Electronic word of mouth communities from the perspective of Social Network Analysis

The paper is focused on the identification of influencers which can have an important impact over the decision making of other users. For this purpose, a popular electronic word-of-mouth (eWOM) community like Ciao.com has been modelled as a social network. Using Social Network Analysis techniques, the existence of influencers is justified by the power law distribution of user participation, and then they are identified using their topological features within the social network. Obtained results reveal that influencers are not determined by the number of performed reviews, but by the variety or scope of their performed reviews and their central position in the consumer network. The main contribution of this research is the identification of influencers based on the participation features of community users. As a difference to other studies, results are not based on surveys or opinions, but on the trace users leave when they post opinions, comments or scores.

Keywords – Word of mouth; Virtual communities; Social Network Analysis; centrality; clustering coefficient

Introduction

The Internet offers consumers access to a large amount of information on a wide range of products and brands thus enabling prices and qualities to be compared as well as the interaction with companies and other consumers (Hennig-Thurau and Walsh, 2003; Khammash and Griffiths, 2011). Additionally, the ongoing growth of electronic commerce is encouraging consumers to produce a huge amount of information that influences other consumers (Chatterjee, 2001; Lee et al., 2011).

In this context, there is a rise in the number of websites where consumers can read and write online product reviews, sharing their opinions on different goods and services. Some of these websites focus on a specific brand (e.g., Sang et al., 2006). It is also usual to find online retailers which create online communities where their customers can express their opinions (e.g. amazon.com, bestbuy.com, barnesandnoble.com). Finally, others have taken the form of web-based consumer-opinion platforms that allow users to review and comment different brands and types of products, attracting the participation of a high numbers of consumers (Jeppesen and Molin, 2003). Some of the more well-known platforms are epinions.com, dooyoo.com, cnet.com and ciao.com. All of them receive more than one hundred thousand visits per day. In the case of Ciao, it includes more than 1 million registered users and reviews on 1.4 million products.

Instead of being directed to small consumer groups with experience in specific areas, these consumer-opinion platforms provide information related to multiple consumer areas and sectors (Hennig-Thurau et al., 2004). Among other aspects, the online product reviews which can be found on these sites usually

include a general product rating (e.g., in the form of stars), the specific scoring of certain attributes which vary depending on the product type analyzed, key phrases (pros and cons) related to the product's perceived strengths and weaknesses, and the full text with all the comments and scores that the reviewer is willing to leave.

A social network is a set of people or groups of people with some pattern of contacts or interactions between them (Newman, 2003; Scott, 2000). According to this definition, consumer-opinion platforms allow consumers to develop social networks as they provide tools and mechanisms to facilitate interactions. Thus, registered users in consumer-opinion platforms are usually enabled to vote on helpfulness of product reviews and post their own comments about them. In addition, many consumer-opinion platforms (e.g. epinions.com, ciao.com) allow members to add other members who share their preferences and criteria in assessing products to their web trust network. The reviews written by members of the trust network appear at the top of the review page of a product. Therefore, a significant function of this tool is to help members to distinguish valuable information sources from less valuable ones (Ku et al., 2012).

The importance of WOM is widely accepted in traditional marketing research (Lee et al., 2008, Cheung et al., 2008). WOM consists of informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers" (Westbrook, 1987). It is usually considered to be a very effective marketing tool with major repercussions on consumer behaviour (Phelps et al., 2004; Khammash and Griffiths, 2011) and an impact on attitude forming and decision making, reducing the risk associated with these decisions (Cheung et al., 2008). In view of the above, consumer-opinion platforms provide an alternative and effective marketing channel to firms, in the form of eWOM, which does not require huge investments

in advertising (Ku et al., 2012; Trusov et al., 2009). Therefore, these large-scale online communities have redefined traditional WOM social networks by allowing consumers to share their opinions with other members very easily (Chen et al., 2008).

