143,423
Público	Digital	49,757
A3Media (*)	TV	47,176
El Mundo	Newspaper	45,289
InfoLibre	Digital	36,779
El País	Newspaper	36,636
El Español	Digital	29,589
Cadena SER	Radio	28,662

(*) It includes *Antena 3* and *La Sexta TV*, as the schedules of both channels are included on the same website.

Table 1. Media included in the Media group.

Group Category	User groups	Number of Twitter users	Number of tweets in the corpus
Candidates	Mariano Rajoy (PP)	1	338
	Pedro Sánchez (PSOE)	1	413
	Pablo Iglesias (Podemos)	1	38
	Albert Rivera (Ciudadanos)	1	322
Parties	PP	1	644
	PSOE	1	1,29
	Podemos	1	1,85
	Ciudadanos	1	1,658
Media	eldiario.es	1	577
	Publico	1	889
	A3Media	6	1,632
	El Mundo	4	769
	InfoLibre	1	405
	El País	3	923
	El Español	2	1,059
	Cadena SER	4	381
Clusters	PP cluster	5,458	757,911
	PSOE cluster	4,500	715,911
	Podemos cluster	11,392	1,711,619
	Ciudadanos cluster	4,161	606,373
Non-aligned users	General users	889,508	5,138,990
Total		915,049	8,943,134

Table 2. Number of Twitter users and tweets for each group.

	Original Tweets that have been retweeted by the users of each cluster		Retweets generated by the users of each cluster (*)			
	Total	%	Max	Total	Mean	St. Dev.
Campaign						
PP	95,588	4.22	960	468,015	4.90	16.06
PSOE	91,450	4.04	666	479,459	5.24	14.02
Podemos	182,862	8.08	1,484	1,090,426	5.96	18.08
Ciudadanos	66,420	2.94	1,472	442,829	6.67	18.98
N	2,262,913					
Election Day						
PP	11,093	2.38	483	34,670	3.13	9.62
PSOE	7,532	1.62	218	22,679	3.01	7.54
Podemos	27,451	5.89	446	135,532	4.94	14.11
Ciudadanos	6,072	1.30	311	29,823	4.91	16.15
N	466,358					

Notes: The unit of analysis is the original tweet.
(*) Calculations have been made based on the total number of original tweets retweeted by cluster users.

Table 3. Retweet activity for each cluster of users.

	Campaign		Day of Election	
	Model 1	Model 2	Model 1	Model 2
Basic aspects				
Time of publication	0.007**	0.006**	0.010**	0.010**
Days until the election	0.002**	0.001	-	-
Number of followers	0.106**	0.107**	0.096**	0.096**
Number of hashtags	0.014**	0.012**	0.004**	0.004**
Presence of images	0.065**	0.062**	0.054**	0.052**
Presence of a URL	-0.017**	-0.016**	-0.021**	-0.021**
Posting user's cluster				
PP		0.010**		0.008**
PSOE		0.011**		0.003*
Podemos		0.038**		0.048**
Ciudadanos		0.012**		0.005**
N	2,262,913	2,262,913	466,358	466,358
R^2	0.017	0.019	0.013	0.016
F	6,643.22**	4,350.73**	1,268.78**	828.75**

Notes: Multicollinearity between independent variables was not detected.
*p<.05; **p<.01.

Table 4. Standardized coefficients of the regression models for the number of retweets.

Category – user group – sentiment	Component											
	1	2	3	4	5	6	7	8	9	10	11	12
Cluster – Podemos – *neg*	**0.772**	-0.219	-0.149	0.140	-0.131	0.126	-0.276	0.199	-0.080	-0.082	-0.182	0.056
Non-aligned users – General users – *neg*	**0.770**	0.004	-0.416	-0.009	-0.082	0.139	0.008	0.169	0.032	-0.019	-0.079	-0.015
Non-aligned users – General users – *pos*	**-0.758**	0.026	0.459	0.009	0.071	-0.127	0.029	-0.147	-0.027	0.025		
Cluster – PP – *neg*	**0.743**	-0.436	-0.101	0.296	-0.016	0.015	-0.005	0.105	-0.0			
Cluster – Podemos – *pos*	**-0.720**	0.193	0.145	-0.134	0.121	-0.105	0.376	-0.180	0.091	0.120	0.197	-0.0
Cluster – PP – *pos*	**-0.678**	0.470	0.115	-0.336	-0.016	0.026	0.013	-0.063	0.082	0.072	-0.037	0.020
Cluster – PSOE – *neg*	**0.650**	-0.132	-0.092	0.581	-0.061	0.077	-0.127	0.104	-0.146	-0.095	-0.030	0.0
Media – *A3Media* – *neg*	**0.637**	-0.605	-0.111	-0.027	-0.035	-0.032	-0.045	-0.079	0.092	0.071	-0.024	-0.016
Candidates – *Rajoy* – *neg*	0.152	**-0.925**	0.025	0.027	-0.043	-0.006	-0.029	0.019	0.015	-0.016	-0.006	-0.0
Candidates – *Rajoy* – *pos*	-0.155	**0.903**	-0.021	-0.066	0.041	-0.002	0.024	-0.017	0.035	0.017	0.009	0.030
Parties – PP – *neg*	0.099	**-0.81**	-0.063	0.129	-0.102	0.233	0.024	0.127	-0.113	-0.076	-0.009	0.053
Parties – PP – *pos*	-0.11	**0.795**	0.079	-0.186	0.138	-0.156	-0.034	-0.142	0.204	0.090	-0.009	-0.026
Media – *A3Media* – *pos*	-0.590	**0.648**	0.111	0.087	0.011	0.049	0.027	0.095	-0.112	-0.081	0.047	0.036
Media – *El País* – *pos*	-0.276	-0.033	**0.803**	0.063	0.181	0.012	0.011	-0.082	0.043	0.080	0.094	-0.
Media – *eldiario.es* – *pos*	-0.128	0.079	**0.779**	-0.223	-0.069	-0.192	0.123	-0.071	0.071	-0.036	0.185	0.060
Media – *El País* – *neg*	0.315	0.040	**-0.765**	0.032	-0.158	0.042	0.004	0.116	-0.027	-0.051	-0.059	0.079
Media – *eldiario.es* – *neg*	0.128	-0.081	**-0.721**	0.297	0.109	0.208	-0.134	0.102	-0.106	0.069	-0.166	-0.055
Media – *El Mundo* – *pos*	-0.152	0.179	**0.454**	0.157	0.354	-0.300	-0.108	-0.425	0.179	0.166	-0.075	0.023
Parties – PSOE – *neg*	0.148	-0.118		**0.826**	-0.282	0.050	0.001	0.075	-0.065	-0.073	0.034	-0.026

