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Antecedents driving the different levels of behavioral engagement in online travel communities

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Antecedents driving the different levels of behavioral engagement in online travel communities

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Abstract: With the rapid development of online travel communities, understanding the determinants of users' engagement with the online travel communities is critically important for researchers and practitioners. The purpose of this study is to understand which environmental cues drive the engagement behaviors. Specifically, by using a rich data set from a large travel knowledge sharing website and seemingly unrelated regression model, we investigate and compare the antecedents leading to two different behavioral engagements including liking and social interaction. We find that information-, source-, and social interaction-level cues are associated with these behavioral engagements. The results also demonstrate the differential effectiveness of these cues between these two engagement behaviors. Our empirical findings provide theoretical and practical implication for online travel community operators to build a vibrant and successful online travel community.

Keywords: online travel community, stimulus-organism-response (S-O-R) paradigm, engagement behavior

1. INTRODUCTION

With the rapid development of information technology, consumers begin to have the increasing conscious of relying on word-of-mouth, no longer depending just on information from the advertisement [1]. Consumers nowadays are no longer the passive information receivers, but the active information explorers and creators, which partially transforms the role in all aspects of business activities. The increasing popularity of online community is partially attributed to the rapid development of the Internet and the change of consumers' role in the business activities. Online community refers to a place where large groups of individuals discuss and interact with each other around a shared interest [2]. Tourism represents one of the most information intensive industries, online user-generated contents has played an essential role in information sources for travelers who has a demand for knowledge of the destination. The integration of online community in tourism has been facilitated by the enhanced development of the Internet, which changed the way of travel information dissemination.

Lee et al. demonstrate that if an online travel community is lack of participation, it will lose the competitiveness [3]. It is consistent with the fact that the success of an online travel community is relied on the active participation among members as well as the interesting user-generated contents sharing. Given the importance of the active interactions in online communities, scholars start to devote their efforts to identifying factors affecting consumers' engagement in online travel communities. Engagement in this study is defined as user continued interaction with an online travel community. Engagement manifests itself in several forms. In the case of online communities, like, sharing, and social discussion are all the behavioral manifestations of engagement. The extant literature has associated a high level of consumer engagement with loyalty, positive word of mouth, and sales growth [4]. For instance, Oh et al. explore how personal and interactive consumer engagement in Facebook, YouTube and Twitter influence the movie box-office revenue [4]. However, there is still a lack of consensus in the literature regarding the antecedents of the customer engagement. Considering that consumer engagement behavior differs in various business fields due to context-dependent nature of this phenomenon, it is of necessity to examine this topic in different service settings in order to know consumer engagement phenomenon in more detail [5]. Moreover, behavioral engagement has many manifestations, no research to our knowledge has ever investigated and compared the factors driving the different behavioral

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engagement.

Taking into account above mentioned, this paper seeks to find the answer to the following questions: (1) what and how do environmental cues in online travel communities stimulate the engagement behaviors? (2) Is there any difference of the environmental cues in influencing different behavioral engagement? To answer these questions, we develop a research model to explain behavioral engagement with respect to online travel community by drawing upon recent literature on online community participation behavior. Specifically, we build on the stimulus-response framework by integrating seven attributes from three distinct levels (that is, information features, community status/ opinion leaders and social interactive features) as stimulus leading to behavior engagement. We also investigate and compare the differential effectiveness of these stimulus in affecting distinct behavioral engagement in order to provide a more nuanced understanding of the impact of these antecedents. An empirical study was conducted with a dataset collected from a major Chinese travel social networking site (SNS) instead of individual survey data that are frequently used in the previous tourism literature.