Given the growing importance of eWOM and consumer-opinion platforms, the way these virtual communities work needs to be analyzed as well as their structure and the behaviour of their users. In this analysis, the identification of possible influencers is of great interest to business given the importance and impact that their reviews can cause on other consumers' purchase intent. The role of the influencer is to evaluate and communicate assessments of products and services, which may influence future purchase decisions (Ferguson y Johnston, 2011). The literature on WOM marketing describes multiple attributes of influencers: they have multiple interests, are early adopters in markets, are trusted by other consumers, and have a large social network (Keller and Berry, 2003; Kiss and Bichler, 2008). Influencers may exercise a major impact on the opinions of other consumers with their broad experiences and deep knowledge in their fields (Cho et al., 2012; Kim and Tran, 2013).

Most earlier studies in the eWOM field usually focus on aspects such as the influence that product reviews can have on purchase intent or on consumers' motives for reading or writing these reviews (e.g. Chen et al., 2004; Cheung et al., 2009; Dellarocas et al., 2007, Gu et al., 2012). However, there has been very little examination of consumer-opinion platforms' internal structures. This paper is a contribution to the field and uses SNA tools in a study of ciao.com, one of the most popular consumer-opinion platforms. More specifically, this paper analyzes the structure of the user network and determine the main antecedents of influencers from a topological point of view.

The remainder of this paper is organized as follows: section 2 reviews the related literature about eWOM. Section 3 proposes the hypotheses of this study. Section 4 details the case study and the methodology to validate the proposed hypotheses. Section 5 describes the obtained results followed by their discussion. Finally, section 6 summarizes the conclusions of this work.

Literature review

EWOM communication includes any positive or negative statement made by customers - potential, real or former - about a product or company, which is made available to other people via the Internet (Hennig-Thurau et al., 2004). EWOM exhibits important differences with respect to traditional WOM communications. First, positive and negative consumer reviews are presented at the same time in the same online place (Chatterjee, 2001). Second, online consumer reviews can be collected and analyzed, as a difference to traditional WOM communications that take place in private conversations which are difficult to observe (Kiss and Bichler, 2008) and require the use of surveys instead of direct observations (e.g., Bowman and Narayandas, 2001). Online communities enable direct observations as the information is publicly available. For instance, the quantity and persistence of eWOM communications have been used to analyze how online consumer reviews impact on sales (Chevalier and Mayzlin, 2006; Dellarocas et al., 2005).

Many studies on eWOM focus on the influence that product reviews could have on consumption decisions and sales in different sectors (Amblee and Bui, 2007; Antweiler and Frank, 2004; Chen et al., 2004; Chen et al., 2006; Chevalier and Mayzlin, 2006; Chintagunta et al., 2010; Dellarocas et al., 2007; Dhar and

Chang, 2009; Duan et al., 2005; Forman et al., 2008; Gu et al., 2012; Lee et al, 2008; Liu, 2006; Tumarkin and Whitelaw, 2001; Yang and Mai, 2010). Papers of this type often measure the impact of a range of the dimensions of online reviews, mainly the volume (the number of reviews received by a product) and the valence (the positive or negative nature of the review).

With respect to volume, Dhar and Chang (2009) highlight the importance of the number of online reviews in the music sales sector, which appears to be positively correlated with the number of blog posts about an album. Amblee and Bui (2007) arrive at a similar conclusion about digital short books on Amazon.com. In the same virtual store, Chen et al. (2004) empirically investigate the impacts of recommendations and consumer feedback and conclude that the number of consumer reviews is positively associated with book sales. Studies by Duan et al. (2005) and Liu (2006), whose data were collected from web sites such as Variety.com or Yahoo Movies, show that the volume of online posting can raise awareness of a product among potential buyers and increase box office revenue. In the finance field, studies by Tumarkin and Whitelaw (2001) and Antweiler and Frank (2004) find that the volume of postings on Internet financial forums affects stock prices and the volume of transactions.

