Journal of Management Information System & E-commerce
June 2017, Vol. 4, No. 1, pp. 12-25
ISSN: 2334-2382 (Print), 2334-2390 (Online)

Published by American Research Institute for Policy Development
DOI: 10.15640/jeds.v5n1a2
URL: https://doi.org/10.15640/jeds.v5n1a2

Why Do Online Buyers Engage in Electronic Word-of-mouth? An Expectancy Disconfirmation Perspective

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Abstract

Electronic word-of-mouth (eWoM) has been studied extensively in both marketing and information systems literature due to its critical impact on online buyers' purchase decisions. Very few studies, however, have examined the dynamics among expectation disconfirmation, satisfaction, and consumers' eWoM engagement behavior. Drawing on expectancy disconfirmation theory, this research examines how buyers' eWoM engagement is influenced by the level of disconfirmation and satisfaction. The logistic regression method was used to analyze 221 survey returns collected from buyers of online tourism products. The results show that low satisfaction and high satisfaction have opposite effects on the buyers' eWoM engagement. There is no such contingency on the relationship between satisfaction and the contribution of visual content, however. Instead, the results reveal that satisfaction has a positive influence on visual content contribution. Theoretical and practical implications are discussed.

Keyword: Electronic Word-of-mouth, Digital Commerce Marketing, Expectancy Disconfirmation Theory.

1. Introduction

With scientific advances in information technology, e-commerce, as a new form of business operations, has been widely adopted in all walks of life. The Internet has become the most popular sales and distribution channel for corporations, while the number of consumers purchasing products and services online is rapidly increasing. The rapid diffusion of e-commerce has created a new form of communication, electronic word-of-mouth (eWoM), which now has become a major information source for online consumers. According to Litvin et al. (2008), eWoM is defined as "*all informal communications directed at consumers through internet-based technology related to the usage or characteristics of particular goods and services, or their sellers.*" Simply speaking, eWoM refers to any statements posted on the Internet by online consumers about products or services after consumption. Easy and convenient access to the Internet enables consumers to express their feelings and share post-purchase experiences freely with other consumers and potential buyers.

A large percentage of online consumers consider this user-generated content an important factor in purchasing decisions. When online consumers plan to purchase products or services from online shopping websites, they may have concerns about quality based on the limited information provided by the sellers. To reduce information asymmetries—the differences in the information that sellers and buyers possess—consumers refer to online consumer reviews. Apart from its significant influence on consumers' perceptions of the trustworthiness of online retailers (Lee and Lee, 2006), this user-generated content also affects the purchasing intentions of potential consumers (Sparks and Browning, 2011) and hence product sales (Berger et al., 2010). With the recognized importance of eWoM in the digital market, eWoM has been receiving increasing attention from researchers.

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A substantial amount of research has investigated the impact of eWoM, while relatively few studies examine the antecedents of online reviews. Because consumers' motivation to engage in eWoM is dynamic, extant studies may not fully capture the antecedents of eWoM. The objective of this study, therefore, is to provide a better understanding of the factors that motivate online consumers to contribute user-generated content. The theoretical framework of this study is expectancy disconfirmation theory (EDT). According to EDT, the discrepancy between consumers' expectations and products' perceived performance has a salient influence on consumer satisfaction. Drawing on EDT, we investigate the following two research questions: (1) do disconfirmation and satisfaction have an effect on the customer's intention to contribute eWoM content, and (2) if so, what types of eWoM content are most likely to be affected by such perceptions or feelings? A questionnaire is used to collect data from online consumers who have booked hotels through online travel agents and a regression model is used for data analysis. The findings of this study provide insight into online consumers' engagement in eWoM and contribute practical recommendations for marketers interested in encouraging WoM engagement. The remainder of this paper is organized as follows. Section 2 reviews the literature. In section 3, we present our hypothesis development, followed by an introduction to our data collection and research design in section 4. Section 5 discusses the research findings and analysis. The last section discusses the implications and limitations.

Literature Review

Electronic word-of-mouth has been studied from diverse perspectives, including two major lines of research that focus respectively on the antecedents and the outcomes of eWoM. The research on antecedents analyzes review-generating factors, and the research on outcomes examines the impacts of eWoM on consumers' and companies' perspectives.

Impacts of eWoM

Research on the impact of eWoM has analyzed the perspectives of consumers and of companies. It has been observed that the majority of studies focus on the influence of eWoM in the decision-making process, and that they affirm that eWoM and interpersonal influence rank as the most important information sources for consumers making purchase decisions. Their influence is particularly salient for "experience goods," which are characterized by the difficulty of evaluating them before consumption (Litvin et al., 2008). In addition to the impact on consumers' decision-making process, researchers also examine eWoM's effects on perceived trustworthiness or credibility, risk reduction, product acceptance, loyalty, brand awareness, product comparison and booking intention. While some studies focus on the consumer perspective, others emphasize the effects of eWoM from the company's perspective. Analyzing these effects properly can give companies a competitive advantage in their business operations and help them improve the quality of their products/services, identify consumers' needs and implement new policies (Loureiro and Kastenholz, 2011; Jun et al., 2010).