2. THEORETICAL BACKGROUND AND HYPOTHESES

2.1 Consumer engagement

Having a good understanding of consumer engagement is virtually essential for both researchers and managers. Up to now, the concept of engagement has not been defined explicitly. Previous studies show that engagement describes consumers' attitudes, activities, psychology, the state of involvement, the emotion of interested [1]. In general, consumer engagement refers to consumers' interactions with others as well as interaction experiences [6]. There are some similarities between the concept of engagement and involvement and interactivity, the latter two factors reflect consumers' interest and attitude towards a certain product or service, while engagement provides a greater range and extend to the emotional and cognitive aspects [7]. User involvement is generally defined as a person's perceived relevance or psychological identification with the object based on inherent needs, values and interests [8]. As such, psychological engagement (including vigor, absorption, and dedication dimensions) is a much broader construct than involvement. Involvement only overlaps the dedication dimension of psychological engagement. Dedication can be regarded as a particularly strong involvement [8]. Pagani and Mirabello regard engagement as a higher-level measurement of consumers' relationship with the social media [1]. Braojos-Gomez et al. suggest that social online consumer engagement can be found in social media such as Facebook, Twitter, a firm's website and positively related to a firm's website performance [9]. Calder and colleagues identify two types of engagement, personal engagement focus on the content and individuals, while social-interactive engagement mainly reflects the interactivity with others [10]. Consumer engagement on online community involves a series of activities, such as exchanging user-generated content, having interactions with others. For example, consumer engagement on an online travel community includes travelogue sharing, giving comments and likes, travelogue reproduce etc.

2.2 The stimulus-organism-response framework

The stimulus-organism-response framework (S-O-R) was proposed by Mehrabian and Russell [11], which described the mechanism of how environment cues affects human behavior. The S-O-R framework posits that different stimulus of the environment influence the consumer's cognitive or affective experiences (organism), which in turn result in consumer's responses [12][13]. In the context of online community, stimuli can be conceptualized as an influence that arouses the perceived value of an individual or organism. The response includes psychological reactions or behavior reactions. The S-O-R framework demonstrates that stimulus coming from the environment influence the cognitive and emotional state of individual or organism, which in turn lead to behaviors.

The use of the S-O-R model as a theoretical and appropriate overarching theory for this study is of two reasons. First, the S-O-R theory has been extensively and successfully applied in diverse online contexts [14] [15]. Previous studies can support the applicability of this model to show the consumer cognitive reactions and behaviors for the stimulus [16]. Second, accounting for the key function of community environment cues in influencing the engagement among community, the S-O-R model offers a structured method to explore the mechanism for how the community features act on consumer perceived value and, in turn influence the behavior of engagement. Hong and Joqinapelly propose that in online stores, stimuli can be atmospheric cues (e.g., interactivity and vividness) that can influence consumers' cognitive and emotional state (e.g., perceived value), and then result in the response of purchasing behavior [17].

In this study, the stimuli refer to the online travel community environmental cues that are related to the consumers. Previous study demonstrates that three building blocks (information, source and receiver) have an effect on consumers' information assessment [18]. Accordingly, this study proposes that the information, source and social interaction level representing the stimuli, trigger the perceived value of the members among the online travel community, which then result in the engagement behavior.

2.3 Research model and hypotheses

2.3.1 The influence of information features

With the rapid development of tourism and Web 2.0 technologies, many online travel communities come into being, where consumers can exchange information about tourism destinations and service in the form of travelogue. Previous studies suggest that textual content of online reviews plays an important role in assessment of the products and service on the internet, and affects consumers' attitude towards the certain product and service significantly [16] [19]. Moreover, Lu et la. show that travel photos play an essential part in tourist sites [20]. Therefore, this study focus on two attributes of the sharing travelogues information feature: the length and the information vividness of the travelogues. Filieri explores that the depth of information can be showed by the length of the sharing post [21]. Longer post generally includes rich diversity information of the travel destination and can reflect the bloggers' authenticity, which can enhance the recognition and engagement among the visitors. In addition, the increased vividness in product presentations influences consumers' perceived enjoyment significantly [22]. Moreover, the vividness of posts can provide hedonic benefits for members in the online travel community, which can act as a place for pressure release and it is essential in today's society. Thus, the following hypotheses are proposed:

H1a: There is a positive relationship between information vividness and the liking behavior.