Other studies highlight the influence of the valence on consumer behaviour. Chevalier and Mayzlin (2006) find that an improvement in the reviews of any given book led to an increase in relative sales on Amazon.com, with negative reviews having a greater impact than positive reviews. Yang and Mai (2010) arrive at the same conclusion in the online video game market. Dellarocas et al. (2007) show that, apart from volume, the average valence of online user reviews provides a valid framework for making predictions about future movie sales. Meanwhile, Chintagunta el al. (2010) find that the valence is the main driver of

box office performance in the same market. Using panel data collected from Amazon.com, Gu et al. (2012) show that positive reviews improve the sales of popular products more than those of niche products, while negative reviews harm niche products more than popular products. In a similar line, Lee et al (2008) investigate the effects of negative online consumer reviews on consumer attitude to mp3 multimedia players, concluding that consumers attitudes become less favourable as the proportion of negative online reviews increases.

The quality of the reviews and the reputation of the reviewers are specifically considered to be important factors affecting purchase decisions by some researchers who are more focused on the impact triggered in consumers by the perceived usefulness and credibility of the information. Forman et al. (2008) use the online helpfulness vote on Amazon.com as an indicator of the quality of the reviews and finds that consumers do not only take into account the volume and the valence of the reviews, but also their quality. Using consumer reviews for books, Chen et al. (2006) mine data taken from the same site and find that reviews with a high proportion of helpful votes (higher quality reviews) have a stronger impact on consumer purchase decisions and are associated with increasing sales.

Although a wide variety of aspects of online consumer reviews have been studied, the literature on eWOM shows that the networks formed by the consumers who are involved in them has only been analysed to a very limited extent. Given the influence that eWOM and consumer-opinion platforms have on purchasing behaviour, the structures of these virtual communities and user behaviour need to be examined. However, research on the internal structures of consumer-opinion platforms is practically non-existent. In fact, at the time of writing this paper, practically only the recent study by Ku et al. (2012) using data from Epinions.com can be highlighted. These authors seek to identify *reputable*

reviewers in consumer-opinion communities according to the web trust network built up between its members and their review behaviour.

Hypotheses

Power-law distribution means that the majority of the nodes only have a small number of links while only a small fraction of nodes have a large number of links (Barabási, 2001). Therefore, power laws characterise the transition from disorder to order and the presence of self-organising mechanisms (Abu-Rahmeh, 2009). This is the case of product reviews, which tend to focus on a reduced group of top products. Additionally, if the internal structure of the major consumer-opinion platforms can be modelled as a scale-free network, it will also be possible to identify those users who play the role of influencers (Martinez-Torres et al., 2010; Breschi et al., 2009). By using SNA, it is possible to determine the distribution followed by the product and user networks. Therefore, we hypothesize:

H1: *Product reviews in online consumer-opinion platforms follow a power law distribution.*

H2*: User participation in online consumer-opinion platforms follow a power law distribution.*

One major challenge of consumer-opinion platforms consists of determining the characteristics that are more suitable for identifying an influencer within the platform. Many virtual stores (e.g., Amazon.com) and consumer-opinion platforms (e.g., Ciao.com) have rating systems that enable consumers to vote on

whether posted reviews have been helpful to them (Chen et al. 2006). The number or proportion of helpful votes that a review receives can serve as an indicator for its content quality for other consumers. Also, a high number of reviews with a higher number of helpful votes can be an indicator of the reviewer's quality (Amazon.com uses this criterion) and, in the final instance, of his/her reputation. It therefore seems evident that the reputation of the reviewer, measured according to the ratings that other consumers give his/her reviews, is, a priori, a good indicator for characterising possible influencers.

Reviewer's exposure in the online review community is another magnitude that could also be important for this. It can be measured by how many times a reviewer posts reviews on an online community website. Hu et al. (2008) state that apart from being influenced by higher quality reviewers, consumers pay more attention to reviewers with high exposure. Likewise, reviews written by lower exposure reviewers might be less likely to change consumers' uncertainties and transaction costs for buying a product.

In the context of eWOM communication, online reviews are often shared by unknown individuals (Cheung and Thadani, 2012) and because of this some studies suggest that this might affect their credibility (e.g., Park et al., 2007; Park and Lee, 2009). It is also common to find concerns about the possible fraudulent involvement on the consumer platform of the manufacturers themselves, writing reviews of their own products. However, it is usual to require that reviews must be posted by registered users. This fact contributes to raising consumers' perceived credibility with the consequent impact on their purchases (Forman et al, 2008).

