THE EFFECT OF PRICE VS. SAFETY FEATURES INFORMATION ON CONSUMER DECISIONS IN AIRBNB

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1. INTRODUCTION

The development of information communication technology and economic difficulty dated from early 2000s caused the emergence of the sharing economy, a new socio-economic phenomenon (Cohen & Kietzmann, 2014). Although people buy and sell products or services in general market, the people share their own assets or properties in the sharing economy (Botsman & Rogers, 2010). The online platform, especially the online website, is one of primary factor of the sharing economy business, because most of sharing transactions are processed through the online environment (Heinrichs, 2013). In this respect, the online communication between users (providers) and users (recipients) is substantially important in the sharing economy, as the other businesses in online environment are (Lampinen, Lehtinen, Cheshire, & Suhonen, 2013). Thus, several studies investigate the influence of online information to the online users' attitude or behaviour in various settings (Kim, Yoon, & Zo, 2015).

However, previous cases are somewhat biased, because they perform their study primarily in online shopping context and because they tend to focus on the relationship between the online information and the online users. For these reasons, the online information's influence is rarely researched in the sharing economy context and the internal relationship of online information impact is hardly issued.

This study aims to analyse the internal relationship between high scope and low scope cues in the the sharing economy context. As a representative example of the sharing economy business, Airbnb is selected as the research's main target for data collection and analysis. In Airbnb, host reputation information, price information, safety feature information, and number of online reviews are chosen for this study, and totally four hypotheses are suggested based on the cue utilization theory (Purohit & Srivastava, 2001).

By examining the influences of price and safety feature to the number of online reviews in two different groups, which are divided by the host reputation, the hypotheses testing is performed. The results indicate that the effect of price to the online review is changed depending on the host reputation, but that the effect of safety feature to the online review is not affected by the host reputation. Based on these results, interpretation of the results, theoretical and practical implications, limitations, and directions for the future research are provided.

2. RESEARCH BACKGROUND

2.1. The sharing economy

The the sharing economy is defined as a "peer-to-peer based activity of obtaining, giving, or sharing the access to goods and services, coordinated through community-based online services (p. 3)" (Hamari, Sjöklint, & Ukkonen, 2015). According to Time magazine, the sharing economy is one of "ten ideas that will change the world" (Walsh, 2011). Forbes magazine anticipates over 3.5

billion dollars will be generated as direct benefits in the sharing economy business (Geron, 2013).

People participated in the sharing economy share their own properties or assets with others demanding those resources with payment for the sharing, for-profit structure, or without payment for the sharing, non-profit structure (Botsman & Rogers, 2010). In terms of business model, the sharing economy can be regarded as the “network orchestras” that companies create a peer-to-peer network to enable the peers to buy or sell product and services, to give and receive comments, and to cooperate for similar purposes (Libert, Wind, & Fenley, 2014).

Among the many businesses in the sharing economy, Airbnb is often referred as a representative example because of its famous as a sharing economy business and its significance in the related industry (Edelman & Luca, 2014). As a commercial hospitality exchange service, Airbnb has a value of about 10 billion dollars, the value of about 20 times of Hyatt hotels’ valuation (Libert et al., 2014). Besides, Airbnb is called as a “networked hospitality exchange service" (Ikkala & Lampinen, 2014).

Like other businesses of the sharing economy, Airbnb provides not only the product information, which is the information about the accommodation place, but also the provider information, which is the information about the owners of the place, since the online communication of users is crucial part of the sharing economy business, based on the online platform (Edelman & Luca, 2014).

2.2. Cue utilization theory

Cue utilization theory focuses on how people take advantage of multiple information cues for determining the products’ quality (Purohit & Srivastava, 2001). This theory assumes that a product or service has several characteristics and show those traits with multiple cues and thereby a consumer can evaluate the quality of product or service (Q. Wang, Cui, Huang, & Dai, 2016). As recognized its prevalence, the online business context is increasingly investigated based on cue utilization theory, so the significant influence of online information cues about products or services is examined (Wells, Valacich, & Hess, 2011).

The developed studies of cue utilization theory study the interrelationship between high scope cues and low scope cues, both cues divided based on the information’s characteristics (Purohit & Srivastava, 2001). On the one hand, a high scope cue is generally exampled by seller reputation and brand reputation (Akdeniz, Calantone, & Voorhees, 2013). Since the valence of high scope cue is formed through over a period of time, it is not easily established and also changed. This tendency makes it possible to provide consumers quite high degree of reliability only with a positive high scope cue (Purohit & Srivastava, 2001). On the other hand, product price, warrant, or money-back guarantee are usually selected as a low scope cue (Akdeniz et al., 2013). Unlike the valence of high scope cues, low scope cues’ is formed in comparatively short period, so the valence of low scope cue is easy to be established or changed. Thus, people are not likely to evaluate the product’s quality as positive only because of positive low scope cues (Purohit & Srivastava, 2001).