H1b: There is a positive relationship between information vividness and the social interactions behavior.

H1c: There is a positive relationship between the travelogue's length and the liking behavior.

H1d: There is a positive relationship between the travelogue's length and the social interactions behavior.

2.3.2 The influence of source feature

Previous studies propose that expertise among online community can help motivate online trust strongly [13]. Mayer et al. suggest expertise as an individual's capability forming within certain field by the accumulated knowledge to complete the tasks [11]. Source expertise can enhance the confidence of a certain viewer to believe the authenticity and reliability of the blog. Furthermore, source expertise can help emerge an atmosphere of following, which can positively increase the engagement among members. Willemsen et al. suggest that visitors are more likely to identify with the experts and adjust their original attitudes [19]. Expert is not the only one that affects visitors' attitudes and perceived value, the relationship of leader and followers also play an important role in the source influence. Bohórquez et al. explain that if the followers have the similar value and interests with the people they follow closely, the followers will be driven by the bond with the certain people [23]. Previous studies investigate that centrality is regarded as an essential role in identifying the most important people at the central position of a certain social media or those that are connected well in social network analysis [11]. Degree centrality refers to the number of links related to a node, including in-degree centrality and out-degree centrality. In-degree centrality describes the number of links point to the node, while the out-degree centrality is regard as the number of ties point to the others [24]. In this field, individuals with high in-degree centrality can assemble adherents with similar interests, which can reinforce community cohesiveness enormously. While the individuals with high out-degree centrality can be described as the followers who are influential and gregarious actors [25], which can enhance the viability of the certain community and makes great contribution to the engagement behaviors. Hence, it is reasonable to propose the following hypotheses:

H2a: There is a positive relationship between the expertise and the liking behavior.

H2b: There is a positive relationship between the expertise and t the social interactions behavior.

H2c: There is a positive relationship between the degree centrality of a contributor and the liking behavior.

H2d: There is a positive relationship between the degree centrality of a contributor and the social interactions behavior.

2.3.3 The influence of social interaction feature

Interactivity can be defined as the indispensable features that affect consumers' participation and usage [12], and the perceived relationship can be a bonding that contact each other closely. Interactivity can collect the feedback of others, which is helpful for the new users to have a latest and comprehensive recognize of the search object. The information and emotion exchange also cultivate and stimulate the habit of engagement behaviors. Because of the opportunity to communicate and share among members, interactivity improves the sense of involvement and social presence. In this field, the extent of social interaction can be reflected in the breadth and depth of the interactivity, which can be described by the average length of the reviews [7]. A survey reveals that nearly 95% of travelers have a habit of reading online reviews if they have intention of hotel reservation, and more than 33% travelers suppose that online reviews is an essential and critical tool for decision making [17]. Moreover, Hu and Chen suggest that if the reviews are with appropriate length and no grammar errors, they are more likely to be received as helpful [26]. And the more reviewers can provide more reviews, which can reflect the activity and the engagement of the community. In addition, the numbers of travelogues can also be a reflection of interactivity among a certain community. Previous studies suggest that User-generated content (UGC) is regard as a helpful and important resource on the internet, and it is also considered as an electronic word-of-month which is valuable in today business activity [26]. UGC can be regard as the prerequisite of online community vitality and the foundation of a certain online community, because without perceived useful UGC, there would be no need to visit and no generated traffic. In this case, the number of travelogues can be a premise of interaction and engagement behaviors. Therefore, we hypothesize:

H3a: There is a positive relationship between the number of travelogues and the liking behavior.

H3b: There is a positive relationship between the number of travelogues and the social interactions behavior.

H3c: There is a positive relationship between the average review length and the liking behavior.

H3d: There is a positive relationship between the average review length and the social interactions behavior.

H3e: There is a positive relationship between the number of reviewer and the liking behavior.

