Understanding consumers adoption of e-wom through information quality and product ranking

Abstract

Online reviews (ORs) are fostering the spread of Word-Of-Mouth in the online environment (e-WOM). The popularity of e-WOM is constantly growing among consumers who use them before buying a product/service. Therefore, it is important for marketers to understand the antecedents of e-WOM. In this paper we have used the elaboration likelihood model to investigate the antecedents of consumers’ adoption of ORs for hedonic products. Drawing on this theory, we have measured the influence of information quality, information quantity, and products ranking on consumers’ adoption of ORs. Predictions were tested by using regression analysis with data from 608 users of online travel reviews from different countries. Contrary to previous findings, this research shows that highly involved consumers are mainly influenced by peripheral cues, including the ranking of services/products but not by information quantity. Finally, the research shows that product ranking, and not information quantity or negative reviews, is a strong antecedent of e-WOM’s adoption.

Keywords: e-word-of-mouth, elaboration likelihood mode, information quality, information quantity, product ranking, adoption of online reviews.

1. Theoretical background

Online reviews are the electronic version of word-of-mouth. E-wom refers to any positive or negative statement made by potential, actual or former customers about a product or company, that is made available to a multitude of people and institutions via the Internet (Hennig-Thurau et al., 2004:39). In this research, we use the term ORs to refer to online reviews on products and services created and published online by consumers. Consumers write ORs to describe their own experience with products and services and graduate their level of satisfaction. This information after being published online becomes immediately available to several potential buyers. The importance of online reviews is growing among marketers and many e-travel agencies are providing their sponsored products with customer’s reviews (e.g. Venere.com, e-booking.com) or are encouraging consumers to post product reviews on their websites (Mayzlin, 2006). In few years, e-wom has become one of the hottest topic of research in marketing and e-commerce studies. The majority of studies on e-wom have found that e-wom play an influence on products’ sales (Godes and Mayzlin, 2004; Duan et al., 2005; Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Ye et al., 2009; Zhu and Zhang, 2010). Moreover, researchers have also investigated the motivations and attitudes of customers towards ORs; among them, a many researchers have adopted the ELM to explain the power on consumer purchasing intentions among differently involved consumers (Park et al., 2007, Park and Lee, 2008; Lee et al., 2008; Sher and Lee, 2009; Gupta and Harris, 2010). However, previous studies in e-WOM focus on purchasing intentions as a dependant variable (Park & Lee 2008; Sher & Lee 2009; Park et al., 2007; Lee & Lee 2009). Instead, here we explore information adoption which is the process in which people purposefully engage in using information (Cheung et al, 2008; Sussman and Siegal, 2003) when booking accommodation. Information adoption has been defined as the process in which people purposefully engage in using information and the capability of a message to produce some behavioural modification in the receiver (Cheung et al., 2008; Sussman and Siegal, 2003). Consumers that adopt information from an OR would agree with an ORs content and the subsequently purchase the reviewed accommodation. The present research lies in this tradition of studies and it adopts the elaboration likelihood model (Petty and Cacioppo, 1986)
to analyze the mechanisms that more strongly predict the adoption of ORs among highly involved consumers.

2. Elaboration likelihood model
The Elaboration likelihood model (ELM) was developed by Petty and Cacioppo (1986) to explain the resulting differences in influence results in different individuals and contexts in face-to-face communications. Based on the ELM, people’s attitude change may occur via two routes of influence, the central route and the peripheral route. Therefore, highly involved consumers use a central route to persuasion, by spending more time and efforts to understand marketing messages. In this case, customers focus on the quality of arguments and generate cognitive responses to the message. Conversely, individuals take the peripheral route when less motivated or less capable to think about the message. Therefore, they make less cognitive efforts, use simple decision rules to evaluate the message rather than analyzing its content (Petty and Cacioppo 1986). Low involved consumers spend less time and effort for understanding the messages related to product and use peripheral cues to form an attitude towards them besides the strength of the arguments or ideas in the message.

Previous research on e-wom have adopted information quantity (number of reviews) as a peripheral cue to information processing (Park et al., 2007; Park and Kim, 2008; Gupta and Harris, 2010) and found that it predicts customers’ adoption of ORs among low involved customers (Park et al., 2007; Gupta and Harris, 2010). However, in e-wom people may use other peripheral cues to process information and make a decision. One of the first peripheral cues consumers may use when they look for products and services is their rankings. Such rankings are not based on the alphabetical order of accommodations, rather on the overall customers’ evaluations. Rankings may orient consumers’ choices and help them to rapidly process information without reading the content in ORs. Thus, we argue that rankings may influence the adoption the ORs. In sum, our model includes both central and peripheral cues of information influence, respectively information quality dimensions, and information quantity and product ranking. The inclusion of both variables will enable us to understand whether high involvement customers read and make an effort to think about the content in ORs, or they are more willing to be influenced by information shortcuts to make a decision.