The study of the topological features of the user network within the consumer platform (which cannot be easily manipulated) can be used to identify influencers (our dependent variable). More specifically, influencers should occupy

a more central position in the network formed by registered users in the online consumer-opinion platform. Accordingly, we propose the following hypothesis:

H3a: *Influencers in online consumer-opinion platforms can be identified by means of their centrality measures.*

H3b: *Influencers in online consumer-opinion platforms occupy a central position in the registered users' network.*

Another important aspect related to the reputation of a reviewer in an online consumer-opinion platform is his/her expertise with regard to the reviewed products. The expertise level of a reviewer is likely manifested in his or her review behaviour and probably a high level reviewer is a very active contributor in a certain domain or product category (Ku et al., 2012; Martinez-Torres and Diaz-Fernandez, 2013). This active contribution should be reflected not only on the number of reviews, but also on a wide range of products (i.e. products of different brands, technical features or benefits) that the influencer is able to review. Thus we propose the following hypothesis:

H4: *Influencers in online consumer-opinion platforms review a wide variety of products in the same product category.*

Case study and methodology

Ciao.com is an online opinion portal where registered users can critically review and rate products. It is one of the most popular consumer networks and receives more than 20,000 page views per day. Final consumers can benefit from

reviews by other users and price information from online shops. However, making reviews requires to become a membership (available free of charge). Registered users can write comments and score products using qualitative ratings that correspond to numerical values (currently, the website contains over 2,000,000 consumer reviews). Their review can also be scored by other members.

Ciao website is structured through categories of products and services. Among the huge sets of categories, this research has considered mobile phones as they include a wide variety of items receiving a variable number of reviews. A specific web crawler has been developed to extract data from this category (Martinez-Torres, 2014). A web crawler is a software program that follows the link structure on the web, retrieving the desired information. In this case, the web crawler was programmed to follow the link structure within the mobile phones category. Extracted indicators are detailed in Table 1.

Table 1. List of indicators extracted from ciao website.

Indicators	Description
product	Name of the mobile phone
n_rev	Number of reviews
user	Alias of each registered user who has sent at least one review
score	Scores of mobile phone reviewed
rev_rating	Score of the review (by other members)

Using the designed web crawler, 1005 different mobile phones were analyzed at ciao.com. Up to 17044 reviews were performed by 13644 different registered users. For each review, the alias of the registered user, the score of the reviewed item and the received score of the review (user, score and rev_rating of Table 1) were stored.

The proposed methodology consists of modelling communities as social networks. Basically, a social network is a graph where nodes represent actors and edges represent the interactions among them. The main advantage of using SNA

techniques is that several topological features of the nodes can be extracted as part of the global network. These features are related with their participation activity, and they can reveal patterns of behaviour of users within communities (Martinez-Torres, 2013). For instance, the patterns of participation have already been used to analyze the structure of communities or to characterize those users occupying relevant positions (Sowe et al., 2006; Toral et al., 2010). The main limitation is that SNA does not take into account the quality of posted ideas and comments, but their quantity. However, analyzing the content of shared opinions one by one would be a high time consuming task.

The collected information has been used to build a two mode network where nodes of the graph are divided into two sets: mobile phones and registered users that have reviewed them. Figure 1 shows the obtained two mode network. Mobile phones are represented as black nodes while users are drawn as white nodes.