H3f: There is a positive relationship between the number of reviewer and the social interactions behavior.

2.3.4 Control variables

Post viewing number, interval time, gender of contributors, heterogeneity of destination and location were included as control variables in our research model. Prior research reports that the larger number of post viewing can cause greater intention to post on online community [27]. In addition, higher page views will be generated with the longer the interval time. Previous studies explore gender differences in online behavior and show that females are more likely to participate in engagement activities, and enjoy making suggestions than males [22].

Heterogeneity of destination reflects the types of the destination, according to a survey conducted by World Tourism Cities Federation and Ipsos [28], natural and heritage destinations are more popular than urban destinations among Chinese tourists. Moreover, foreign tourism destinations often reflect a higher consumption cost than destinations at domestic, and the high cost probably decrease the communication enthusiasm.

3. RESEARCH METHOD

3.1 Data collection

To test the hypotheses, we collected data from one of the first travel social networking websites and the largest travel social media platform in China, Mafengwo.cn (http://www.mafengwo.cn/). We downloaded web pages of travelogues and its replies from Mafengwo into our database. In total, we collected 29302 travelogues for 26 worldwide destinations.

3.2 Measures

The focus is to compare the difference from the two different engagement behaviors, this study proposes two dependent variables: the number of likes and the number of interaction behaviors (the sum of numbers of user interacts and author interacts). According to Li and Bernoff, they identified six groups of different levels of involvement behavior online, including creators, critics, collectors, joiners, spectators and inactives orderly from the most engaged behavior to no activity [1]. Critics refer to the comments related to the posted contents published by others, and joiners show the participation in a social network. Wong describes identification as the basic engagement, and regards commitment that people are passionate to devote quantity of time and/or money as advance engagement [29]. According to Ghuneim's typology of engagement, adoption was regarded as the low degree of engagement, commenting was measured as the medium degree, content creation is the high degree of engagement and social behavior is regarded as the highest degree of engagement [30]. On the foundation of these studies, the behavior of giving likes to a certain product or service can be regarded as the behavior of joiners or adoption, thus, we select the number of likes as the initial behavioral engagement measure. While, according to these studies, comments were taken as the advanced behavioral engagement. Therefore, we select the number of interactions as advanced behavioral engagement measure.

As for independent variables, the travelogue's length is measured by the word count of a travelogue. Information vividness is measured by the number of photos in a travelogue. Expertise is measured by the bloggers' ranking scores in the community weighted by system, collecting the first 20% of the data orderly from high to low according to Pareto Principle. The degree centrality of a contributor is reflected by the addition of the number of followers and the number of followings. The average review length is measured by the average word count of a review. The number of travelogues is measured by the number of travelogues a certain users create. Table 1 provides the description statistics of the key variables. Table 2 shows the correlation matrix of the variables.

Table 1. Description statistics of key variables

variable	mean	std.dev.	Min	Max
Likes	40.69	461.09	0	29692
Interactions	15.32	63.28	0	2587
TravelogueLength	44669.62	6733.22	0	13955
Pictures	54.25	72.76	0	2010
Rating	9.48	6.61	0	45
Followings	82.46	286.67	0	10245
Followers	266.22	9256.64	0	1553840
NumberOfTravelogues	9.77	21.83	0	259

Ave Review Length	26.31	19.44	0	382
Reviewer Number	15.03	58.91	1	2204
Expert	0.2	0.4	0	1
View Number	2127.49	9643.58	3	479023
Interval Time	378.5	345.79	0	2784
Male	0.33	0.47	0	1
Exotic	0.4	0.49	0	1
Natural	0.78	0.42	0	1
Heritage	0.06	0.23	0	1
Urban	0.17	0.38	0	1