As discussed, Airbnb provides product information and provider, called as host, information in the website and these information cues are main criteria for the other users who want to share the other’s place for their stay, called as guests, to make decisions. In case of high scope cues in Airbnb, a super host badge, a badge given to certain hosts who qualify a super host by meeting the four requirements to be a super host, and an identification (ID) verification badge, a badge given to certain hosts who verify their personal ID by submitting their personal information to Airbnb, can be selected. In case of low scope cues in Airbnb, price and safety feature, meaning how many safety features are equipped in the place, can be chosen. Finally, the guests’ perceived quality about the product, accommodation place, can be represented by the number of reviews that the place receives, because only the hosts who actually stayed the place can write a review about the place, the number of reviews indicates the least number of guests who actually selected the place for their stay.

3. RESEARCH HYPOTHESES AND MODEL

Based on cue utilization theory and Airbnb’s situation, this research suggests four hypotheses as follows, and the research model based on the hypotheses is appeared in **Figure 1**.

H1: If a host has a good reputation, the guests are likely to perceive the accommodation quality to be higher with higher price relatively to cheaper price.

H2: If a host has a poor reputation, the guests are not likely to perceive the accommodation quality to be higher with higher price relatively to cheaper price.

H3: If a host has a good reputation, the guests are likely to perceive the accommodation quality to be higher with more safety features relatively to less safety features.

H4: If a host has a poor reputation, the guests are not likely to perceive the accommodation quality to be higher with more safety features relatively to less safety features.

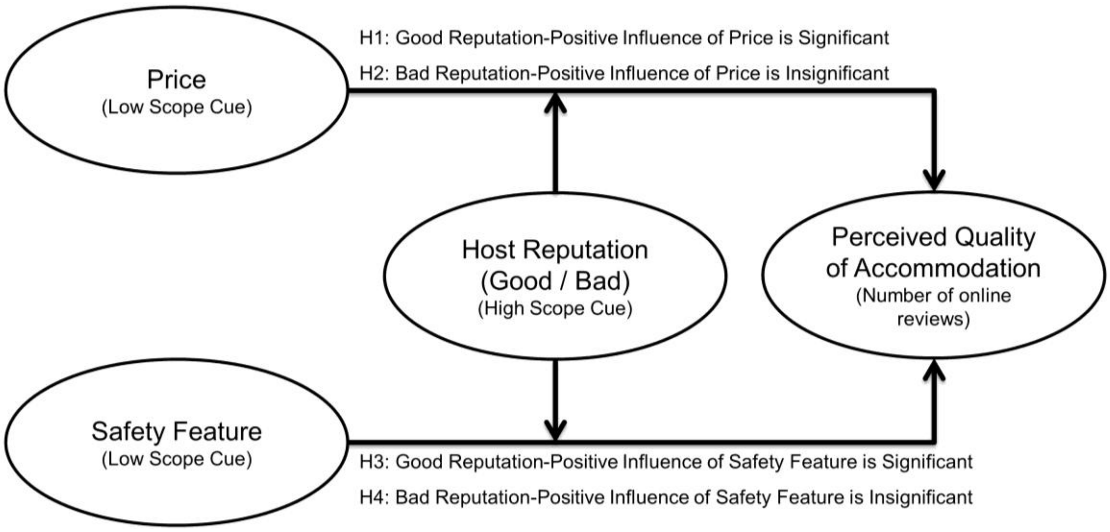


Figure 1. The Research Model

4. RESEARCH METHODOLOGY

For the research goal, this study, at first, divides all the cases into two different groups, a good reputation group and a poor reputation group, based on the high scope cue of Airbnb, specifically the average number of badges of collected data set. After the division, the influences of two low scope cues of Airbnb, price and safety feature, to perceived quality of accommodation, the number of reviews, are examined. Finally, by comparing the results of each influence relationship, the hypotheses are proved as support or reject. This information is explained in **Table 1**.

Table 1. The instrument development and methodology summary

	Online cues in Airbnb	Measuring method
High scope cue	Host reputation	Counting the number of badges, a super host badge and an ID verification badge, which are used for signifying hosts' online reputation in Airbnb.
Low scope cue	Price	Using the dollarized price for a day at each accommodation.
	Safety feature	Counting the number of safety features, smoke detector, carbon monoxide detector, first aid kit, safety card fire extinguisher, and lock on

		bedroom door, which are equipped in each accommodation.
Perceived quality of accommodation	Online review	Counting the number of online reviews which written by other experienced guests.

The research date is collected from Airbnb website (www.airbnb.com) and the three targeted cities are Bangkok in Asia Pacific continent, London in Europe continent, and New York in America continent. From each city, about 300 cases are collected through web-harvesting method from 21st, December, 2015 to 24th, December, 2015. Out of 918 collected cases, 854 cases are finally used in the analysis. This data collection information is summarized in **Table 2**.