Review-generating factors

Research investigating the generation of online reviews primarily studies the factors that motivate consumers to engage in eWoM, the profiles of review contributors, the means of engaging in eWoM and the types of content generated. According to Nielsen (2006), the well-known "90-9-1" rule can be applied to online consumers' participation in electronic word-of-mouth, which means that around 90% of users read online reviews but never contribute, 9% of them contribute from time to time, and only 1% of users contribute feedback frequently. It is essential to discover why some online consumers engage in eWoM while others never do so, as eWoM is not only a means of communication, but also an important way to help online travel agents build connections with customers.

Past research on review-generating factors focuses on several important motivations for consumers who engage in eWoM: for example, "sense of community belonging," "social identity," "pre-purchase expectations," and "service failure and recovery" (Bronner et al., 2011). The empirical findings are that eWoM engagement is either (1) self-directed, which includes personal (self-centered) motivations like self-expression, self-enhancement, and gaining self-esteem, or motivated by (2) a desire to help other buyers, the most frequently mentioned motivating factor in the literature; (3) social benefits, which include sense of belonging, interconnectivity, group commitment and a chance to meet people; (4) consumer empowerment, that is, increasing consumers' abilities or providing conditions related to greater information about or understanding of the goods; or(5) a desire to help the company, as consumers often believe that companies will be more accommodating or willing to change when consumers publicize their views (Bronner et al., 2011, Yoo et al., 2008, Hennig-Thurau 2004).

Expectancy disconfirmation theory

EDT is a cognitive framework and rational approach widely used to measure post-purchase satisfaction based on the differences between customers' expectations and the perceived performance of products or services. EDT is based on cognitive dissonance theory, which was introduced by Leon Festinger in 1957. According to Festinger, people are always seeking consistency in their beliefs and attitudes about the world. When a dissonance emerges between reality and cognition, it generates unpleasant feelings and leads to a change in cognition to achieve consonance. The EDT framework was proposed by Oliver in 1977.It is considered one of the most important and influential models for understanding consumer satisfaction and analyzing how dissonance between expectation and perceived performance affects satisfaction. In this study, we adopt the widely used conceptualization of disconfirmation as the difference between actual and expected product performance (Oliver, 1977).

That is, disconfirmation is a continuum between unfavorable (negative) disconfirmation and favorable (positive) disconfirmation. According to EDT, satisfaction can be viewed as a function of the disconfirmation between pre-purchase expectations and perceived performance, and the disconfirmation is defined as the incongruence of expectations with the actual performance of a product or service. Because EDT has been proven to have a strong ability to explain various outcomes of human behavior, we contend that EDT can be used as the basic theoretical framework of this research. In this study, we examine the antecedents of online users' eWoM contribution behavior from the perspective of their cognitive drivers using EDT and seek to explain this behavior as a function of a discrepancy between belief and satisfaction. This perspective extends the literature about the mechanisms of eWoM generation in the digital market.

Hypothesis Development

EDT holds that in the pre-purchase stage, consumers tend to seek previous user experiences and reviews on websites to reduce uncertainty and perceived risk before making purchase decisions. Their expectations of the product or service are built upon the content generated by previous users. After the consumption of products or services, buyers evaluate the actual performance of the product or service, which might or might not be consistent with the pre-purchase expectations, and hence determine the extent to which the expectations are (dis) confirmed. When there is a discrepancy between the pre-purchase expectations and the perceived performance of the product or service, a cognitive dissonance may occur. In such cases, people tend to retain consistency between their expectations and reality, as perceived inconsistency results in a feeling of discomfort that leads to attempts to reduce or eliminate it. There are four ways for an individual to reduce dissonance: (1) change his or her behavior or cognition to avoid inconsistency, (2) justify his or her behavior or cognition by adjusting cognition, (3) add new cognition to justify his or her behavior or cognition and4) ignore or deny the existence of dissonance. The causality between disconfirmation and satisfaction has been verified by a large body of marketing literature (Oliver, 1980; Anderson, 1993). Thus, consistent with EDT, we have:

Hypothesis 1: Disconfirmation between expected and actual performance has a positive effect on online buyers 'satisfaction.

In the marketing literature, it has been found that in bricks-and-mortar business settings, one outcome of customer dissatisfaction is consumer complaint behavior, though this link is weak and conditioned by numerous buyer-seller interpersonal factors (Oliver, 1987;Singh, 1991). We argue that in the setting of digital markets, consumers are inclined to speak about their unpleasant experiences due to the convenience of online sharing and the anonymous nature of the Internet. The more disappointed the consumer is, the more likely it is that s/he will engage in eWoM. However, satisfied consumers are also likely to engage in eWoM by providing reviews because the urge to share happiness is inherent to most people (Shi, 2014), and the possibility of such engagement increases as the level of satisfaction rises. All in all, we contend that the more extreme the satisfaction (either very low or very high), the more likely it is that a buyer will engage in eWoM. The less extreme the satisfaction level, the less likely it is that s/he will provide a review online. These hypotheses follow:

Hypothesis 2: An extreme satisfaction level, either very low or very high, leads to a higher likelihood of eWoM engagement than a moderate satisfaction level does.

Hypothesis 2a: When the satisfaction level is low, satisfaction has a negative influence on the likelihood of eWoM engagement.

Hypothesis 2b: When the satisfaction level is high, satisfaction has a positive influence on the likelihood of eWoM engagement.