Table 2. Correlation matrix of variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Log(Like Number)	1													
Log(Interaction Number)	0.66	1												
Log(Picture Number)	0.14	0.26	1											
Log(Travelogue Length)	0.3	0.29	0.17	1										
Expert	0.28	0.26	0.07	-0.04	1									
Log(Following Number+Follower Number	0.39	0.37	0.09	-0.04	0.71	1								
Log(Travelogue Number)	0.12	0.03	0.03	0.13	0.58	0.59	1							
Log(AveReview Length)	0.22	0.31	0.05	0.21	-0.01	0.04	-0.08	1						
Log(Reviewer Number)	0.76	0.88	0.2	0.28	0.27	0.39	0.02	0.26	1					
Log(View Number)	0.77	0.71	0.1	0.32	0.27	0.4	0.08	0.29	0.82	1				
Log(Internal Time)	0.15	0.07	-0.06	-0.14	0.24	0.35	0.25	0.07	0.14	0.39	1			
Male	-0.03	-0.05	0.01	-0.16	0.19	0.17	0.18	-0.06	-0.04	-0.04	0.06	1		
Exotic	0.21	0.11	-0.06	0.16	-0.05	-0.03	0.01	0.06	0.17	0.29	0.09	-0.08	1	
Heritage	-0.02	-0.04	0.01	-0.04	0.14	0.14	0.05	-0.07	-0.03	-0.03	0.05	0.09	0.11	1

4. DATA ANALYSIS AND RESULTS

4.1 Model specification

In order to address the research question, we rely on seemingly unrelated regression model to investigate how the environment cues embedded in a travelogue page were related to the dependent variable (the number of likes and the number of interactions). We took the log of the dependent variable and some of the independent and control variables to smooth large values. The models are as followed:

$$\begin{aligned}\log(likes) = \alpha &+ \beta_1 \cdot \log(TravelogueLength) + \beta_2 \cdot \log(PictureNumber) \\ &+ \beta_3 \cdot Expert + \beta_4 \cdot \log(FollowingNumber + FollowerNumber) \\ &+ \beta_5 \cdot \log(AveReviewLength) + \beta_6 \cdot \log(TravelogueNumber) \\ &+ \beta_7 \cdot \log(ReviewNumber) + \gamma_1 \cdot \log(ViewNumber) \\ &+ \gamma_2 \cdot \log(InternalTime) + \gamma_3 \cdot Male + \gamma_4 \cdot Exotic + \gamma_5 \cdot Urban + \varepsilon\end{aligned} \tag{1}$$

$$\begin{aligned}\log(\text{int}\,eractions) = {} & \alpha + \beta_1 \cdot \log(Trave\log ueLength) + \beta_2 \cdot \log(PictureNumber) \\ & + \beta_3 \cdot Expert + \beta_4 \cdot \log(FollowingNumber + FollowerNumber) \\ & + \beta_5 \cdot \log(Ave\,\mathrm{Re}\,viewLength) + \beta_6 \cdot \log(Trave\log ueNumber) \\ & + \beta_7 \cdot \log(\mathrm{Re}\,viewNumber) + \gamma_1 \cdot \log(ViewNumber) \\ & + \gamma_2 \cdot \log(InternalTime) + \gamma_3 \cdot Male + \gamma_4 \cdot Exotic + \gamma_5 \cdot Urban + \varepsilon\end{aligned} \tag{2}$$

4.2 Hypotheses testing

Seemingly unrelated regression is used to estimate the influence of information, source and social interaction level features on the engagement of the community, which can improve the estimation efficiency. We perform the analysis estimating the liking behavior (model 1 and model 2) and interaction behavior (model 3 and model 4) separately. Control variables were entered into the model firstly, then all the information, source, social interaction level features variables were entered into the model. The result is listed in table 3.