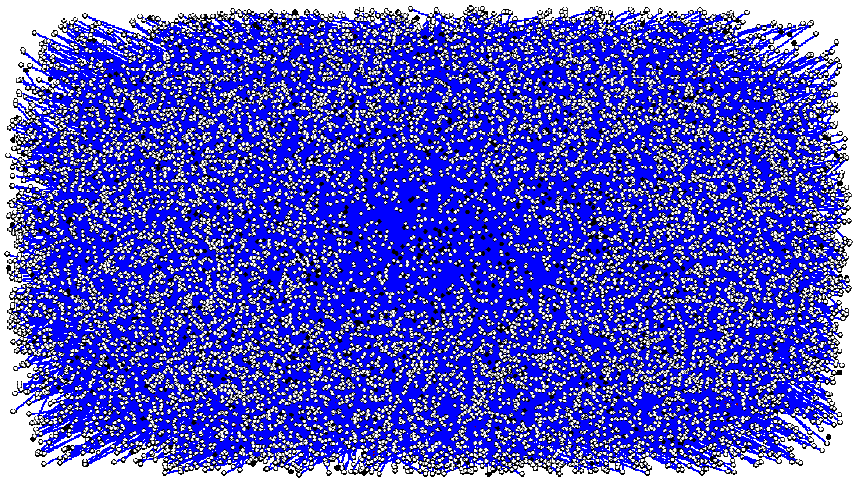

Figure 1. Two mode network corresponding to mobile phone category at ciao.

Two one mode networks can be derived from the original two mode of Figure 1: the network of products and the network of users. As this research is focused on analyzing eWOM communities, the network of users will be considered. This network is derived as follows: whenever two registered users

have reviewed a mobile phone, an edge among them is set in the corresponding one mode network. The network of users is detailed in Figure 2.

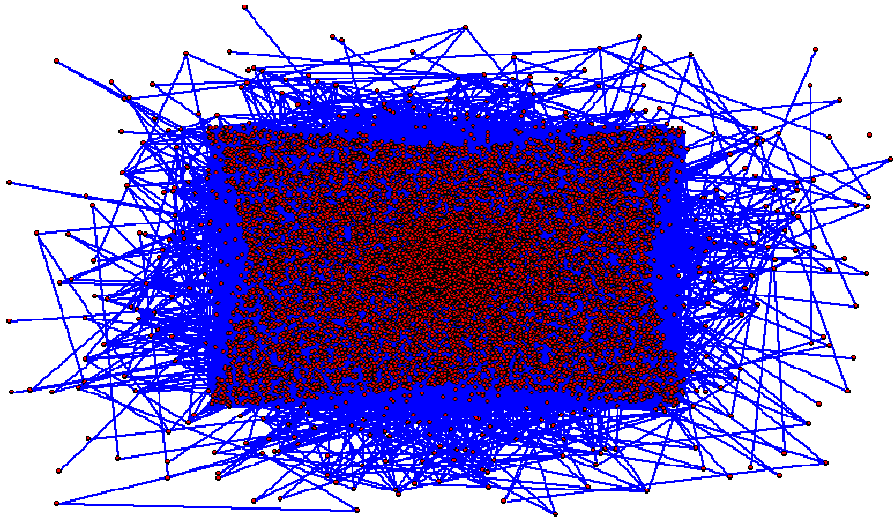

Figure 2. Network of users (one mode network derived from Figure 1).

From a mathematical point of view, the network of users can be represented as an adjacency matrix *A*, where *a(i,j)=1* if nodes *i* and *j* are connected and *a(i,j)=0* otherwise. Several properties of the network can be computed using Social Network Analysis tools:

Size. The number of nodes represents the total number of products and users in case of Figure 1 (two mode network) and the total number of registered users in case of Figure 2 (one mode network).

Degree. The degree of a node is the number of edges associate to this node. In Figure 1, the degree of a black node (representing a mobile phone) is the number of received reviews, while the degree of a white node is the number of reviews a registered user has done. In Figure 2, the degree of a node is measuring the number of interactions between a particular node and the rest of the network.

Degree centrality. This definition considers that a node is more central as it is more connected with the rest of nodes. Mathematically, degree centrality of node *i* is defined as

$$C_D(i) = \sum_{j=1}^{n} a_{i,j} \quad (1)$$

Closeness centrality. It is a measurement of centrality based on the idea of distance among nodes. It is defined as the total distance between a node and the rest of nodes of the network. Therefore, those nodes closer to the rest of nodes have a high value of closeness centrality and they are said to occupy a more central position in the network. Mathematically, closeness centrality of a node can be computed using the definition of Wassermann and Faust (1994), which considers the size of the network.

$$C_C = \frac{(n-1)}{\sum_{j=1}^{n} d(i,j)} \quad (2)$$

Where n is the size of the network and $d_{(i,j)}$ is the minimum length of a path connecting nodes i and j (the shortest path connecting two nodes is called geodesic).

