How can trustworthy influencers be identified in electronic Word-of-Mouth Communities?

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Abstract:

Given eWOM's growing importance and the interest of companies in having their products positively rated, it is necessary to analyze the behavior of influencers in online communities and determine the activities that might explain their level of trustworthiness. This paper focuses on identifying the different attributes obtained from online communities' system-generated profiles to consider trustworthy reviewers. A structural equation model has been developed to measure trustworthiness as a construct, using the peer-nominated approach and a variety of indicators. Findings reveal a range of behavior patterns that can identify influencers based on their trustworthiness. A reviewer's involvement and sociability have strong relationships with the trust that he/she evokes in other users. Actions such posting reviews, scoring other members' reviews and adding them to his/her trust network have a great relationship with trustworthiness. Also, a reviewer's specialization and experience have significant, although weaker, relationships with his/her level of trustworthiness.

This research makes significant managerial contributions in detecting the most trustworthy and influential reviewers, and their characteristic actions to focus their use of viral marketing techniques on this subset of users with the aim of sparking interest in certain products in a faster, more credible

and more efficient way in terms of costs.

Keywords: Influencers; Reviewer’s Trustworthiness; electronic Word-of-Mouth Communities.

1. Introduction

Traditional word-of-mouth (WOM) is an informal communication channel that allows consumers to share experiences about specific services and products. It is usually considered to be an important marketing tool with an impact on consumer decision-making and perceived risk reduction (Cheung et al., 2008; Lee et al., 2008; King et al., 2014). However, WOM is restricted to the inner circle of consumers, e.g., friends and relatives. Today, the growing popularity of the Internet and user-generated content has widened the scope of traditional WOM and spawned an electronic version called eWOM (electronic word-of-mouth). Many websites offer customers the opportunity to post comments about their experiences with products or services that they have purchased. Hence, eWOM has redefined traditional WOM networks by facilitating information sharing among consumers (Ilhan et al., 2018). Moreover, the continuing growth of electronic commerce encourages consumers to produce a large amount of information that influences other consumers in making purchase-related decisions (Lee et al., 2011; Banerjee et al., 2017).

The important role that eWOM has on purchase intention has been confirmed by several studies. Jalivand and Samiei (2012) found that e-WOM was one of the most effective factors influencing brand image and purchase intention of brands in consumer markets. Bataineh (2015) focused on examining the impact of perceived eWOM on purchase intention by taking the corporate image as mediating variable. This research concluded that eWOM quality (helpful and clear information), eWOM credibility (believable sources), and eWOM quantity (as a sign of how much the product is valuable and popular) positively impact purchase intention. In a study by Mikalef et al. (2017a), eWOM was found to have both direct and indirect (by affecting consumers’ trust) effects on purchase intentions in social commerce settings. In this study, eWOM was also found to positively impact purchase intention through value co-creation. Other works have studied consumer motivations and stimuli to engage in eWOM (Chu and Kim, 2011; Mikalef et al., 2017b). Finally, other studies have conclusively established a significant impact of eWOM on sales in different sectors. Chevalier and Mayzlin (2006) found that an improvement in the reviews of any given book led to an increase in relative sales on Amazon.com. Using data collected from this same website, Chen et al. (2008) found that higher quality reviews have a stronger impact on consumer purchase decisions and are related to rising sales. Li et al. (2019) examined the influence of eWOM on the sales of tablet computer products. Their study revealed that both sentiments expressed in textual reviews and numerical ratings have significant impacts on the sales performance. Studies by Liu (2006) and Duan et al. (2008), whose data were collected from online movie review websites, showed that the volume of online reviews can increase the attention of consumers and increase box office revenue. Li et al. (2020) performed a meta-analysis examining the impact of a number of eWOM factors on product sales. The results of their research showed that aspects such as the number of reviews, star ratings, review helpfulness or sentiment have a positive influence on product sales. In a similar line, the impact of eWOM on consumption decisions and sales was also investigated by Chintagunta et al. (2010), Forman et al. (2008), Gu et al. (2013), Lee et al. (2008) and Yang and Mai (2010), among others.

In view of the impact that eWOM reviews may have on their customers' purchasing behavior, companies are extremely interested in both identifying influencers and monitoring their eWOM activity. The identification of influencers allows firms to exploit them for viral marketing techniques and sparking more rapid interest in their products. Therefore, eWOM websites can afford firms a significant marketing channel that is very efficient in terms of costs (Ku et al., 2012).

Research on eWOM has been focused in analyzing and identifying those reviews features which affect helpfulness and usefulness (Mudambi and Schuff, 2010; Xhindler and Bickart, 2012; Korfiatis et al., 2012; Baek et al., 2012). However, the trustworthiness of a reviewer making a review is less usual. Source credibility theory expounds how the perceived credibility of the source of communication affects a communication's persuasiveness (Banerjee et al., 2017). This theory could explain at some point why the acceptance of a review can be affected by the perceived trust on the reviewer. An extension of this theory can be found in McCroskey and Jenson (1975), who identify different source characteristics which affect credibility. Given eWOM's growing importance and the interest of companies in having their products positively rated, it is necessary to analyze the behavior of reviewers in online communities and determine the activities that might explain their level of trustworthiness. This leads us to formulate our research question:

RQ: Which is the reviewer's behavior that makes him/her trustworthy?

In the present study, we address the RQ by presenting a predictive model in which trustworthiness is measured using a variety of reflective indicators, once the different approaches to identify influencers had been analyzed in the literature. In contrast to some previous studies, this model is not based on a priori threshold settings about which users can be considered reputable or trustworthy reviewers (Ku et al., 2012; Arenas-Márquez et al., 2014; Bao and Chang, 2014), but on different attributes obtained from online communities' system-generated profiles.