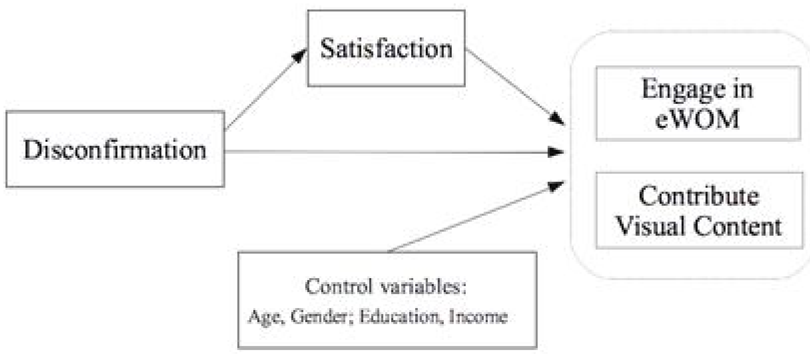
Two main types of user-generated content are most common: textual/narrative content and visual content. Textual/narrative content refers to descriptions of the experiences or goods in the form of text, while visual contents photos or videos of the product shared by consumers. It is widely known that visual content provided by consumers can significantly reduce potential buyers' perception of risk and increase the perceived trustworthiness of the product (Dimoka etal., 2012). Nevertheless, the contribution of visual content requires considerably more effort than textual reviews while also raising greater privacy concerns (Barnes, 2006);hence only a small proportion of review contributors are willing to provide such content. As in our preceding discussion, we hypothesize that:

Hypothesis 3: An extreme satisfaction level (very low or very high) leads to a higher likelihood of visual content contribution than a moderate satisfaction level does.

Hypothesis 3a: When the satisfaction level is low, satisfaction has a negative influence on the likelihood of visual content contribution.

Hypothesis 3b: When the satisfaction level is high, satisfaction has a positive influence on the likelihood of visual content contribution.
Our theoretical model is presented in Figure 1.

Figure 1 Research Model



Methodology

Sampling and data collection

According to the official figures released by Internet Live Stats, around 40% of the world's population has an Internet connection today, and China ranks as the country with the most Internet users (nearly 22% of the total population), which makes China an ideal sample base for investigating online consumer behavior. A questionnaire was distributed through Sojump (http://www.sojump.com), a widely used online survey website. To ensure data quality, this study used Sojump's premium sampling service. Because past experience of booking a hotel significantly reduces the discrepancy between expectation and performance, which in turn leads to low variance in disconfirmation, this research chose first-time purchases as the research context.

The data collection was conducted during one week in 2017. Consumers who had experienced first-time booking through online travel agencies (OTAs) within the past twelve months were selected as the sample for this study. Total of226 questionnaires were collected. After 5 questionnaires were discarded for having either unengaged responses (zero standard deviation for all 7-point questions) or irrelevant responses (e.g., giving the website name for the question asking the name of the hotel booked online), 221 questionnaires remained for data analysis.

Measurements

Performance and disconfirmation The disconfirmation between consumers' expectations and the perceived performance of hotel services was measured by using a combination of the additive difference model and the SERVQUAL model. The questionnaire items adopted to measure the disconfirmation were chosen from the standard SERVQUAL questionnaire, and the score was assessed with the additive difference model.

(1) Servqual

The questionnaire items, which were used to measure the disconfirmation between consumer expectations and perceptions of services provided by the hotel, were adopted from the SERVQUAL model. The SERVQUAL model was developed by Parasuraman et al. (1988) and has been widely applied in the measurement of service quality in different industries. Unlike product usage, service quality is relatively difficult to evaluate. Hoffman and Bateson (2006) defined service quality as "an attitude formed by a long-term, overall evaluation of a firm's performance" that normally focuses on the gap between customers' expectations and perceptions. SERVQUAL is theorized as a second-order construct with five dimensions: tangibles (physical facilities, equipment and employee appearance), reliability (employees' ability to perform the promised service dependably and accurately), responsiveness (employees' willingness to help customers and provide prompt service), assurance (employees' expertise in providing services and gaining the trust and confidence of customers) and empathy (employees' ability to provide personalized attention and care to the customers). Cranach's α of these five first-order constructs ranged from0.71 to 0.813, all greater than the recommended 0.70 cutoff recommended by Nunnally(1967).

(2) Difference Score Model (Diff)

Several alternative measurements of disconfirmation are reported in the literature of disconfirmation (Spreng, 1996).We used the Difference Score Model (DIFF), which is the most widely used measurement (Spreng, 1996). Its mathematical representation is

$$DIFF_i = P_i - S_i$$

where P_i and S_i are the perceived and expected performance on attribute i, respectively.
Satisfaction

The questionnaire items for satisfaction were adapted from (McKinney, 2002) and (Ribbink, 2004).Sample items included "I am generally pleased with this booking," "The experience of this booking is enjoyable," etc. Cronbach's α of this scale was 0.93. Engagement in eWoM Data on the engagement of online consumers in eWoM were collected by directly asking about their engagement in eWoM regarding a specific online booking experience in the past twelve months. A binary scheme was used to denote the existence of the experience of engaging in eWoM. Respondents who answered yes to "in relation to this online booking experience, did you post a rating, review, experiences, suggestions or critical remarks on the online travel agent?" were coded "1" to indicate the existence of engagement in eWoM and "0" to indicate nonexistence. Disclosure of visual content The disclosure of visual content was measured as a binary variable. The respondents who reported having engaged in eWoM for a specific booking experience were asked what types of feedback they provided. Respondents who included photos in reviews were coded "1" to indicate the provision of visual content and respondents who did not provide visual content were coded "0."