Betweenness centrality. It is an alternative measure of centrality based on the idea that a node occupies a more central position depending on the extent this node is performing an intermediary role in the communication network. Formally, the betweenness centrality of a node is defined as the proportion of all geodesics between pairs of other nodes that include this node. Mathematically, betweeness centrality can be computed using this formula (Freemann, 1977).

$$C_B = \frac{\sum_{i \neq j \neq l} g_{jl}(i)}{g_{jl}} \quad (3)$$

where $g_{jl}(i)$ is the number of shortest paths connecting the two nodes j and l that contains node i.

Clustering coefficient. It measures whether the one hop neighbours of a particular node interact with each other. Basically, the clustering coefficient is a measure of local cohesiveness through the neighbour interactions of a node. Mathematically, the clustering coefficient of a node i is defined as twice the ratio between the number of edges $|e_{jl}|$, which connect the k_i neighbours, divided by the

total number of possible edges $k_i(k_i-1)$, being N_i the set of neighbours of node i, and E the set of edges:

$$CC_i = \frac{2|e_{jl}|}{k_i(k_i-1)},\ j,l \in N_i, e_{jl} \in E \qquad (4)$$

Results

The degree distributions of the products and users in the two mode network are illustrated in Figure 3 and Figure 4, respectively. Both of them have been fitted to a power law distribution, where the probability of obtaining a certain frequency is given by the equation $Cx^{-\alpha}$, being C a normalization constant and α the power law exponent.

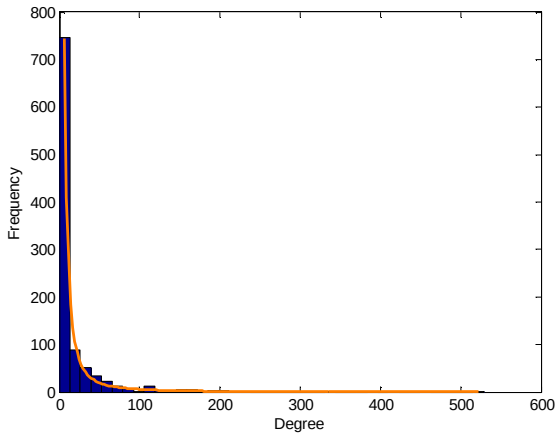

Figure 3. Degree distribution of products and power law fit.

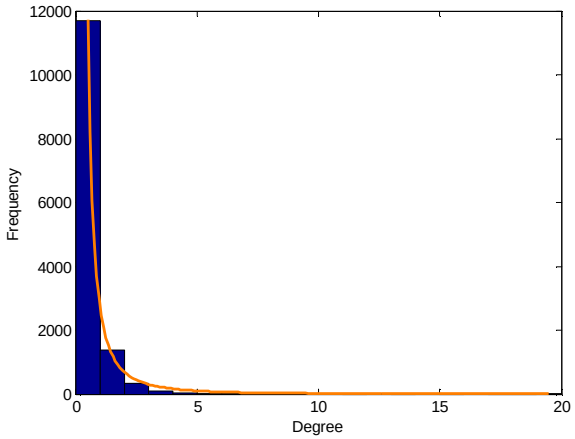

Figure 4. Degree distribution of users and power law fit.

The α coefficient was estimated according to the goodness-of-fit based method described in Clauset et al. (2007). The obtained result is α=2.29 for the case of products and α=3.5 for the case of users. The Kolmogorov-Smirnov test D value for both networks are below the critical value given by $1.63/N^{0.5}$. Therefore, the null hypothesis applies and both products reviews and user participation networks follow a power law distribution. Consequently, hypotheses H1 and H2 are confirmed. This finding shows that the internal structure of the consumer-opinion community can be modelled as a scale-free network where the majority of the links are associated to a small number of nodes.