Table 3. Regression output

	Model 1	Model 2	Model 3	Model 4
Log(Picture Number)		-0.002		0.068* * *
		(0.004)		(0.002)
Log(Travelogue Length)		0.023* * *		0.016* * *
		(0.003)		(0.001)
Expert		0.002		0.012*
		(0.008)		(0.006)
Log(Following Number+Follwer Number)		0.052* * *		0.055* * *
		(0.005)		(0.003)
Log(Travelogue Number)		0.106* * *		0.001
		(0.007)		(0.005)
Log(AveReview Length)		-0.018* *		0.150* * *
		(0.006)		(0.004)
Log(Reviewer Number)		0.491* * *		1.095* * *
		(0.011)		(0.007)
Log(View Number)	1.195* * *	0.758* * *	1.000* * *	0.021* *
	(0.006)	(0.011)	(0.005)	(0.007)
Log(Internal Time)	-0.257* * *	-0.181* * *	-0.322* * *	-0.089* * *
	(0.005)	(0.006)	(0.005)	(0.004)
Male	0.023* * *	-0.002	-0.015	-0.027* * *
	(0.005)	(0.005)	(0.004)	(0.003)
Exotic	-0.117* * *	-0.046 * * *	-0.196* * *	-0.044* * *
	(0.006)	(0.006)	(0.006)	(0.004)
Heritage	0.103* * *	0.047* * *	0.063* * *	-0.006
	(0.011)	(0.010)	(0.009)	(0.007)
Urban	0.110* * *	0.081* * *	0.009* * *	-0.012*
	(0.008)	(0.007)	(0.007)	(0.005)
Constant	-2.112* * *	-1.682* * *	-1.331* * *	-0.501* * *
	(0.016)	(0.020)	(0.014)	(0.013)
R-squared	0.629	0.666	0.583	0.795

* < 0.05, * * < 0.01, * * * < 0.001

We calculate the variance inflation factor (VIF) measure for all the variables. Because all of the VIF values are below 5, it is reasonable to infer that multicollinearity in the data is not a concern. The model 1has a R-squared value of 0.629, and the model 2 has a R-squared value of 0.666. The results reveal that the word count of a travelogue and the degree centrality of a contributor are positively related to the liking behavior, supporting H1c and H2c. The number of travelogues and reviewers are significantly associated with the liking behavior, thus H3a and H3e are supported. The regression coefficients indicate that the number of reviewers (β =0.49, $p<0.01$) and the number of travelogues (β =0.11, $p<0.01$) are the most important factors in attracting users to engage in a certain online community, which is consistent with the fact that travelogues are the foundation of the community.

As for the model of social interactions behavior estimation, the model 3 has a R-squared value of 0.584, and the model 4 has a R-squared value of 0.795. All of the coefficients are positive and significantly associated with the number of interactions except the number of travelogues. Thus, H1b, H1d, H2b, H2d, H3d and H3f are supposed. The result shows that the number of reviewers (β =1.09,$p<0.01$) and average length of review (β =0.15, $p<0.01$) are the two most important factors in social interactions behaviors, which reflect the crucial role of reviews in the social interactions behavior. While it is surprising to find that the average length of review negatively influences liking behavior and the number of travelogues are not significantly related to the social interactions behavior. Maybe it is the reason that users among online community mainly concentrate on the social interactions with review context. When the consumers visit a certain online travel community just for information browsing, travelogue is the critical factor in leading to the higher-level engagement behavior, for examples, interacting with other members, which acts as the key attribute and can enhance the sense of recognition and belonging.

4.3 Coefficient difference testing

This study conducts a regression coefficients difference test, and the results are reported in Table 4. The test shows that there is no significant difference between the liking behavior and social interaction behavior for source features. It is likely that the source features among online communities are enhanced effect. Information from expert or individuals who have large amounts of followers can be regarded as authority and reliable. Therefore, on the foundation of credibility, it plays an important role in liking behavior as well as social interaction behavior. However, compared with the liking behavior, social interaction behavior requires longer travelogues, more information vividness, longer review length and more reviewers. It is consistent with the fact that the more active and successful online travel communities are often associated with higher-quality travelogues as well as deeper engaged users who are more likely to communicate and discuss with others in online travel communities.