Measurement model

We conducted confirmatory factor analysis (CFA) in AMOS to examine the validity of the constructs. Twenty-three items for three constructs (satisfaction, perceived performance, and expected performance) were included in the measurement model and allowed to load on their intended latent variables. The three factors were allowed to correlate freely. The three-factor measurement model showed an acceptable fit (χ^2 =477.249, d.f. = 215; CFI = .92; IFI = .92; RMSEA = .075). All of the items had significant and adequate loadings on their intended factors.

Table 1. Demographic Profile of Respondents

	N	%
Sex		
Male	105	48.6
Female	111	51.4
Age		
Under 18	19	8.8
18-25	75	34.7
26-30	97	44.9
31-40	18	8.3
41-50	6	2.8
51-60	1	0.5
Education (Edu)		
High school graduate or less	2	0.9
College diploma	28	13.0
Bachelor's degree	171	79.2
Postgraduate degree or above	15	6.9
Monthly Income (Income, in CNY)		
Below $2500	13	6.0
$2,501 - $5,000	36	16.7
$5,001 - $8,000	80	37.0
$8,001 - $12,000	66	30.6
$12,001 - $20,000	16	7.4
$20,000 or above	5	2.3
Online booking experience in the past 12 months		
Min = 1, Max = 36, Mean = 4.96, STDDEV = 4.081		

Descriptive analysis

Profile of respondents For all tests in this research, we controlled for the effects of the age, gender, education and income level of the participants. Table 1shows the demographic characteristics of the respondents. As shown in Table 2, the percentage of female respondents (51.4%) is slightly higher than that of male respondents (48.6%). Respondents between 18 to 50 years old accounted for 91% of the respondents. A majority of all respondents (79.2%) reported having received a bachelor's degree, with a large percentage (77.3%) earning a monthly salary of $5,001 or greater. Overall, the respondents had made five bookings on average in the past 12 months. Independent variables Because we used a logistic regression method for model testing, construct scores were calculated for the three factors. The straight average method was used to score satisfaction (SATIS), which was modeled as a reflective construct.

Disconfirmation (DISCO) was calculated in three steps.

(1) We used the DIFF approach to derive the score for each item of disconfirmation. Therefore, disconfirmation is also a second-order construct. We followed the procedure suggested in Diamantopoulos and Winklhofer (2001) and Liu et. al. (2012) for scoring second-order factors as in steps 2 and 3.

(2) The scores for the sub-dimensions of disconfirmation were calculated by taking the straight average of their respective indicators.

(3) We scored disconfirmation, a second-order formative construct, by taking the weighted averages of their sub-dimension scores, with the weights being the principal component analysis weights.

Table 2a shows the distribution of satisfaction and disconfirmation. Table 2b shows the distributions of the two dependent variables. Around half of the respondents reported having engaged in eWoM, and 76reportedhaving contributed visual content.

Table2a. Descriptive Statistics for the Independent Variables

	Min.	Max.	Mean	Std. Dev.
SATIS	1.7	7.0	5.106	1.22
DISCO	-3.2	1.1	-0.2	0.7

Notes: DISCO = Disconfirmation; SATIS = Satisfaction.

Table 2b. Summary Statistics for the Dichotomous Variables

		n	%
ENGAG	eWoM engagement	110	50.9
VISUAL	Visual content contribution	76	35.2

Hypothesis testing

Confirming the effects of disconfirmation on satisfaction Because the linkage between disconfirmation and satisfaction has been confirmed by a large body of research, this test serves as a confirmation of this effect to support our discussion of other hypotheses. The linear regression results are shown in Table 3.

Table 3. Antecedents of Satisfaction

	B	Standardized	Significance
DISCO	1.195	.688	**
Age_d1	-.228	-.053	
Age_d2	-.143	-.056	
Age_d3			
Age_d4	.448	.102	*
Age_d5	.622	.084	
Age_d6	2.877	.160	**
Gender	-.153	-.063	
Education_d1	-.378	-.030	
Education_d2			
Education_d3	.564	.188	**
Education_d4	.423	.088	
Income_d1	-.377	-.074	
Income_d2	-.771	-.236	**
Income_d3	-.419	-.166	**
Income_d4			
Income_d5	-.616	-.132	**
Income_d6	-.530	-.065	
Experience	-.005	-.018	
(Constant)	5.343		**

Remarks: * $p<0.05$, ** $p<0.01$

Relationship between satisfaction and the likelihood of eWoM engagement Because the dependent variable ENGAG is a binary variable that represents 1 (occurred) or 0 (not occurred), we used a logistic regression to formulate the relationship between the independent variables and the occurrence probability of ENGAG.

In addition, piecewise regression was used to test whether satisfaction has a negative influence on the likelihood of eWoM participation when satisfaction is low and a positive influence when satisfaction is high. Piecewise linear regression, also referred to as segmented regression, is a convenient statistical method that examines the different linear relations in a certain range of an independent variable (Cheon etal., 1993, Neter etal., 1996). The specification of the piece wise model is as follows:

$$Model\,E_1:\quad LR_{ENGAGE} = \ln\left(\frac{P_e}{1-P_e}\right) = \beta_{e0} + \beta_{e1}SATIS + \beta_{e2}(SATIS - c)\ \times\ dummy_c + \epsilon_e$$

where P_e is the conditional probability of a customer having eWoM engagement;β_{e0} denotes the constant and β_{ej}, $j > 0$is thecoefficient for the j[th] predictor. In addition, *c* is the tipping point of the satisfaction level (high vs. low), and *dummy* is 1 if $SATIS > C$ and 0 otherwise, which is used to check for significant change in the slope when $SATIS$ is on either side of the tipping point. If we can find negative coefficient $\beta_{e1}$and positive coefficientβ_{e2}, $\beta_{e1} + \beta_{e2} > 0$and both are significant, then hypotheses 2, 2a and 2b are all supported.$\epsilon_e$is the error term of the model.