With respect to hypotheses H3 and H4, the analysis of the topological features of influencers requires first to define which users can be considered as such. Based on previous studies, the posting activity (exposure) of the reviewers and their reputation can be considered the two most important characteristics of influencers. The first one can be measured using the number of posted reviews on the consumer-opinion platform. Regarding the reputation of reviewers, it can be measured according to the ratings received from the rest of the community. Figure 4 shows that the 84.5% of users only post one review. Therefore, the threshold value to be considered as an influencer can be selected either as 2 (which

corresponds to the 15.5% of users that sent at least two reviews) or 3 (which corresponds to the 4.4% of users that posted at least three reviews). The rating received from the rest of the community also follows a similar power law distribution. The different possible threshold values are shown in Table 2.

Table 2. Threshold values for the selection of influencers.

Cases	Posted reviews	% users
(a)	≥ 2	15.5
(b)	≥ 3	4.4
	Rev_rating	**% users**
(c)	≥ 50	12.3
(d)	≥ 60	9.1
(e)	≥ 70	6.0
(f)	≥ 80	3.8
(g)	≥ 90	3.0
(h)	≥ 100	2.5

The dependent variable in this study is the condition of being an influencer which is determined by the thresholds in Table 2. The eight cases of Table 2 were considered, and eight binary logistic regressions were performed using the topological properties of nodes (centrality measures) as independent variables.

Table 3. Logistic regression results for the eight considered cases.

Case	Variables	Logistic coefficient (standard error)	Wald
(a)	**degree**	-0.003 (0.000)	32.803***
	Closeness	30.628 (1.932)	251.255***
	betweeness	7113.895 (461.478)	237.637***
	CC	-12.600 (0.413)	929.461***
	Nagelkerke R^2	0.840	
(b)	**degree**	0.001 (0.000)	5.445*
	Closeness	16.200 (2.439)	44.130***
	betweeness	1369.163 (145.300)	88.794***
	CC	-9.597 (0.459)	436.375***
	Nagelkerke R^2	0.721	
(c)	**degree**	-0.002 (0.000)	19.756***
	Closeness	22.756 (1.716)	175.895***

	betweeness	2204.314 (195.039)	127.733***
	CC	-9.329 (0.255)	1342.689***
	Nagelkerke R^2	0.702	
(d)	**degree**	-0.001 (0.000)	3.901*
	Closeness	17.231 (1.517)	129.000***
	betweeness	1100.862 (137.632)	63.977***
	CC	-8.127 (.235)	1198.723***
	Nagelkerke R^2	0.620	
(e)	**degree**	0.000 (0.000)	0.189
	Closeness	14.010 (1.650)	72.127***
	betweeness	1020.512 (122.133)	69.818***
	CC	-7.480 (0.264)	805.633***
	Nagelkerke R^2	0.597	
(f)	**degree**	0.000 (0.000)	0.012
	Closeness	16.664 (2.611)	40.732***
	betweeness	1043.436 (123.785)	71.055***
	CC	-8.562 (0.398)	462.481***
	Nagelkerke R^2	0.665	
(g)	**degree**	0.000 (0.000)	0.848
	Closeness	17.177 (3.140)	29.924***
	betweeness	933.355 (117.366)	63.243***
	CC	-8.768 (0.471)	346.476***
	Nagelkerke R^2	0.675	
(h)	**degree**	0.000 (0.000)	0.360
	Closeness	23.394 (3.812)	37.651***
	betweeness	339.915 (80.079)	18.018***
	CC	-9.103 (0.496)	336.668***
	Nagelkerke R^2	0.630	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 3 shows the results obtained for the eight logistic regressions and Table 4 details the classification tables of influencers and non-influencers as well as the percentages of correct classification. The total percentage correct is high in all cases. Obviously, the percentage corresponding to correct classification of influencers is lower as they represent only a small fraction of community users. The Hosmer and Lemeshow test was not significant in all cases, so the predicted and observed probabilities match up.

Table 4. Classification matrices.