Overall, this paper makes relevant contributions to the literature by identifying trustworthiness through objective system-generated measures taken from online communities. In this research, data are captured from a real eWOM community and the actions studied that users could follow to increase their influence in the community. This paper is also one of the few works that determine and empirically validate a range of behavior patterns that can identify an influencer based on their trustworthiness. We address separately the behavior of reviewers using a pattern behavior approach (indicators to measure the independent variables), and behaviors derived from other users using a peer-nominated approach (indicators to measure the dependent variable), while other authors address them jointly (Ku et al., 2012; Banarjee et al., 2017). This paper also has a major managerial implication: accurate identification of trustworthy reviewers allows firms to focus their use of viral marketing techniques. This paper also provides some pointers for users interested in boosting their trustworthiness in the community.

The remainder of this paper is organized as follows: Section 2 reviews the related literature. Section 3 proposes the study's hypotheses. Section 4 details the research methodology to validate the proposed hypotheses. Section 5 describes the results obtained from the application of Partial

Least Squares structural equation modeling. Section 6 discusses the results and their implications. Finally, Section 7 summarizes the conclusions of this work.

2. Literature review

There is a consensus in the academic literature that people and customers are highly influenced by information received from others, especially WOM information (Roelens et al., 2016). While traditional WOM takes place in private conversations that are difficult to observe and measure (Liu and Park, 2015) and its influence diminishes quickly over time and distance, eWOM websites enable direct observations, as positive and negative consumer reviews are publicly available and can be collected and analyzed (including a general rating, specific scoring of some of the product's specific attributes, and the comments that the reviewer is willing to leave).

An influencer can be defined as an individual who influences the opinions of other people and facilitates the spread of information within a community (Keller and Berry, 2003). They are also called innovators (Martínez-Torres and Olmedilla, 2016), opinion leaders (Bao and Chang, 2014), and spreaders (Kiss and Bichler,, 2008). According to Bao and Chang (2014), eWOM opinion leaders have a notable ability to communicate with other consumers about their product experience. Their influence also reaches many consumers, creating buzz and sparking most interactions among others (likes, readings, comments, etc.), and their reviews are a trusted source that provides helpful information. Therefore, influencers represent a relevant target group for marketers, as they can easily reach a large-scale audience at a very small marketing cost and with fast delivery. From the viewpoint of the consumer, they reduce the risk associated with consumer buying decisions. The role of influencers within the eWOM context is even more important, as they can influence other customers on a global scale and their opinions can be spread through an almost unlimited network.

Many studies on eWOM focus either on the impact of product reviews on consumption decisions and sales (Chevalier and Mayzlin 2006; Dellarocas et al., 2007; Hu et al., 2008; Lee et al., 2008; Yang and Mai, 2010; Floyd et al., 2014), or on determining factors associated with the helpfulness of reviews (Baek et al., 2012; Schindler and Bickart, 2012; Wu, 2013; Ngo-Ye and Sinha, 2014). However, reviewers' trustworthiness has only been analyzed to a very limited extent. Some studies have been more focused on analyzing the reviewer's characteristics impacting on review helpfulness than impacting on reviewer trustworthiness or credibility (Ghose and Ipeirotis, 2011; Ngo-Ye and Sinha, 2014; Xu, 2014).

2.1. Approaches for analyzing influencers

Generally, the literature shows three approaches to identifying influencers when working with objective (profile-generated) measures: the patterns of behavior approach (Biran et al., 2012; Huang et al., 2010; Ku et al., 2012), the peer-nominated approach (Bao and Chang, 2014; Booth and Matic, 2011; Liu et al., 2015; Nair et al., 2010), and the network structure approach (Arenas-Márquez et al., 2014; Liu et al., 2017; Hinz et al., 2011; Kiss and Bichler, 2008). The first of these three approaches relies on the way that a person behaves to be considered an influencer. Biran et al. (2012) identify credibility in a person's actions, persistence and being influential in directing where the conversation goes. Furthermore, the communicativeness of influencers has frequently been measured by counting their numbers of posted reviews or their years of experience as reviewers (Kwok and Xie, 2016). However, posting reviews is not the only participation mechanism for reviewers. They can also rate products or even the perceived helpfulness of reviews written by other customers (Resnick et al., 2000; González-Rodríguez et al., 2016). Huang et al. (2010) address their level of expertise regarding a specific category of products or services as another influencer pattern. In this line, some studies state that reviewers may have a major influence on the opinions of their followers and peers, based on their expertise and popularity (Cheung and Thadani, 2012; Kiss and Bichler, 2008). Influencers are often expected to write more reviews in specific categories. This is referred to as the degree of review focus in the study by Ku et al. (2012).

The peer-nominated approach relies on feedback provided by the rest of the eWOM community. This feedback can be obtained in the form of the subjective measures collected in a survey (Nair et al., 2010) or using the objective measures provided by the system-generated user profile (Bao and Chang, 2014). For example, the study by Booth and Matic (2011) determines a numeric rank of a blogger's influence using a set of objective measures such as viewers per month, links, post frequency, and media citation score, among others. Liu et al. (2015) use the "popular author" approach to evaluate a reviewer's power of influence, linking popularity to a high number of visits, which increases his/her influence on other readers or potential consumers. Bao and Chang (2014) select as opinion leaders the top 1% by number of reviews written, number of votes received, and number of helpful votes received. It is worth noting that some of the previous studies include a combination of peer-generated variables, e.g., views per month or votes received, and reviewer-generated variables, e.g., number of reviews written or links.