3. Information quality in e-wom
In the present study, ORs’ quality is defined as the quality of the content of an electronic review from the perspective of information characteristics (Park et al., 2007). Previous research on e-wom adopted the information quality construct as a composite dimension (Park et al., 2007; Park and Lee, 2008). Moreover, different authors have used different dimensions to measure information quality in e-wom. Lee et al. (2008) and Park et al. (2007) have used relevance, reliability (objectiveness), understandability, and sufficiency. Thus, we have used the set of measures proposed by Wang and Strong (1996) to measure information quality, namely information quantity, completeness, timeliness, accuracy, relevancy, understandability, value added (ibid.). We believe that these measures are more complete and more fitting the nature of information quality in ORs. Thus, drawing on the ELM model we argue that high involved consumers will make an effort to read ORs and will use information quality to evaluate the content of ORs. We then hypothesize:

\( HI: \) There is a positive relationship between information quality and customers’ adoption of ORs

3.1 Information quantity
Info quantity is the extent to which the quantity or volume of available data is appropriate for a specific task (Wang and Strong, 1996). Researchers have adopted information quantity (number of reviews) as a peripheral cue to information processing (Park et al., 2007; Park and
Kim, 2008; Gupta and Harris, 2010). Information quantity in this study is conceptualized as the amount of ORs per product. The quantity of ORs per product is an indicator of product popularity because it is perceived as the market performance of a product (Chevalier and Mayzlin, 2006). Other scholars found that information quantity influences the adoption of ORs in low involved consumers (Park et al., 2007), and predicts products’ sales (Dellarocas et al., 2007; Liu 2006; Duan et al., 2005). Thus:

$H_2$: There is a positive relationship between information quantity and customers’ adoption of ORs

3.2 Product ranking

Product Rankings refers to the rankings or classifications of products and services made by reviews’ websites and based on the overall customers’ satisfaction expressed by numerical scales. Product ranking does not refer to the quality of the arguments, rather to the ranking of products based on overall consumers’ satisfaction levels. For example, in TripAdvisor reviewers can use a scale from 1 (terrible) to 5 (excellent) to rate accommodations. Rankings are the average evaluation of overall customer’s satisfaction judgements on different aspects of the services offered by a product or a service such as an accommodation (i.e. cleanliness, staff, quality of breakfast and so on). These single evaluations are analyzed statistically by a system that provides a final score, classifying accommodations according to the overall level of satisfaction. Product rankings are argued to be a shortcut in the information elaboration process, since they restrict the number of alternative products available for specific criteria of choice (i.e. price). Thus, consumers may not be willing to scroll down the entire list or to check all the alternative accommodations available and to read their reviews. Current e-wom literature lacks the investigation of product ranking as an antecedent of customers’ adoption of e-wom. Thus we hypothesize:

$H_3$: There is a positive relationship between product rankings and customers’ adoption of reviews.

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4. Methodology

4.1 Data Collection and constructs

The present research is based on travelers’ evaluation of online reviews on accommodations. This study is based on a quantitative research method, which is more useful when the area of investigation is conceptually known. E-wom has been already conceptualized by scholars in different fields (Brown et al., 2007); for this reason, we have chosen the questionnaire as a research technique appropriate for this purpose and regression analysis as the most suitable measurement technique to assess our hypotheses. In total, the questionnaire consisted of 34 closed questions. Closed questions were measured through a Likert scale from 1 to 7, ranging from totally agree to totally disagree. In order to ensure the appropriateness of participants, the sample was selected along purposive lines with an attempt to concentrate on high involvement consumers. Thus, respondents who participated to this study had to state their level of involvement with travelling and who had recently adopted ORs for searching information on accommodations for planning their holydays. Respondents were solicited through means of personal contact in the first instance; snowballing method was then used to expand the sample and generate additional contacts. We have calculated that approximately more than 1000 questionnaires were sent off to respondents from February 2009 to June 2011. A total number of 621 were received back, 13 were excluded because of incoherence. The items used to measure the constructs of this study are displayed in table 2.