We used the progressive search approach (Neter etal. 1996) to examine alternative models by altering within the range [2, 6] with the search step of ±0.1 to determine the optimal tipping pointer cutoff that led to significant β_{e1}, $\beta_{e2}$for the best model fit. It turned out that c=5.3 achieved the optimal model fit. Five alternative models with significant $\beta_{e1}$and$\beta_{e2}$are presented in Table 4 as E_{10}toE_{14},E_{10} to E_{14}, which were created with five different cutoffs.

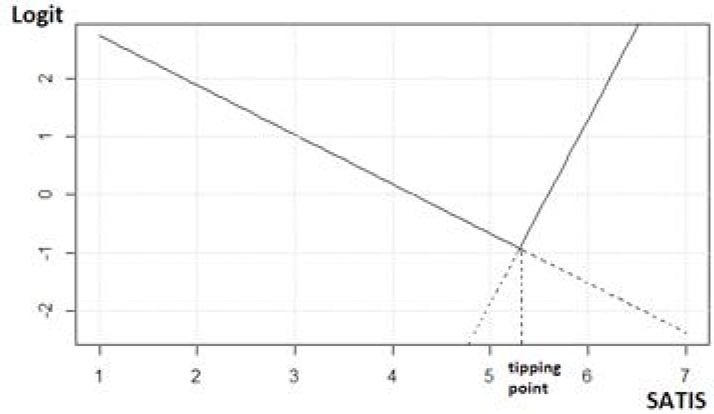
Table 4.Antecedents of ENGAG – Logistic Regression Models

Models	E_0	E_{10} c= 5.3	E_{11} c= 5.1	E_{12} c= 4.7	E_{13} c= 5.6	E_{14} c= 5.7	E_2 c= 5.3
SATIS	1.63	-.847**	-1.100**	-1.187**	-.642**	-.542**	-1.029**
$(SATIS - c) \times dummy_c$		4.010**	3.115**	2.851**	4.911**	5.197**	4.932**
DISCO							.099
Age_d1							24.436
Age_d2							23.536
Age_d3							23.499
Age_d4							23.930
Age_d5							22.497
Age_d6							
Gender							.927*
Education_d1							-1.182
Education_d2							-1.692
Education_d3							-1.798
Education_d4							
Income_d1							.911
Income_d2							1.363
Income_d3							1.360
Income_d4							1.786
Income_d5							1.140
Income_d6							
Experience							.019
(Constant)	-7.97	3.058**	3.798**	3.997**	2.345*	1.983*	-20.156
Nagelkerke R^2	0.13	.329	.274	0.245	.318	.301	.425
Cox & Snell R^2	0.1	0.247	.205	0.184	0.239	0.225	0.32
χ^2	63.66**	9.46	27.54	10.9*	11.7	15.3	4.12

Remarks:
- Control variables are categorical; hence they are coded into dummy variables.
- * p<0.05, ** p<0.01

The column for E_{10}in Table 4 shows that the coefficient for SATIS is significant ($\beta_{e1} = -.847, p < 0.001$); the coefficient for the term$(SATIS - c) \times dummy_c$ is also found to be significant ($\beta_{e2} = 4.010, p < 0.001$). Meanwhile, we have $|\beta_{e2}| > |\beta_{e1}|$, which indicates that a tipping point exists at approximately c = 5.3. A Hosmer and Lemes how test is conducted to evaluate the goodness of fit of the logistic regression models. The results of the Hosmer and Lemes how test for E_{10}arenot significant (i.e.,$\chi^2 = 9.46, p = 0.221$), suggesting a fairly good fit for the proposed model. The other four alternative models with significant β_{e1}andβ_{e2} are reported in Table 4 as E_{11}toE_{14}. It can be seen that E_{10} shows the highest predictive power ($Nagelkerke\ R^2 = 0.329$, $Cox\ \&\ Snell\ R^2 = 0.247$), in which the tipping point is c = 5.3. When satisfaction is lower than the cutoff, the influence of satisfaction on the urge to engage in eWoM is negative. The higher the satisfaction level, the less likely it is that the consumer will post reviews or comments on the OTA website. In contrast, when the satisfaction level is higher than the cutoff, the influence is positive. That is, the more satisfied the buyer, the more likely it is that s/he will engage in eWoMon the OTA website. When satisfaction is around the cutoff point, the buyer feels the most "normal" satisfaction level and hence is least likely to engage in eWoM. Hypotheses 2, 2a and 2b are therefore all supported. The regression line of the model E_{10} is illustrated in Figure 2