Table 4. The difference test of regression coefficients

level	Coef.	Std. Err.	P>z	95% CI
information	0.06	0.01	0.000	0.05-0.07
source	0.01	0.01	0.146	0.00-0.03
social interaction	0.67	0.02	0.000	0.63-0.70

5. DISCUSSION AND IMPLICATION

Active engagement behaviors among online travel community are essential factors to evaluate the viability and future potentials. Moreover, it is also a valuable driver for the financial performance of the travel industry (Lee et al., 2014) [31]. This study finds that compared with males, the females are more likely to engage to the online community. The length of a travelogue is positively attributed to both the liking behavior and social interactions behavior. Visitors may believe that the longer length of a travelogue can not only include more useful information about the destination and accommodations. Furthermore, the effect of following and follower can not be ignored, which can enhance both the liking and social interactions behaviors. For liking behavior, the number of reviewers and travelogues are the most important attributes. It is consistent with the fact that travelogues are the foundation of an online community. On the basis of high quality travelogues, visitors with similar interest can have more enthusiasm and generate viscosity of users. While as for social interaction behavior, all of the factors are positively associated to it. Among this, the number of reviewers (β =1.09,$p<0.01$) and average length of review (β =0.15, $p<0.01$) are the two most important factors in social interactions behavior, which reflect the crucial role of reviews in the social interaction behaviors. When consumers visit a certain online travel community just for information browsing, travelogue is the critical factor leading visitors to having a sense of identity and becoming actively engaged in the certain online travel community, while in this situation, interaction begins to act as the key attribute, which can enhance the sense of recognition and belonging, and even increase the re-visit frequency. Furthermore, the authority of information source can enhance the engagement behavior the whole journey.

Our findings provide several theoretical contributions and practical implications. First, it is a pioneering work on exploring the factors driving two different engagement behaviors. Second, for information searching visitors, travelogue is the foundation of a certain online travel community, managers can provide economic awards to users who post a travelogue and it is also the driver for further engaged behaviors. Third, in order to improve the online travel community recognition among travelers, review is an essential factor, managers should explore strategies to increase users’ discussion enthusiasm to enhance this activity.

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REFERENCES

[1] Pagani M, Mirabello A. (2011). The Influence of Personal and Social-Interactive Engagement in Social TV Web Sites. International Journal of Electronic Commerce, 16(2),41-67.

[2] Sun Y, Fang Y, Lim K. (2012). Understanding sustained participation in transactional virtual communities. Decision Support Systems, 53(1), 12-22.

[3] Lee H, Reid E, Kim W. (2014). Understanding Knowledge Sharing in Online Travel Communities Antecedents and the Moderating Effects of Interaction Modes. Journal of Hospitality & Tourism Research, 38(2), 222-242.

[4] Oh C, Roumani Y, Nwankpa K J, Hu H F. (2016). Beyond likes and tweets: Consumer engagement behavior and movie. Information & Management,

[5] Dovaliene, A., Masiulyte, A., Piligrimiene, Z. The relations between customer engagement, perceived value and satisfaction: the case of mobile applications. Procedia - Social and Behavioral Sciences, 2015, 213, 659-664

[6] Brodie R, Ilic A, Juric B, Hollebeek L. (2013). Consumer engagement in a virtual brand community: an exploratory analysis. Journal of Business Research, 66(1) 105–114.

[7] Mudambi S M, Schuff D. (2010). What makes a helpful online review? A study of customer reviews on Amazon.com. MIS Quarterly, 34(1), 185-200.

[8] Schaufeli W B, Martinez I M, Pinto A M, Salanova M, Bakker A B. (2002). Burnout and Engagement in University Students: A Cross- National Study. Journal of Cross-Cultural Psyschology, 33(33), 464-481

[9] Braojos-Gomez J, Benitez-Amado J, Llorens-Montes F. (2015). Impact of IT infrastructure on customer service performance: the role of micro-IT capabilities and online customer engagement. Proceedings of the 19th Pacific Asia Conference on Information Systems, Singapore, 1–16.