Case		Estimated		
	Observed	**Non-influencers**	**Influencers**	**Percentage correct**
(a)	**Non-influencers**	12037	67	99.4
	Influencers	185	208	52.9
	Total percentage correct			98.0
(b)	**Non-influencers**	11880	72	99.4
	Influencers	207	338	62.0
	Total percentage correct			97.8
(c)	**Non-influencers**	10619	313	97.1
	Influencers	421	1144	73.1
	Total percentage correct			94.1
(d)	**Non-influencers**	11007	316	97.2
	Influencers	529	645	54.9
	Total percentage correct			93.2
(e)	**Non-influencers**	11583	122	99.0
	Influencers	400	392	49.5
	Total percentage correct			95.8
(f)	**Non-influencers**	11922	79	99.3
	Influencers	230	266	53.6
	Total percentage correct			97.5
(g)	**Non-influencers**	12037	67	99.4
	Influencers	185	208	52.9
	Total percentage correct			98.0
(h)	**Non-influencers**	12123	55	99.5
	Influencers	180	139	43.6
	Total percentage correct			98.1

The logistic regression results reveal that there is an almost null dependence, and in many cases not significant, of the degree of nodes. A high degree value of a node implies that this node is connected to many other nodes. According to the way the community has been modelled, this means that this user is posting reviews for popular products which in turn receive reviews from many other consumers. This result makes sense as most users typically post only one review and they usually write about popular products which are evaluated by many other similar users. On the other hand, the results also show a positive and significant dependence of influencers on closeness and betweeness centralities. The more central a nodes is in terms of distance and mediation, the higher the probability of being an influencer. Finally, it can be reported a negative but significant dependence on the clustering coefficient. The clustering coefficient

measures the ratio between the interactions of nodes located in 1-hop neighbourhood of a given node and its degree. As the degree is not significant, this result can be interpreted as a low value in the numerator of the clustering coefficient, which in turn means influencers usually review a wide variety of products (e.g. mobile phones and smartphones from different manufacturers and with different features).

In summary, obtained results confirm that influencers can be identified by means of centrality measures such as closeness and betweeness centrality, and the clustering coefficient, which confirms hypotheses H3a and H3b. Furthermore, hypothesis H4 can also be accepted and it can be concluded that influencers exhibit a more comprehensive knowledge in the field of mobile phones than the rest of users and their reviews are based on a wider knowledge of this market.

Conclusions and implications

With the growth of electronic commerce, there is also an increase in the number of web-based consumer-opinion platforms that allow users to read and provide information related to multiple areas and sectors (Lee et al., 2006). These online consumer reviews have a major influence on decision making processes of other consumers.

The literature on eWOM usually focuses on aspects such as the impact of different dimensions of online reviews (volume, valence, quality of the reviews, reputation of the reviewers, etc.) on purchase decisions and sales. However, there are very few studies that analyse the networks formed by the users of these consumer-opinion platforms. This study provides a new contribution to the existing literature and enables the distribution followed by the product and user networks in a well-known consumer-opinion platform (Ciao.com) to be reflected

upon. SNA tools have been used to study the topological features of the reviewer network and identify influencers.

The findings show that both product reviews and user participation networks follow a power law distribution which allow the users who play the role of influencers to be identified. The analysis of the results also reveals that influencers have a more central position in the user network and a significant dependence on centrality measures (such as clonesss, betweeness and clustering coefficient). Finally, it can be concluded that influencers usually review a wider range of products (different brands or technical features) which reflect their greater expertise with regard to a certain field or product category.

This study has managerial implications for different aspects. Online reviews provided by users in the main consumer communities let firms approach their customers (Lee, 2007) and uncover topics and trends that are relevant (Gamon et al., 2005). In this context, the identification of influencers is of great interest to businesses, given the impact that their reviews can cause on other consumers' purchase behaviour. As Ku et al. (2012) state, firms should pay special attention to negative reviews from these users and take appropriate actions improving their products or services, otherwise negative eWOM could spread quickly through the influencers.

Furthermore, the identification of influencers enables viral marketing techniques, like those that make use of the social network to stir up interest in certain products or drive loyalty towards a brand. Viral marketing techniques work better when they focus on the influencers (firms could provide them with new products), as they have the ability to diffuse messages more quickly, credibly and efficiently through opinion websites (Kiss and Bichler, 2008).

Finally, given the importance of the number of reputable members for the success of consumer-opinion platforms (Ku et al., 2012), firms that host sites such as Ciao.com should develop effective strategies to identify influencers, recognize their reputation explicitly and provide incentives to retain them.

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