4.2 Sample Profile
Socio-demographic characteristics of the sample are presented in Table 2.

----------------------------- add Table 1 here -----------------------------

4.3 Data analysis
The most fundamental assumption in multivariate data analysis is the normality of the data (Hair et al., 2006). We have used the skewness value to test normality. All the variables considered in the study never exceed ± 2.58 or ± 1.96 so the distribution is normal. Both convergent and discriminant validity of the model were assessed. We used the variance inflation factors (VIFs) method to assess multicollinearity. All of the regression coefficients had VIFs below the 5 threshold, as suggested by Hair et al. (2006), implying that no multicollinearity existed among the constructs used. The correlations of potentially overlapping constructs were used to assess discriminant validity. No pair of measures had correlations exceeding the criterion (0.9 and above) as suggested by Hair et al. (2006). Convergent validity was measured for each construct with Cronbach’s α, which is the most widely used measure of reliability among researchers (Nunnally, 1978). All items had an overall Cronbach’s alpha value of .829 which identifies a very good reliability for predictor tests and hypothesized construct measures (see table 2).

5. Results
The hypotheses were tested by performing a regression analysis, adopting the stepwise as an estimation method. Regression analysis results are presented in Table 3. The resulting relationship between information quality, product ranking and consumers’ adoption of ORs was strong and highly significant (R² = .505; Adj. R² = .453; F= 126.259; p<0.001; df = 2). The model explained 45% of variance, showing a good explanatory power. However, not all the independent variables considered in our model showed the same explanatory power. The strongest antecedents of consumers’ adoption of ORs were product ranking (stand. β = .583; p<0.001), and information quality (stand. β = .416; p<0.001). Then, information quantity (stand. β = -.004, p< n.s.) did not show any predicting power in the causal relationship. Thus, the control variables considered in this research, namely negative reviews (stand. β = -.022; p< n.s.), and perceived risks (stand. β = .015; p< n.s.), did not show to play a moderating role on this relationship, too.

-----------------------------Add Table 2, 3 here-----------------------------

6. Discussion
Online reviews represent the electronic form of WOM and their diffusion and use among customers is constantly growing. This research investigated the strongest influencers of highly involved consumers in the purchase of hedonic products. The validity of our model is proved by its capacity of explaining a good percentage of variance (45%). From a theoretical point of view, our results are new and very interesting. Accordingly, product ranking, which is a peripheral cue to information processing, predicted the adoption of ORs among highly involved customers more strongly than information quality.

From a theoretical point of view, our results are new and very interesting. In fact, product ranking, which is a peripheral cue to information adoption, strongly predicted the adoption of ORs among highly involved customers. This result calls for a further development of the elaboration likelihood model for tourism products in the e-WOM context. In fact, since our sample was predominantly composed by people with high involvement (since planning a vacation elicits high involvement), results show that for making a decision on an accommodation customers strongly rely on peripheral cues to information adoption. Findings highlight that travellers adopt both central (information quality) and peripheral cues (products ranking). This result shows the dynamics of e-WOM’s influence on consumer decision; in
Thus, more reviews is not always better. To be purchased compared to a hotel which is ranked in the first position and has been reviewed for example by 20 users may be more likely another which has been reviewed by only 20 users consumers may not find the difference between a accommodation on such websites have an acceptable number of reviews. Therefore, websites contain a larger number of reviews compared to the past. The majority of do not care too much about the number of negative predicting value of information quantity Contrary to previous findings (Park et al., 2007; Gupta and description of an accommodation, which is not possible through other information sources. ORs are written by customers for customers; therefore they represent customers with different information needs. ORs potentially satisfy a wide plethora of needs because they are written by a variety of consumers, with each one reporting their own needs, opinion, evaluation, and experience. Increasingly, ORs are easy to read and understand and they provide a current description of an accommodation, which is not possible through other information sources. Contrary to previous findings (Park et al., 2007; Gupta and Harris, 2010), we have found that information quantity is negatively related to customers’ adoption of ORs. The low and negative predicting value of information quantity may be explained by the fact that consumers do not care too much about the number of ORs for each product. Today, the most popular websites contain a larger number of reviews compared to the past. The majority of accommodation on such websites have an acceptable number of reviews. Therefore, consumers may not find the difference between a hotel which is reviewed by 80 users and another which has been reviewed by only 20 users important. Accordingly, a hotel which is ranked in the first position and has been reviewed for example by 20 users may be more likely to be purchased compared to a hotel which is ranked 10th and has been reviewed by 80 reviewers. Thus, more reviews is not always better.
References