[10] Calder B J, Malthouse E C, Schaedel U. (2009). An experimental study of the relationship between online engagement and advertising effectiveness. Journal of Interactive Marketing, 23(4), 321–331.

[11] Mayer R C, Davis J H, Schoorman F D. (1995). An integrative model of organizational trust. Academy of Management Review, 20(3), 709–734.

[12] Benlian A. (2015). Web Personalization Cues and Their Differential Effects on User Assessments of Website Value. Journal of Management Information System, 32(1),225-260.

[13] Hu X, Huang Q, Zhong X, Davison R M, Zhao D. (2016). The influence of peer characteristics and technical features of a social Shopping website on a consumer's purchase intention. International Journal of Information Management, 36(6), 1218-1230.

[14] Fang Y. (2012). Does online interactivity matter? Exploring the role of interactivity strategies in consumer decision making. Computers in Human Behavior, 28(5), 1790-1804.

[15] Fang Y. (2014). Beyond the credibility of electronic word of mouth: exploring E-WOM adoption on social networking sites from affective and curiosity perspectives. International Journal of Electronic Commerce, 18(3), 67-101.

[16] Zhang H, Lu Y, Wang B, Wu S. (2015). The impacts of technological environments and co-creation experiences on customer participation. Information & Management, 52(4), 468-482.

[17] Hong S, Joqinapelly T. (2012) Effects of Web Atmospheric Cues on Users' Emotional Responses in E-Commerce. AIS Transcactions on Human-Computer Interaction

[18] Hovland I, Janis L, Kelley H. (1953). Communications and Persuasion: Psychological Studies in Opinion Change. New Haven, CT: Yale University Press, 1953.

[19] Willemsen L, Neijens P, Bronner F. (2012). The ironic effect of source identification on the perceived credibility of online product reviewers. Journal of Computer-Mediated 31 Communication, 18(1), 16-31.

[20] Lu X, Wang C, Yang J M, Pang Y, Zhang L. (2010). Photo2trip: Generating travel routes from geo-tagged photos for trip planning. In Proceedings of the international conference on multimedia, 143–152.

[21] Filieri R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. Journal of Business Research, 68(6), 1261-1270.

[22] Jiang Z, Benbasat I. (2007). Investigating the influence of the functional mechanisms of online product presentations. Information Systems Research, 18(4), 454-470.

[23] Bohórquez V, Mayo M, Esteves J. (2009). Corporate blogs evaluation using corporate leadership discourse and followers' characteristics. Information Management & Evaluation, 42-50.

[24] Freeman C L. (1978). Centrality in social networks: Conceptual clarification. Social Networks 1:215-239.

[25] Hanneman R, Riddle M. (2005). Introduction to social network methods. Riverside, CA: University of California, Riverside.

[26] Hu Y H, Chen K. (2016) Predicting hotel review helpfulness: The impact of review visibility, and interaction between hotel stars and review ratings. International Journal of Information Management, 36(6), 929-944.

[27] Kim H, Sundar S. (2014). Can online buddies and bandwagon cues enhance user participation in online health communities?. Computers in Human Behavior, 37, 319-333

[28] World Tourism Cities Federation and Ipsos. (2014). Research on Chinese Outbound Tourist (City) Consumption. http://en.wtcf.org.cn/download/report201409en.pdf

[29] Wong A. (2007). Social media and marketing: Evolution or revolution?. http://www.slideshare.net/ wah17 /social-media-35304

[30] Ghuneim M. (2008). Terms of engagement: Measuring the active consumer. http://archive.is/d4xw

[31] Lee H, Reid E, Kim W. (2014). Understanding Knowledge Sharing in Online Travel Communities Antecedents and the Moderating Effects of Interaction Modes. Journal of Hospitality & Tourism Research, 38(2), 222-242.