Finally, the network structure approach consists of identifying influencers by modeling the eWOM community as a social network. For this, centrality, cohesion, and structural equivalence are key network concepts that should be considered (Liu et al., 2017). Network centrality is measured by its degree, closeness, and betweenness. Different forms of networks have different degrees of influence on the flow of information (Freeman, 1978). Network cohesion measures the number of connections among a group of actors and is an important structural feature that moderates the influence of interpersonal networks (Liu et al., 2017). Structural equivalence refers to the different network positions that share a similar pattern of connections with the rest of the network. As equivalent nodes are connected to a similar set of actors, they are more likely to receive similar information or social influence (Liu et al., 2017). So, once the social network is built, several local topological properties of nodes are used to characterize the condition of being an influencer. For instance, Hinz et al. (2011) consider hubs (nodes connecting with many other nodes) and bridges (nodes connecting densely connected subnetworks) as potential influencers. In this approach, the number of clicks and the number of hyperlinks pointing to a document measure its popularity (Chen et al., 2014). Kiss and Bichler (2008) focus on several centrality measures for the selection of a subset of users that can optimize the dissemination of information.

2.2. Influencers' trustworthiness

Therefore, influencers have been studied in an analysis of what they do (patterns of behavior approach), of what other people do because of the influencers' behavior (peer-nominated approach), or of the position of the influencers in a social network (network structure approach). However, in any of these three approaches there are very few specific studies regarding reviewers' trustworthiness. In some works, influencers are considered to be a trustable source of helpful information (Bao and Chang, 2014). This idea is based on three notions (Yu et al., 2011): (1) information shared by a "friend" could be very influential because it comes from a trustworthy source and from first-hand experience; (2) certain "friends" are more influential than others; and (3) the quality and content are important for the influence of a post (Cheng et al., 2014). Trust is of paramount importance within the eWOM context. In traditional offline WOM, customers know each other in person, so trust relies on personal feelings and interactions between people. However, in the online world, opinions are exchanged between strangers and can be easily manipulated (Ott et al., 2011). Consequently, trust is an important issue for persuading other customers. There are several mechanisms that can increase the trustworthiness of shared opinions. Many websites, such as Amazon or TripAdvisor, allow consumers to rate the helpfulness of posted reviews, so reviewers that receive many helpful votes are more trustable. In other cases, such as Ciao or Epinions, they make the trust network of a reviewer explicit, so the size of the trust network is an indicator of a reviewer's trustworthiness (Ku et al., 2012; Liu et al., 2015). All this information is part of the system-generated user profile that can be freely accessed on eWOM websites. This information can be used to judge the reputation of reviewers and the credibility of shared reviews (Wu, 2013).

This paper determines and empirically validates a range of behavior patterns that can identify an influencer based on their trustworthiness. We follow the patterns of behavior approach to analyze the behavior of trustworthy reviewers and the peer-nominated approach to analyze how they motivate other members' behavior on the eWOM website. All the considered indicators and antecedents are based on objective measures that can be obtained from the system-generated profile. We have not found any research focused on analyzing relationships between the patterns of behavior of reviewers and peer-generated feedback from other users regarding their trustworthiness. At the time of writing this paper, the closest relevant works that can be found are the studies by Bao and Chang (2014), Ku et al. (2012) and, especially, Banarjee et al. (2017). Unlike our study, these authors use several indicators related to both reviewer activities, such as the number of reviews written, and peer-generated feedback, such as helpfulness votes or number of friends, as independent variables. Bao and Chang (2014) identify opinion leaders by using user reviews and product sales rank, considering the number of reviews that a reviewer has written, the amount of buzz a reviewer has generated, and a reviewer's trustworthiness as the key attributes. Ku, Wei and Hsiao (2012) focus on identifying influencers through the study of reputable reviews, using average helpfulness to determine the dependent variable and a combination of indicators related to the user's activities as a reviewer and the number of members who trust him/her. Banarjee et al. (2017) study reviewer trustworthiness, using the number of followers as the measuring variable for their dependent variable and a number of indicators related to both patterns of reviewer behavior and peer-generated feedback (i.e. reviewer's reputation) as independent variables. Our analysis differs from theirs in that we consider the reviewer's actions as independent variables and feedback from other users regarding their trustworthiness as indicators for our dependent variable, while Banarjee et al. (2017) consider both aspects in their independent variables.

3. Hypotheses

For hypothesis specification, we had recourse to a number of factors identified in literature on eWOM which are related to trust on source of reviews. The works of Ku et al. (2012), Bao and Chang (2014), Banarjee et al. (2017) and some of the dimensions of source credibility expounded by McCroskey and Jenson (1975) have been found especially helpful for this purpose. In this paper, we propose five hypotheses. Our research model is outlined in Figure 1.