Figure 2. A Graphic Representation of the Piecewise Logistic Regression Result



We also tested the conventional (non-piecewise) logistic regression model, which is reported in Table 4 as model E_0. The coefficient of SATIS in this model is not significant (β_{e1} = 0.163, p = 0.15). Meanwhile, the result of its Hosmer and Lemeshow test is significant (i.e.,χ^2 = 63.66, p< 0.001), indicating that this model does not fit the data well. That is, the satisfaction level and the likelihood of eWoM engagement have no significant linear relationship. We obtained the final model $E_2$by adding other demographic covariates into E_0. Of all of the models shown in Table 4, the final model achieves the highest productiveness ($Nagelkerke\ R^2$ = 0.425, $Cox\ \&\ Snell\ R^2$ = 0.32) and the best model fit (χ^2 = 4.12). In addition, we examined the multicollinearity for the models in Table 4. The results showed that the mean variance inflation factors (VIF) for all models are much lower than 10, suggesting that multicollinearity is not a major concern (Mason 1989). Relationship between satisfaction and the likelihood of visual content contribution. We formulate the piecewise logistic regression model as follows to test hypotheses 3, 3a and 3b.

$$Model\ V_1:\quad LR_{VISUAL} = \ln\left(\frac{P_v}{1-P_v}\right) = \beta_{v0} + \beta_{v1}SATIS + \beta_{v2}(SATIS - c) \times dummy_c + \epsilon_v$$

whereP_v is the conditional probability of a customer contributing visual content;β_{v0} denotes the constant and β_{vj}, j > 0is thecoefficient for the j[th] predictor. $\epsilon_v$is the error term. Similarly, the term$(SATIS - c) \times dummy_c$is used to test the second segment of the regression line. Thus if we can find negative coefficient $\beta_{v1}$and positive coefficientβ_{v2}, $\beta_{v1} + \beta_{v2}$ > 0and both are significant, then hypotheses 3, 3a and 3b are all supported. The relationship between satisfaction and the contribution of visual content was tested and reported as shown in Table 5 (models V_{10}~V_{14}). Cutoffs leading to significant β_{v2}werefound at around 5.3,5.6 and 5.7.β_{v1} Inthese models, however, are positive. These results imply that the hypothesized V-shape relationship between SATIS and VISUAL may not exist. We further tested the non-piecewise linear logistic model between SATIS and VISUAL, reported as V_0 in Table 5.

The coefficient of SATIS is significant (β_{v1} = 2.774, p< 0.001). The R^2 measures ($Nagelkerke\ R^2$ = 0.583, $Cox\ \&\ Snell\ R^2$ = 0.420) suggest that the model has good predictivenessand the Hosmer and Lemeshow test result suggests that the model fits well (χ^2 = 12.120, p = 0.097). Therefore, we conclude that hypotheses 3, 3a and 3b are not supported. Instead, the results indicate a linear relationship between SATIS and VISUAL. That is, the more satisfied the buyer is, the more likely s/he is to contribute visual content to the OTA website. By adding other demographics as covariates toV_0, we obtained the final model V_2 with $Nagelkerke\ R^2$ = 0.682, $Cox\ \&\ Snell\ R^2$ = 0.491, as shown in Table 5. Note that we did not add the piecewise term into the final model because the additional segment retains the same sign as the first segment (both $\beta_{v1}$and$\beta_{v2}$are positive). This term adds limited predictive power while greatly increasing the model's complexity and therefore is unnecessary.

Table 5. Antecedents of VISUAL – Logistic Regression Models

Models	V_0	V_{10} c= 5.3	V_{11} c= 5.1	V_{12} c= 4.7	V_{13} c= 5.6	V_{14} c= 5.7	V_2 c= 5.3
SATIS	2.774**	1.218	1.334	1.396	1.410*	1.574*	3.484**
$(SATIS - c)$		2.327*	1.643	1.483	2.822*	2.868*	
DISCO							.329
Age_d1							24.177
Age_d2							21.713
Age_d3							21.753
Age_d4							21.161
Age_d5							21.330
Age_d6							
Gender							.781
Education_d1							-19.365
Education_d2							-2.628*
Education_d3							-1.474
Education_d4							
Income_d1							-1.992
Income_d2							-1.851
Income_d3							-1.728
Income_d4							-.325
Income_d5							-1.878
Income_d6							
Experience							-.110
(Constant)	-16.144**	-8.316*	-9.289	-9.792	-9.096*	-9.867**	-39.197
Nagelkerke R^2	.583	.599	.586	.585	.604	.603	.682
Cox & Snell R^2	.420	.431	.422	.421	.435	.434	.491
χ^2	12.120	8.184	11.632	12.064	6.995	7.249	10.386

Remarks:
- Control variables are coded into dummy variables.
- * $p<0.05$, ** $p<0.01$

The possible multicollinearity of the models in Table 5 is examined. Again, the mean variance inflation factors (VIF) for all of these models are much lower than 10, indicating that multicollinearity is not a problem (Mason 1989).

Discussion of findings

This study aims to provide a better understanding of the antecedents of consumers' engagement in eWoM through the lens of EDT. Hypothesis 1 states that the disconfirmation between pre-purchase expectations and actual product performance will have a positive impact on consumers' satisfaction. That is, negative disconfirmation leads to low satisfaction, whereas high satisfaction is the consequence of positive disconfirmation. This hypothesis is supported, reaffirming the findings in the literature.