Parties – PSOE – *pos*	-0.111	0.116		**-0.805**	0.295	-0.010	0.012	-0.079	0.104	0.084	-0.038	0.027
Cluster – PSOE – *pos*	-0.597	0.133	0.09	**-0.621**	0.095	-0.042	0.164	-0.101	0.210	0.133	0.024	-0.062
Parties – Ciudadanos – *neg*	0.013	-0.102	-0.061	0.197	**-0.885**	0.067	-0.126	0.100	-0.058	0.017	-0.116	0.000
Parties – Ciudadanos – *pos*	-0.007	0.106	0.095	-0.188	**0.885**	-0.019	0.118	-0.116	0.083	-0.027	0.0	
Cluster – Ciudadanos – *pos*	-0.332	0.075	0.062	-0.40	**0.621**	0.019	0.264	-0.101	0.273	0.152	0.	
Cluster – Ciudadanos – *neg*	0.422	-0.043	-0.044	0.38	**-0.59**	0.028	-0.233	0.118	-0.232	-0.166	-0.111	0.063
Media – *Cadena SER* – *neg*	0.094	-0.068	-0.100	0.029	-0.016	**0.921**	0.026	0.074	-0.050	-0.021	-0.048	0.001
Media – *Cadena SER* – *pos*	-0.079	0.029	0.145	0.037	0.039	**-0.913**	0.016	-0.081	0.003	-0.005		
Media – *El Español* – *neg*	0.048	-0.269	-0.458	0.326	-0.	**0.501**	-0.121	0.194	0.035	0.010	-0.141	0.05
Media – *El Español* – *pos*	-0.065	0.287	0.452	-0.266	0.097	**-0.501**	0.088	-0.172	-0.062	0.017	0.2	
Parties – Podemos – *pos*	-0.172	-0.010	0.098	-0.029	0.153	-0.018	**0.928**	-0.068	0.046	0.106	-0.001	0.007
Parties – Podemos – *neg*	0.156	-0.005	-0.054	0.071	-0.174	-0.	**-0.925**	0.079	-0.031	-0.113	-0.009	
Media – *Público* – *neg*	0.197	-0.060	-0.165	0.153				**0.869**	0.022	-0.009	-0.124	0.009
Media – *Público* – *pos*	-0.212	0.086	0.200	-0.150	0.126			**-0.845**	-0.004	-0.014	0.170	0.01
Media – *El Mundo* – *neg*	0.173	-0.164	-0.428	-0.104	-0.396	0.317	0.108	**0.442**	-0.128	-0.170	0.084	-0.037
Candidates – *Sánchez* – *neg*	0.045	-0.077	-0.077	0.113	-0.131	0.033	-0.046	0.002	**-0.956**	0.021	-0.015	
Candidates – *Sánchez* – *pos*	-0.048	0.088	0.083	-0.131	0.140	-0.005	0.035	-0.007	**0.955**	-0.002	0.011	-0.029
Candidates – *Rivera* – *neg*	0.076	-0.044	-0.023	0.099	-0.031	0.026	-0.095	0.022	0.0	**-0.95**	-0.080	0.002
Candidtes – *Rivera* – *pos*	-0.083	0.056	0.034	-0.101	0.035	0.002	0.122	-0.012	-0.004	**0.957**	0.082	0.005
Media – *InfoLibre* – *pos*	-0.133	-0.002	0.213	0.018	0.129	-0.088	0.002	-0.099	0.002	0.	**0.894**	-0.026
Media – *InfoLibre* – *neg*	0.138	-0.016	-0.186	-0.015	-0.116	0.146	-0.020	0.121	-0.029	-0.065	**-0.885**	0.009
Candidates – *Iglesias* – *pos*	-0.015	-0.009	0.002	-0.002	0.028	-0.002	0.002	-0.020	0.002	-0.006	-0.003	**-0.956**

Candidates – Iglesias – neg	0.015	-0.006	-0.007	-0.006	0.012	-0.001	0.007	-0.028	-0.049	-0.003	-0.03	**0.956**
% explained variance	31.16	9.48	8.35	6.57	4.90	4.50	4.20	3.79	3.65	3.30	2.96	2.58
% cumulative explained variance	31.16	40.64	49.00	55.58	60.48	64.98	69.19	72.98	76.63	79.93	82.89	85.48

Notes: N = 432. *pos* = positive sentiment, *neg* = negative sentiment.

Table 5. Principal Component Analysis results for the emotional reactions among the Twitter user groups.