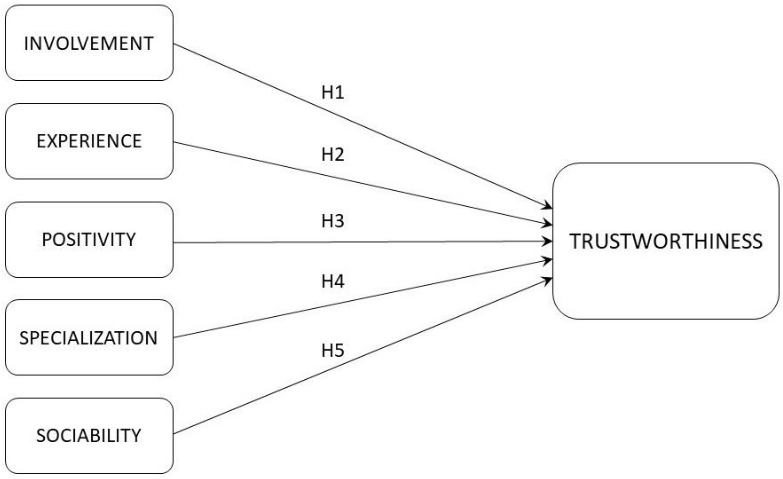

Figure 1. Proposed research model

In traditional WOM, a person trusts the communicator of an experience because of their relationship, with the latter's credibility mainly based on face-to-face communication (González-Rodríguez et al., 2016). However, in eWOM, consumers must establish confidence in a reviewer by relying on personal profile information (Xu, 2014). Sometimes, this confidence is afforded because of their perception of the user as an expert in the field/topic (Huang et al., 2010; Henning-Thurau et al., 2003; Yang and Mai, 2010; Hussain et al., 2017) which relates to the level of perceived usefulness in his/her reviews (Chen et al., 2014). This expertise, demonstrated by the reviewer's knowledge, is what enables him/her to contribute to the community with a high number of reviews (Ku et al., 2012). A high number of reviews enhance a reviewer's exposure in the eWOM community, which draws consumers' attention to his/her posted reviews (Hu et al., 2008) and reinforces their perceived helpfulness (Liu and Park, 2015; Liu et al., 2017; Lee et al., 2011; Park and Nicolau, 2015). A high number of reviews has been also associated with product sales and consumers' purchase intention (Cheung and Thadani, 2012; Park and Lee, 2009). Banarjee et al. (2017) found that the amount of reviewer's involvement, measured by counting his/her number of reviews written, was positively associated with the perceived reviewer trustworthiness. We, therefore, propose the following hypothesis:

H1. *Reviewer's involvement relates positively to his or her trustworthiness in the eWOM* *community*.

Furthermore, the level of expertise is not only based on the number of reviews that a user has written but also the number of years he/she has been a member of the community (Kwok and Xie, 2016); consequently, reviewers with high experience are expected to be more trusted and have more followers (Banarjee et al., 2017). This experience and knowledge regulate influence on information adoption in eWOM, as they perceive and rate a review as helpful if they have previous experience and knowledge (Cheung and Thadani, 2012). Reviewers' experience has been found to be positively associated with the perceived reviewer trustworthiness (Banarjee et al., 2017). Therefore, we can hypothesize:

H2. *Reviewer's experience relates positively to his or her trustworthiness in the eWOM community*.

The process of evaluating the credibility of online reviews is increasingly complicated, as there are more and more user-generated contents and more people using this information on e-commerce websites. Furthermore, consumers do not always read all the content of an online review because of a lack of time or of interest, etc. In these cases, it is important to give them some signs that allow them to discriminate reviews that are interesting from those that are not. According to traditional communication theories, the credibility of a message depends on informational aspects, such as the reliability and trustworthiness of the source or the consistency and quality of the arguments (Wathen and Burkell, 2002). Nevertheless, it is unclear if these factors would be enough in eWOM evaluation, where reviews and responses are posted by strangers and are easily aggregated and displayed online. Thus, both informational and normative influences would be interesting to explore (Cheung et al., 2009). Additionally, when consumers look for information to make decisions, they can usually find and use different formats and contents within the online reviews which can play an influential role in product selection (Mikalef et al, 2017c). Some of them are marketer or producer-generated content, such as price, image or product information and details, while other are user-generated content, such as positive or negative review texts and numerical ratings. These product ratings are often used by consumers to express their positive, negative or neutral perceptions of product reviews on eWOM websites (Resnick et al., 2000) and the reviews rated most useful are usually displayed by default in search results.

The positive or negative nature of a WOM message (valence) is considered among the most important eWOM attributes and have been largely examined (Park et al., 2018). Using an eye-tracking approach on Amazon.com online reviews, Mikalef et al. (2017c) found significant differences in the types of information and formats used for product purchase compared with those omitted. Concerning the user-generated content, this study concluded that the negative reviews had more influence while eliminating a product than the positive reviews while selecting one, so they may be helpful to remove products from a long list of candidates. On the other hand, several studies find that positive reviews have a greater impact on sales than negative reviews, as concluded by Casaló et al. (2015) who suggest that the influence of TripAdvisor on travelers' hotel booking behavior is stronger for hotels with high online ratings. Also, Gu et al. (2013) found that positive reviews had a greater impact on sales of the most popular products. When the analysis focuses on the perceived helpfulness of online reviews, which is frequently used to study the trust evoked by a reviewer among other users (Bao and Chang, 2014; Liu et al., 2015; Ngo-Ye and Sinha, 2014), some authors conclude that reviews with a positive valence are rated more useful than those that give products low scores. Using data of TripAdvisor, Fang et al. (2016) found that reviewers with more positive reviews received more helpful votes than reviewers who emphasized negative aspects. In the same line, studies by Yu et al. (2011) and Tsao et al. (2015) concluded that reviews with a positive valence are rated more useful than those that give products low scores. Furthermore, Norman et al. (2010) found that positivity impact on followers' perceived trust in leaders and, according to McCroskey and Jenson's (1975) character dimension, kindness and sympathy increase source credibility. Therefore, in the eWOM context, reviewers whose rating scores show a tendency towards positive values can be considered to be more trusted by other users (Banarjee et al., 2017) and we propose the following hypothesis:

H3. *Reviewer's positivity relates positively to his or her trustworthiness in the eWOM community.*

EWOM websites are typically organized in categories and subcategories of products and services so as to facilitate a search for reviews on a topic. They force users to select the category in which they share their opinions. The more a consumer purchases within a product or service category, the more likely he or she is to get complex knowledge about that category (Childers, 1986). Therefore, a reviewer who focuses on a specific category can be considered to be an expert on the topic covered in that category (Ku et al., 2012; Liu et al., 2015). Users who have many related transactions are more experienced and are more likely to use professional knowledge when writing reviews, which reinforces their credibility (Park et al., 2007). Hence, we hypothesize:

H4. *Reviewer's specialization relates positively to his or her trustworthiness in the eWOM community.*