Drawing on EDT, we predict in hypotheses 2, 2a and 2b that both very low and very high satisfaction leads consumers to actively engage in eWoM. When satisfaction feelings are moderate, consumers are less likely to express their opinions or share their experiences on the purchase website. These hypotheses are supported by our analysis using piecewise logistic regression models. Likewise, we hypothesize a V-shaped relationship between satisfaction and the likelihood of visual content contribution in hypotheses 3, 3a and 3b. Our analysis, however, shows no support for these hypotheses. It is revealed in further testing that satisfaction has a positive influence on the contribution of visual content. One plausible explanation for this result is that contributors of different types of content have different motivations (Stoeckl et al., 2007). Extreme satisfaction may have a positive effect on consumers' engagement in eWoM, but different motivations may encourage contributors to disclose voluntary information like visual content when they post online reviews.

For example, mood management theory posits that people tend to use information selectively to maintain or alter their prevailing mood states (Wegeneret al., 1994, Zillmann, 1988a). We therefore postulate that consumers have a propensity to share product photos or videos to prolong an enjoyable mood when they feel satisfied with a product. However, when a buyer is dissatisfied, visual content does not help cancel out the bad mood (and indeed may do the opposite). S/he is hence unlikely to contribute media-rich content through eWoM when dissatisfied.

Implications and Future Research

Drawing on EDT, this research studies online consumers' eWoM engagement and contribution behavior and attempts to explore the dynamics between expectation discrepancy, satisfaction and eWoM engagement. It has a few important implications for both research and managerial practices. The findings of this study add interesting insights to the literature on review-generating factors by highlighting disconfirmation and satisfaction askey motivators of online consumers who engage in eWoM. Further, we examine the effects of disconfirmation and satisfaction on visual content contribution and find that the predicted V-shaped relationship between satisfaction and the likelihood of visual content contribution does not exist. These unexpected results enrich the extant body of knowledge about eWoM contribution behavior. EWoM engagement, particularly the contribution of media-rich content, has been recognized as critical in social-media marketing. It is therefore essential for practitioners to understand the prominent motivators of such behavior. Our findings shed light on the mechanisms of customer review generation.

The findings of this study should be interpreted in light of certain limitations. First, the variable of disconfirmation may not have been fully or properly captured by the measurement method used in the study. As the respondents of this study were asked whether they had experience of booking hotels and providing feedback before filling in the questionnaires, and were then asked to recall a recent booking experience, their evaluations of disconfirmation between pre-purchase expectations and the actual performance of hotel services were based on a past transaction-specific experience. The time effect was ignored in this study; however, time may impact consumers' perceptions of expectations and performance. In addition, perceived monetary price and buyer involvement may also have a strong influence on consumers' urge to engage in eWoM when disconfirmation is perceived. Thus, future research is suggested to address these limitations.

References

Anderson, R. E. (1973). Dissatisfaction: The expectancy perceived. *Journal of Marketing Research*, 10(1), 38–44.

Anderson, E., & Sullivan, M. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing Science*, 12(2), 125-143.

Barnes, S. B. (2006). A privacy paradox: Social networking in the United States. *First Monday*, 11(9).

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly:* 351-370.

Bronner, F., & de Hoog, R. (2011). Vacationers and eWoM: Who posts, and why, where, and what? *Journal of Travel Research*, 50(1), 15–26. http://doi.org/10.1177/0047287509355324

Cheon, M. J., Groven, V., &Sabherwal, R. (1993). The evolution of empirical research in IS: A study in IS maturity. *Information andManagement*, 24(3), 107-119.

Chou, S. Y. (2012). Online reviews and pre-purchase cognitive dissonance: A theoretical framework and research propositions. *Journal of Emerging Trends in Computing and Information Sciences,* 3(2), 199 –204.

Coulthard, L. J. M. (1988). Measuring service quality: A review and critique of research using SERVQUAL. *International Journal of Market Research,* 46(4), 479–498.

Cui, G., Lui, H.-K., &Guo, X. (2012). The effect of online consumer reviews on new product sales. *International Journal of Electronic Commerce*, 17(1), 39–57. http://doi.org/10.2753/JEC1086-4415170102

Diamantopoulos, A., &Winklhofer, H.M. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, 38(2), 269–277.

Dimoka, A., Hong, Y., &Pavlou, P. A. (2012). On product uncertainty in online markets: Theory and evidence.*MIS Quarterly,* 36(2), 395-426.

Elkhani, N. (n.d.). Review on "Expectancy Disconfirmation Theory" (EDT) model in B2C e-commerce, 95–102.

Engler, T. H., Winter, P., & Schulz, M. (2015). Understanding online product ratings: A customer satisfaction model. *Journal of Retailing and Consumer Services*, 27, 113–120. http://doi.org/10.1016/j.jretconser.2015.07.010

Festinger, L., (1954). A theory of social comparison processes. *Human Relations* 7, 117-140.

Fornell, C., &Larcker, D. F. 1981. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research,* 18(1), 39-50.

Fu, J. R., Ju, P. H., & Hsu, C. W. (2015). Understanding why consumers engage in electronic word-of-mouth communication: Perspectives from theory of planned behavior and justice theory. *Electronic Commerce Research and Applications*, 14(6), 616–630. http://doi.org/10.1016/j.elerap.2015.09.003

Hayes, A. F. (2013). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York: Guilford Press.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., &Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, 18(1), 38–52. http://doi.org/10.1002/dir.10073

Ho, Y.-C. (Chad), Wu, J., & Tan, Y. (2014). Disconfirmation effect on online rating behavior: A dynamic analysis. *SSRN Electronic Journal*, 1–38. http://doi.org/10.2139/ssrn.2516409

Singh, J., &Pandya, S. (1991). Exploring the effects of consumers' dissatisfaction level on complaint behaviours. *European Journal of Marketing*, 25(9), 7-21.