Appendix 1

Figure 1. Conceptual model

Table 1. Socio-Demographic Characteristics of Respondents

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Items</th>
<th>Frequency</th>
<th>%</th>
<th>Dimension</th>
<th>Items</th>
<th>Frequency</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEX</td>
<td>F</td>
<td>336</td>
<td>55.4</td>
<td>ECONOMIC STATUS</td>
<td>Very high</td>
<td>40</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td>M</td>
<td>272</td>
<td>44.6</td>
<td></td>
<td>high</td>
<td>42</td>
<td>7.3</td>
</tr>
<tr>
<td>AGE</td>
<td>15-25</td>
<td>80</td>
<td>13.2</td>
<td></td>
<td>medium-high</td>
<td>104</td>
<td>11.8</td>
</tr>
<tr>
<td></td>
<td>25-35</td>
<td>496</td>
<td>81.6</td>
<td></td>
<td>medium-high</td>
<td>108</td>
<td>31.6</td>
</tr>
<tr>
<td></td>
<td>35-45</td>
<td>24</td>
<td>3.9</td>
<td></td>
<td>medium-low</td>
<td>74</td>
<td>13.2</td>
</tr>
<tr>
<td></td>
<td>45-54</td>
<td>8</td>
<td>1.3</td>
<td></td>
<td>low</td>
<td>112</td>
<td>19.7</td>
</tr>
<tr>
<td>EDUCATION</td>
<td>Primary school</td>
<td>8</td>
<td>1.3</td>
<td></td>
<td>European</td>
<td>520</td>
<td>85.5</td>
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<tr>
<td></td>
<td>Undergraduate</td>
<td>240</td>
<td>38.5</td>
<td></td>
<td>African</td>
<td>48</td>
<td>7.9</td>
</tr>
<tr>
<td></td>
<td>Postgraduate, PhD, Master</td>
<td>280</td>
<td>46.1</td>
<td></td>
<td>Middle-East</td>
<td>40</td>
<td>6.6</td>
</tr>
<tr>
<td>Construct</td>
<td>Items</td>
<td>Factor Loadings</td>
<td>Var. explained</td>
<td></td>
<td></td>
<td></td>
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<td>----------------------</td>
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</tbody>
</table>
| Ranking \(\alpha = .833\) | The ranking of different accommodations facilitate the evaluation of the alternatives available  
                      | Rankings help me to rapidly select the best accommodation among several alternatives | .77             | 34             |
| Information quality \(\alpha = .837\) | The info in online reviews is relevant to my needs  
                      | The info in online reviews is appropriate for my needs  
                      | The info in online reviews is easy to understand  
                      | The info in online reviews is easy to read and to interpret  
                      | The info in online reviews is of sufficient depth and breadth  
                      | The info in online reviews is timeliness  
                      | The info in online reviews is accurate  
                      | The info in online reviews is complete  
                      | The info in online reviews is correct | .78 .80 .74 .68 .66 .72 .78 .59 .66 | 32             |
| Info Quantity \(\alpha = .786\) | The number of reviews per accommodation is large  
                      | The quantity of info per accommodation is large | .67 .69 | >5             |
| Information Adoption \(\alpha = .861\) | To what extent does the content of the OR motivate you to purchase the recommended accommodation?  
                      | I closely followed the suggestions of the comments in online reviews and went to the recommended accommodation | .65 .77 | 5              |

*Table 2. Factor Loadings and Cronbach’s alpha*

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>t</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Info Quality</td>
<td>.259 (n.s.)</td>
<td>.594 (***)</td>
<td>5.786</td>
<td>.790</td>
</tr>
<tr>
<td>Info Quantity</td>
<td>-.056 (n.s.)</td>
<td>-.004 (n.s.)</td>
<td>073</td>
<td>.762</td>
</tr>
<tr>
<td>Product Ranking</td>
<td>.683 (***)</td>
<td>.616 (***)</td>
<td>12.220</td>
<td></td>
</tr>
<tr>
<td>Negative Reviews</td>
<td>-.065 (n.s.)</td>
<td>.022 (n.s.)</td>
<td>476</td>
<td>.883</td>
</tr>
<tr>
<td>Risk</td>
<td>.135 (**)</td>
<td>.015 (n.s.)</td>
<td>302</td>
<td>.701</td>
</tr>
<tr>
<td>R²</td>
<td>.396</td>
<td>.505</td>
<td></td>
<td></td>
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<tr>
<td>Adj. R²</td>
<td>.456</td>
<td>.453</td>
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<td></td>
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<tr>
<td>(\Delta) of R²</td>
<td>-</td>
<td>.60</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Df</td>
<td>1</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>197.771</td>
<td>126.259</td>
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<td></td>
</tr>
</tbody>
</table>

*Table 3. Regression results. Significance Level: \(p^{***}<0.001; p^{**}<0.05; p^{*}<0.10; n.s. = non-sign.\)*