According to Banarjee et al. (2017), reviewers' sociability is positively associated with their trustworthiness. This is a key dimension of source credibility (McCroskey and Jenson, 1975) in which personal interaction among users acquires greater importance. In an offline WOM environment, trustworthiness arises out of relationships (family, friends, etc.), and/or the experience of the source with the commented product or brand. However, in eWOM, there is no real relationship between the reviewer and the user. Therefore, other mechanisms than those used in offline WOM should be considered for improving trust. Today, social network sites enable friendship links and information transfer between known users. They bring people closer together and drive up both trust and trustworthiness (Glaeser et al., 2000). Some eWOM websites include friendship or trust networking mechanisms, so members can not only interact with other users by rating the helpfulness of their reviews or commenting about them, but also following or trusting other members. These purposefully designed trust networking mechanisms are sometimes called circles of trust (Ku et al., 2012; Liu et al., 2015). Therefore, when reviewers comment or rate the reviews of other community members or add them to their trust networks, social links are created that could increase their trustworthiness, so it can be hypothesized that:

H5. *Reviewer's sociability relates positively to his or her trustworthiness in the eWOM community.*

4. Research Methodology and results

4.1. Measurement and data collection

The Ciao UK website was the platform chosen to test the hypotheses proposed in this study. This is a well-known eWOM platform where reviews can be found on a broad range of consumer products and services grouped into 28 main categories. The information is openly accessible to drive dissemination, and no profiles have to be created to read reviews, although only registered users can write reviews and give ratings and evaluations of other reviews (Olmedilla et al., 2016). Ciao UK has almost 45,000 registered users in many different languages. Many are not active review writers, but once they are registered, they gain full access to other services and interactions proposed by the platform, such as the opportunity to score a review's helpfulness or include other users in their circle of trust.

A data set with the activity of 12,886 reviewers on Ciao UK was collected and analyzed for the present study. This number corresponds to users who had written at least one review. All the reviews could be read by other users and receive comments and ratings from them. Data regarding the items in Table 1 were collected for each of these reviewers. These items were in turn used to measure the independent variables that reflect reviewers' activity on the Ciao UK website.

Hyp.	Construct	Indicators	Indicator Description
H1	Involvement	NRev	Number of reviews written by a reviewer
H2	Experience	TimeActRev	Number of days between a reviewer's first and most recent reviews
H3	Positivity	AvProdRating	Average value of rating scores given to products (scale 1-5)
H4	Specialization	NCat	Number of categories for which a reviewer has written reviews
H5	Sociability	NMembT-by	Number of members trusted by a reviewer
		NRevRatings	Number of helpfulness ratings given to other members' reviews

Table 1. Indicators used to measure reviewers' activity on the Ciao UK website

The number of reviews posted by a user (NRev) is a good proxy for measuring reviewers' involvement. It can be obtained from the Ciao public reviewer profile. The publication dates of a member's reviews can be used to determine the duration of his/her activity as an active reviewer on Ciao UK (TimeActRev) by counting the number of days between the publication of the first and the most recent reviews. This indicator is used to measure reviewer's experience and it is better than the time since his/her profile was created, as after creating their profiles they may then be inactive for a certain amount of time and become active at a later date, or vice versa, which would affect this metric.

Furthermore, access is allowed to the user's scores given to the analyzed products as part of the system-generated profile. Ratings range from one to five points. A user's rating pattern can be calculated by as the mean of the scores he/she gives when rating products and services (AvProdRating), which is used for measuring reviewer's positivity. The number of categories of products or services where a reviewer posts reviews (NCat) is also displayed in the public profile, providing a measure of his/her degree of specialization. The higher the value of NCat, the lower the reviewer's specialization and trustworthiness in the eWOM platform (inverse relationship).

Public profiles also enable access to the number of helpfulness ratings that a reviewer gives to reviews written by other users (NRevRatings) and to the list of people belonging to his/her circle of trust. This list can be used to determine the number of members trusted by a user (NMemT-by). Both indicators are used for measuring reviewer's sociability.

Regarding the dependent variable used in this study, it is necessary to make some considerations. As seen previously, this paper focuses on the behavior of reviewers on eWOM websites, and specifically on determining the main actions (independent variables) that might explain their level of trustworthiness in the community. However, the dependent variable has to reflect the trustworthiness achieved by reviewers on the eWOM website. In some earlier studies that use peer-generated measures, the dependent variable was determined by the condition of being or not being an influencer, opinion leader or highly reputed or trustworthy reviewer (Ku et al., 2012; Arenas-Márquez et al., 2014; Bao and Chang 2014). However, this type of dichotomous variable requires several characteristics to be considered for a decision to be made about the thresholds above which a user can be considered an influencer or trustworthy reviewer. To avoid arbitrary decision-making in this respect, trustworthiness shown by reviewers is used as the dependent variable in the present study, and it is configured as a construct reflected by several items based on objective measures that can be obtained from the system-generated profile. Furthermore, when trying to determine the trust evoked by the reviewer among other users, or which reviewers can be considered influencers in an eWOM community, some previous studies with different methodologies use aspects such as helpfulness ratings, likes, comments or readings received (Ku et al., 2012; Bao and Chang, 2014; Ngo-Ye and Sinha, 2014; Rossmann et al., 2016; Liu et al., 2015). A high number of readings, comments, likes or votes indicate that a reviewer's opinions have reached a large number of consumers and that his/her reviews spark the highest number of interactions among other users (Bao and Chang, 2014) and increase user engagement (Rossmann et al., 2016). Other studies focus on aspects such as the number of followers or the number of users who include a reviewer in their trust networks (Banerjee et al., 2017; Mohammadiani et al., 2017; Li et al., 2010). These trust networking mechanisms are available on many online review sites and reviews written by trusted users are highlighted in some way. Taking all the above and the data available on the Ciao UK website into account, we decided to measure our dependent variable using the indicators which are detailed in Table 2.