Lafky, J. (2014). Why do people rate? Theory and evidence on online ratings. *Games and Economic Behavior*, 87, 554–570. http://doi.org/10.1016/j.geb.2014.02.008

Levesque, T. &McDougall, G. H. G. (1992). Measuring service quality: An assessment of the SERVQUAL scale. *Administrative Sciences Association of Canada,* 13(6), 127-136.

Lewis, R.C. (1987). The measurement of gaps in the quality of hotel services. *International Journal of Hospitality Management,* 6(2), 83-88.

Litvin, S. W., R. E. Goldsmith, &B. Pan (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management,* 29, 458-468.

Liu, B. Q., &Goodhue, D. L. (2012). Two worlds of trust for potential e-commerce users: Humans as cognitive misers. *Information Systems Research* 23(4), 1246-1262.

R. Mason, R. Gunst, &J. Hess.(1989).*Statistical Design and Analysis of Experiments: Applications to Engineering and Science*.New York: Wiley.

Mauri, A. G., &Minazzi, R. (2013). Web reviews influence on expectations and purchasing intentions of hotel potential customers. *International Journal of Hospitality Management*, 34(1), 99–107. http://doi.org/10.1016/j.ijhm.2013.02.012

Neter, J., Kutner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). *Applied linear statistical models* (Vol. 4). Chicago: Irwin.

Nunnally, J. C. (1967). *Psychometric theory.* New York: McGraw Hill.

Vicki McKinney, Kanghyun Yoon, &Fatemeh “Mariam” Zahedi. (2002).Themeasurement of web-customer satisfaction: An expectation and disconfirmation approach. *Information Systems Research* 13(3), 296-315. http://dx.doi.org/10.1287/ isre.13.3.296.76

Oliver, R. L. (1977). Effect of expectation and disconfirmation on postexposure product evaluations: An alternative interpretation. *Journal of Applied Psychology* 62(4), 480-486.

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research* 17(4), 460-469.

Oliver, R. L. (1987). An investigation of the interrelationship between consumer (dis) satisfaction and complaint reports. *NA-Advances in Consumer Research* 14, 218-222.

Parasuraman, A., Zeithaml, Valerie A. & Berry, Leonard L. (1988). SERVQUAL: a multiple-item scale for measuring consumer perceptions of service quality.*Journal of Retailing*, 64(1), 12-40.

Picazo-Vela, S., Chou, S. Y., Melcher, A. J., & Pearson, J. M. (2010). Why provide an online review? An extended theory of planned behavior and the role of Big-Five personality traits. *Computers in Human Behavior*, 26(4), 685–696. http://doi.org/10.1016/j.chb.2010.01.005

Ribbink, D., Van Riel Allard, C. R., Liljander, V., &Streukens, S. (2004). Comfort your online customer: Quality, trust, and loyalty on the Internet. *Managing Service Quality,* 14(6), 446–456.

Rust, R. T., J. J. Inman, J. Jia, &A. Zahorik. (1999). What you don’t know about customer-perceived quality: the role of customer expectation distributions. *Marketing Science* 18(1), 77-92.

Serra Cantallops, A., & Salvi, F. (2014). New consumer behavior: A review of research on eWoM and hotels. *International Journal of Hospitality Management*, 36, 41–51. http://doi.org/10.1016/j.ijhm.2013.08.007

Sobel, M. E. (1982). Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models.*Sociological Methodology*, 13, 290-312.

Sparks, B. A., & Browning, V. (2010). Complaining in cyberspace: The motives and forms of hotel guests' complaints online. *Journal of Hospitality Marketing and Management,* 19(7), 797-818.

Spreng, R. A., &Mackoy, R. D. (1996). An empirical examination of a model of perceived service quality and satisfaction. *Journal of Retailing*, 72(2), 201–214. http://doi.org/10.1016/S0022-4359(96)90014-7

Spreng, R. A., & Page, T. J. (2003). A test of alternative measures of disconfirmation. *Decision Sciences*, 34(1), 31–62. http://doi.org/10.1111/1540-5915.02214

Heng Tang and Xiaowan Lin. Institutional Communication Facilitators for The Reduction of Experience Products Uncertainty in E-Marketplaces – The Initial Interaction Perspective. The Pacific Asia Conference on Information Systems (PACIS). Chiayi, Taiwan. 2016.

Tse, A. C. (2003). Tipping behaviour: A disconfirmation of expectation perspective. *International Journal of Hospitality Management*, 22(4), 461–467. http://doi.org/10.1016/j.ijhm.2003.07.002

Wegener, D. T., & Petty, R. E. (1994). Mood management across affective states: The hedonic contingency hypothesis. *Journal of Personality and Social Psychology*, 66(6), 1034.

Yoo, K. H., &Gretzel, U. (2008). What motivates consumers to write online travel reviews? *Information Technology andTourism*, 10(4), 283-295.

Zhan Shi, HuaxiaRui, &Andrew B. Whinston. (2014). Content sharing in a social broadcasting environment: Evidence from twitter. *MIS Quarterly,*38(1), 123-142.

Zillmann, D. (1988a). Mood management through communication choices. *American Behavioral Scientist*, 31(3), 327–341.