Construct	Indicators	Indicator Description
Trustworthiness	NMembT	Number of members who include a reviewer in their trust networks
	NTrustMembT	Number of trustors of the members who include a reviewer in their trust networks
	NHelpRatings	Number of helpfulness ratings received by a reviewer from other members
	NComments	Number of comments received by a reviewer from other members
	NReadings	Number of readings received by a reviewer from other members

Table 2. Indicators used to measure trustworthiness on the Ciao UK website

The dependent variable reflects a reviewer's trustworthiness on the basis of five indicators that can be obtained from the public profile of reviewers: the number of received helpfulness ratings (NHelpRatings), the number of comments (NComments), the number of readings (NReadings), the number of users who trust the reviewer (NMembT) and the trust that a user's followers elicit (NTrustMembT). Regarding this last indicator, it is logical to assume that the greater a reviewer's trustworthiness, the greater the number of influential followers he/she will have in his/her trust networks. Therefore, the higher the value of each of these five indicators, the greater the reviewer's trustworthiness in the eWOM platform. Table 3 gives the descriptive statistics of the data set variables.

Variable	Min	Max	Mean	SD
NRev (No. of reviews written)	1	2437	8.162	55.790
NRevRatings (No. of helpfulness ratings given to other members' reviews)	0	33837	94.159	926.728
TimeActRev (No. of days between first and most recent reviews)	0	5377	91.880	465.316

Variable	Min	Max	Mean	SD
AvProdRating (Average value of rating scores given to products)	1	5	3.827	1.472
NCat (No. of categories for which a reviewer has written reviews)	1	28	1.858	2.766
NMembT-by (No. of members trusted by a reviewer)	0	67	0.641	4.009
AvTrustMemT-by (Average trustworthiness of members trusted)	0	203	2.228	11.237
NMembT (No. of members who trust a reviewer)	0	203	0.642	5.197
NTrustMembT (No. of trustors of the members who trust a reviewer)	0	4124	16.023	137.141
NHelpRatings (No. of helpfulness ratings received)	1	125286	266.469	2428.913
NComments (No. of comments received)	0	32629	94.115	869.823
NReadings (No. of readings received)	1	136764	301.859	2713.238

Table 3. Descriptive statistics of data set variables (*N* = 12886)

4.2. Data analysis method

Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to test the conceptual models' hypotheses. Structural equation modeling (SEM) methods can analyze many stages of both dependent and independent variables and integrate the hypothesized paths and the measurements into a simultaneous assessment, which allows better estimations. SEM methods such as PLS have potential advantages over linear regression models when analyzing path diagrams that involve latent variables with multiple indicators (Geffen et al, 2011). Even when the scenarios per item for constructs are simple, PLS-SEM has some advantages such as a higher consistency in terms of statistical significance and less contradictory results in terms of detecting mediation effects, a higher ability to minimize problems of multi-collinearity or the ability to analyze single items loading paths (Ramli et al., 2018). PLS was also chosen because it is more appropriate for predictive purposes and for analyzing relatively new phenomena (Chin and Newsted, 1999), such as eWOM websites. Furthermore, PLS is a widely-used SEM method in Information Systems and Management research (Bugshan and Attar, 2020; Sen and Lerman, 2007, Falahat et al., 2020).

SmartPLS 3 software (Ringle, Wende, and Becker 2015) was selected to evaluate the validity and reliability of the outer model (also called the measurement model) and to test the inner model (also called the structural model). As has been shown in Tables 1 and 2, the dependent variable (Trustworthiness) has five reflective indicators, Sociability has two indicators, and the other four independent latent variables are single indicator variables, which is not a problem in PLS-SEM models (Hair et al., 2012).

4.3. Validity and reliability of the outer model

Construct reliability was measured using Cronbach's Alpha and Composite Reliability (CR). These coefficients show how well the items selected are measuring the same construct (Götz et al., 2010). Values closer to 1 indicate greater reliability.

Model	Cronbach's alpha	Composite reliability (CR)	AVE
Sociability	0.769	0.895	0.810
Trustworthiness	0.981	0.985	0.929

Table 4. Cronbach's alpha, Composite Reliability, and Average Variance Extracted (AVE)

Table 4 shows the values of the two coefficients for Sociability and Trustworthiness constructs. Cronbach's alpha coefficients are larger than 0.7, which reflects good reliability (Hair et al., 2005). Additionally, CR coefficients are well above 0.7, which confirms this internal consistency (Hair et al., 2011).

Convergent validity was assessed by examining Average Variance Extracted (AVE). It measures the amount of variance that a construct captures from its indicators in relation to the variance due to measurement error. Fornell and Larcker (1981) recommend that AVE should be at least 0.50. The results given in Table 4 support the convergent validity for both constructs.

	Trustworthiness'	**0.964**
Correlations between Trustworthiness and independent variables	Experience	0.548
	Involvement	0.867
	Positivity	0.280
	Sociability	0.901
	Specialization	0.589

Table 5. Discriminant validity (Correlations and AVE square roots of Trustworthiness).

Discriminant validity indicates how a construct is different from other constructs. Table 5 shows that Trustworthiness' AVE square root was greater than its correlation with the remaining constructs in the model, which evidence the discriminant validity (Fornell and Larcker, 1981). As can be observed, this requirement is fulfilled in all cases.

Item	Experience	Involvement	Positivity	Sociability	Specialization	Trustworthiness
NHelpRatings	0.532	0.930	0.265	0.831	0.568	**0.966**
NComments	0.527	0.838	0.250	0.843	0.546	**0.979**
NReadings	0.544	0.920	0.266	0.828	0.572	**0.970**
NMembT	0.528	0.750	0.289	0.924	0.588	**0.963**
NTrustMembT	0.507	0.735	0.279	0.920	0.566	**0.941**
TimeActRev	**1.000**	0.520	0.426	0.528	0.681	0.548
NRev	0.520	**1.000**	0.311	0.747	0.623	0.867
AvProdRating	0.426	0.311	**1.000**	0.336	0.614	0.280

Item	Experience	Involvement	Positivity	Sociability	Specialization	Trustworthiness
NRevRatings	0.452	0.752	0.251	**0.927**	0.516	0.904
NMemT-by	0.510	0.575	0.372	**0.873**	0.658	0.697
NCat	0.681	0.623	0.614	0.640	**1.000**	0.589

Table 6. PLS loadings (bold) and cross-loadings.

The data presented in Table 6 include a cross-loading evaluation of discriminant validity. Loadings (λ) reflect the correlations between a construct and each of its indicators, whereas cross-loadings indicate correlations between a construct and the indicators of other constructs (Henseler et al., 2009). The loadings of a construct should be greater than its cross-loadings to confirm discriminant validity. As Table 6 shows, all indicators get a higher value with their own construct.

The communality (λ^2) of an observed variable is the part of its variance that is explained by a factor or construct. A value of $\lambda >= 0.707$ indicates that each measure represents at least 50% ($0.707^2 = 0.5$) of the variance of the underlying construct (Henseler et al., 2009). As also shown in Table 6, all the loadings of the reflective indicators of each construct are above this threshold. Therefore, they can be considered reliable.

4.4. Inner model

R^2 can be defined as the proportion of variance explained by the independent variables of a model and it measures the predictability of dependent variables. R^2 values of 0.67, 0.33 and 0.19 can be considered strong, moderate and weak, respectively (Chin, 1998). The latent variables of the model that are not endogenous have no R^2 value. As can be observed (Table 7), the R^2 value (0.906) shows a strong predictive power in the model since a large part of Trustworthiness' variance is explained by the independent variables. Furthermore, Table 7 includes the Stone-Geisser test (Q^2) for measuring the predictive relevance of the Trustworthiness construct. It was calculated using a blindfolding process. The Q^2 value is above 0, which is evidence of the predictive relevance and suitable fit of the model (Stone, 1974).

Model	R^2	Q^2
Full Model	0.906	0.794

Table 7. R^2 and Q^2 for Trustworthiness

Analysis of path coefficients (β) enables the proposed research hypotheses to be tested. β coefficients measure the degree to which the predicting variables contribute to the explained variances of the endogenous variables. According to Chin (1998), absolute β values between 0.1 and 0.2 show a moderate influence, although a value above 0.2 is desirable. The bootstrap resampling method enables the t statistic and p values to be calculated. These values are used as measures of statistical significance for β coefficients (Hair et al. 2014). Table 8 includes path coefficients and t values for the proposed model.

Effect size measures are used to evaluate the degree to which the findings have practical importance. Unlike p-values and statistical significance testing, which consider whether an effect is absent or present (Fairchild et al., 2009), effect size (practical significance) provides the magnitude of the effect identified in a statistical test (Khalilzadeh and Tasci, 2017). Large samples such as ours allow the detection of associations that may not be revealed by small samples. However, it is necessary to be aware of the associated p-value problem: as the sample size grows, the power of the test also increases and p-values rapidly fall to zero, which could lead to support being claimed for hypotheses of impractical significance (Lin et al., 2013). Thus, conclusions have to be based not only on statistical significance but also on effect size measures, which allow the sensitivity of the dependent variable to changes in the independent variables to be estimated and are less biased toward sample size (Khalilzadeh and Tasci, 2017).

Cohen's f^2 is a common measure of effect size. Values of 0.02, 0.15 and 0.35 respectively represent small, medium and large effects. Values of below 0.02 indicate that there is no effect (Cohen, 1988). As suggested by Hair et al. (2014), we used GPower 3.1 software to conduct a power analysis (Faul et al., 2009). Given the size of our sample (12,886 reviewers), an error probability of under 5% and a maximum of 5 predictors in our study, we achieved a statistical power of 80% for effect sizes (f^2) larger than or equal to 0.0006091907. Thus, statistically significant relationships can be obtained for very small effect sizes in this study. Table 8 also summarizes the f^2 effect sizes.

Hypotheses	Statistical significance		f² effect sizes			
	β (Path Coefficients)	T-Value	f^2	Conf. Intervals		Effect Size
				2.5%	97.5%	
H1. Involvement → Trustworthiness	0.458***	7.892	0.894	0.461	1.582	Large
H2. Experience → Trustworthiness	0.087***	5.080	0.042	0.023	0.066	Small
H3. Positivity → Trustworthiness	-0.025***	3.468	0.004	0.001	0.009	-
H4. Specialization → Trustworthiness	-0.124***	5.053	0.051	0.023	0.088	Small
H6. Sociability → Trustworthiness	0.601***	10.603	1.492	1.149	2.061	Large

Significance: ***= $p < 0.001$,**= $p < 0.01$,*= $p < 0.05$.

Table 8. Path coefficients (β), statistical significance (t) and f^2 effect sizes

As can be observed, the five hypotheses are supported and statistical significance is obtained in structural paths for a p-level of 0.001 in all cases. However, path coefficients and effect sizes show that the Involvement and the Sociability or a reviewer have a much stronger relationship with his/her Trustworthiness than the other three variables. Table 8 also shows that there is no practical significance for Positivity (f^2=0.004). As seen previously, in this case, statistical significance was obtained because of the large size of the sample.

5. Discussion and implications

5.1. Discussion and research contributions

Given eWOM's growing importance, it is necessary to analyze the behavior of users in online communities and determine the activities that might explain their level of trustworthiness. Using both the patterns of behavior and peer-nominated approaches to identify trustworthy reviewers, this study, therefore, presents a model that have a strong predictive power. In this research, trustworthiness is measured using the peer-nominated approach and a variety of reflective indicators.

In our model, Involvement (H1) and Sociability (H5) are the best predictors of a reviewer's level of Trustworthiness, with both presenting strong and direct relationships with the construct. Both activities boost his/her exposure in the community, which, in line with earlier studies such as Bao and Chang (2014), Kwok and Xie (2016) and Banerjee et al. (2017), decisively contributes to enhance trust among other users at his/her reviews receiving more readings, ratings, comments and followers.

The model also confirms, albeit weaker, a direct relationship between Experience (H2), measured by the number of days between the first and last posted review (the time a user has been an active reviewer), and a reviewer's trustworthiness. This variable contributes to improving the community's perceptions regarding his/her expertise and level of trustworthiness, although not to such a great extent as Involvement and Sociability. Something similar occurs with the degree of Specialization, which is calculated according to the number of product and service categories that a reviewer covers (H4), although in this case, the relationship is inverse. As was concluded in previous research (Huang et al., 2010; Ku et al., 2012), reviewers who focus on a small number of categories are considered more specialized, which in turn increases their trustworthiness and influence, although not to a very great extent. Therefore, activities such as posting reviews, scoring the reviews of other community members or adding them to his/her circle of trust, have a much greater effect on reviewer's trustworthiness than the experience and specialization associated with the number of posted reviews or the number of categories that they cover.

Finally, in the case of H3, there is no practical significance, and statistical significance was a consequence of the large sample size. Prior studies concluded that positive reviews are more effective (Yu et al., 2011; Tsao et al., 2015) and that reviewer positivity was moderately associated with his/her trustworthiness (Banerjee et al., 2017). A trustworthy review is perceived by readers as the honest, sincere, truthful, and non-commercial opinion of a customer who has experienced a product or a service (Filieri, 2016). Details of the experience are considered as an evidence that consumers actually tried the reviewed products or services. Product type and consumer character are sometimes presented as decisive factors. More than 12,000 reviewers on a wide range of products and services were considered for this study. Therefore, when research does not focus on a certain type of product or consumer, the valence of the reviews does not seem to be relevant for explaining a reviewer's trustworthiness. Depending on the nature of their specific attributes, products can be generally classified as either search products or experience products (Cui et al., 2012). Search products are described as goods, which quality can be evaluated by consumers through objective and specific attributes before purchase. Contrariwise, experience products are typically evaluated by affective attributes, which come from the consumers' experiences with the product. Therefore, subjective and emotional dimensions are more important with experience products while objective and informative dimensions are more prominent in the case of search products. Given their different dimensions, trustworthiness can be affected by the category of the product or service.

5.2. Practical implications

The present study has several managerial implications. Reviews of products and services on the main eWOM websites enable firms to get closer to potential consumers (Lee and Youn, 2009) and to take into account the considerations included in the reviews to improve their products and marketing campaigns (Wei et al., 2010). Therefore, it is essential to detect who the most trustworthy and influential reviewers are, and which actions really characterize this type of users and explain their level of trustworthiness, which is the main contribution of this paper. The correct identification of these users allows firms to focus their use of viral marketing techniques on this subset of users with the aim of sparking interest in certain products and services in a faster, more credible and more efficient way in terms of costs (Dobele et al., 2007; Kiss and Bichler, 2008). Inviting them to visit companies, try out products and services and subsequently post related-online reviews could also be an incentive for other reviewers to become more active (Banerjee et al., 2017) and take the actions required to drive up their levels of trustworthiness.

Additionally, the paper also provides some pointers for users interested in boosting their trustworthiness in the community. As has been shown in the present study, apart from writing interesting content, other actions are also needed, such as raising their level of exposure and the community's perception of their level of expertise and increasing their interactions with other members. In some cases, eWOM platforms could also incentivize activities that help users to boost their trustworthiness and receive greater acknowledgment through their reputational and reviewer rankings.

5.3. Limitations and future research

The present research has some limitations that should be addressed in future studies. First, the data used have been taken from one specific platform, Ciao UK. Although reviews on a wide range of consumer products and services have been considered, it would be advisable for future studies to assess the predictive power of the proposed model on other eWOM websites. It would also be interesting to include other characteristics associated with reviewers' profiles and the characteristics of their reviews. For example, it would be interesting to include measures of the level of trustworthiness linked to the possible positioning of reviews on the main search engines. It might also be interesting to consider aspects related to texts published by reviewers, such as their length and, especially, the language and expressions used. Nevertheless, it should be borne in mind that when data for a high number of users is handled, both data collection and analysis processing might be extremely challenging.

6. Conclusion

This paper focuses on the behavior of reviewers in eWOM communities and determining the actions that might explain their level of trustworthiness within the community. A structural equation model has been developed and demonstrated to have a strong predictive power and ability to measure trustworthiness using several reflective indicators. Findings reveal that a reviewer's involvement and sociability have strong relationships with his/her level of trustworthiness. Actions such as posting reviews, adding other members to his/her trust network or scoring their reviews have a great effect on trustworthiness. Also, a reviewer's experience and specialization present significant, although weaker, relationships with his/her trustworthiness. This research makes significant contributions that can be used by firms when planning their viral marketing strategies and by users wishing to increase their level of trustworthiness in the eWOM community.

CRediT authorship contribution statement

F.J. Arenas-Marquez: ´ Conceptualization, Methodology, Formal analysis, Writing - original draft. M.R. Martínez-Torres: Conceptualization, Methodology, Writing - original draft. S.L. Toral: Conceptualization, Methodology, Data curation, Writing - review & editing

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