Table 2. The data collection

General data source	Airbnb website (www.airbnb.com)
Targeted cities	Bangkok (Asia Pacific), London (Europe), and New York (America)
Number of accommodation	306 cases for each city searched randomly by Airbnb website.
Collection method	Web-harvesting with R programming language
Collection period	2015.12.21 ~ 2015.12.24 (4 days)
Total number of used data	854 cases (Out of 918 cases, 64 unusable cases are deleted)

5. RESULTS

Table 3 shows the descriptive statistics of the variables. As discussed, the host reputation, total number of badges, is used as criteria to separate good reputation group and poor reputation group. The least value of host reputation is 0, the host has no badge, and the highest value of host reputation is 2, the host has both badges which are super host badge and ID verification badge. The mean of the variable is 0.82 and none of the data is excepted for the group separation. As a low scope cue, the price variable ranges between 9 dollars and 500 dollars. The mean of the variable is 68.04 dollars (SD = 48.530). The safety feature, another variable of low scope cue, appears from 0 feature to 6 features and the mean value is 2.01 (SD = 1.581). Finally, the minimum of online review is 0 and the maximum of online review is 277. The mean value of online review is 19.39 (SD = 29.630).

Table 3. Descriptive statistics of high scope and low scope cues

Variable	Minimum	Maximum	Mean	Frequency	Percent
Host reputation	0	2	0.82	854	100%

Variable	Minimum	Maximum	Mean	Std.
Price	9	500	68.04	48.530
Safety feature	0	6	2.01	1.581
Online review	0	277	19.39	29.630

For the analysis, the raw data is divided into several levels based on the distribution of the collected data, because valid result is hard to be shown with the raw data appeared as numerical numbers (Suh & McAvoy, 2005). As for the host reputation, good reputation group and poor reputation group is divided in accordance with the mean value of the data (0.82), so the cases which has less than one badge belongs to poor reputation group and the cases which has equal to or more than one badge belongs to good reputation group. As for the other variables, all the variables are divided into same number of levels, five levels, following Suh and McAvoy's (2005) suggestion of using quartile splits; after arranging the data in order of frequency from minimum to maximum, dividing the data into five different levels by breaking it at 20 (1), 40 (2), 60 (3), 80 (4) percent. The level distribution of each variable is provided in **Table 4**.

Table 4. Level distribution of high scope and low scope cues

Variable	Level distribution
Host reputation	1: Poor reputation (The number of badges is lower than 1) 2: Good reputation (The number of badges is equal to or more than 1)
Price	1: Equal to or less than 29 dollars 2: More than 29 dollars and equal to or less than 47 dollars 3: More than 47 dollars and equal to or less than 68 dollars 4: More than 68 dollars and equal to or less than 98 dollars 5: More than 98 dollars
Safety feature	1: Equal to or less than 0 feature 2: More than 0 features and equal to or less than 1 features 3: More than 1 features and equal to or less than 2 features 4: More than 2 features and equal to or less than 3 features 5: More than 3 features
Online review	1: Equal to or less than 2 reviews 2: More than 2 reviews and equal to or less than 5 reviews 3: More than 5 reviews and equal to or less than 12 reviews 4: More than 12 reviews and equal to or less than 29 reviews 5: More than 29 reviews

First of all, the correlation analysis is performed as indicated in **Table 5**. All the correlation estimates result in adequate values. Although the correlation between price and online review can be issued because of its somewhat high value (-0.80), according to Tabachnick and Fidell (2007), the statistical concerns caused by singularity or multicollinearity can be issued only when the correlations are higher than 0.90.

Table 5. Correlation analysis

	Price	Safety feature	Online review
Price	1		
Safety feature	-0.29	1	
Online review	-0.80*	0.39	1

*p<0.05

The results of regression analysis and tests of hypotheses are provided in **Table 6**. As for the price, the influence of price to the online review is appeared differently depending on the host reputation level. When the host reputation is good, the host has more than one badge, the negative influence of price is significant ($b = -0.090$, $p < 0.05$). However, the influence of price to the online review is not significant, if the host has poor reputation ($b = 0.05$). Therefore, it is found that the effect of price to perceived quality of accommodation can be affected by the host reputation in Airbnb. In case of safety feature, different from the price, another low scope cue is not vulnerable to whether the host has good reputation or not. The influences of safety feature to the online review both in good reputation group ($b = 0.037$) and in poor reputation group ($b = -0.039$) are not statistically significant. Thus, it is appeared that the effect of safety feature to perceived quality of accommodation quality is unrelated with the host reputation. Consequently, the assumptions of cue utilization theory is applied to only the relationship between the price and the perceived quality of accommodation quality in Airbnb, meaning is not applied to the relationship between the safety feature and the perceived quality of accommodation quality.

Table 5. Results of regression analysis and tests of hypotheses

Hypotheses	Path	Estimates	t-value	Result
H1	Price→Online review (Good reputation)	-0.090	-2.278*	Reject
H2	Price→Online review (Poor reputation)	0.05	0.069	Accept
H3	Safety feature→Online review (Good reputation)	0.037	0.921	Reject
H4	Safety feature→Online review (Poor reputation)	-0.039	-0.547	Accept
R^2	Good reputation		0.099	
	Poor reputation		0.037	

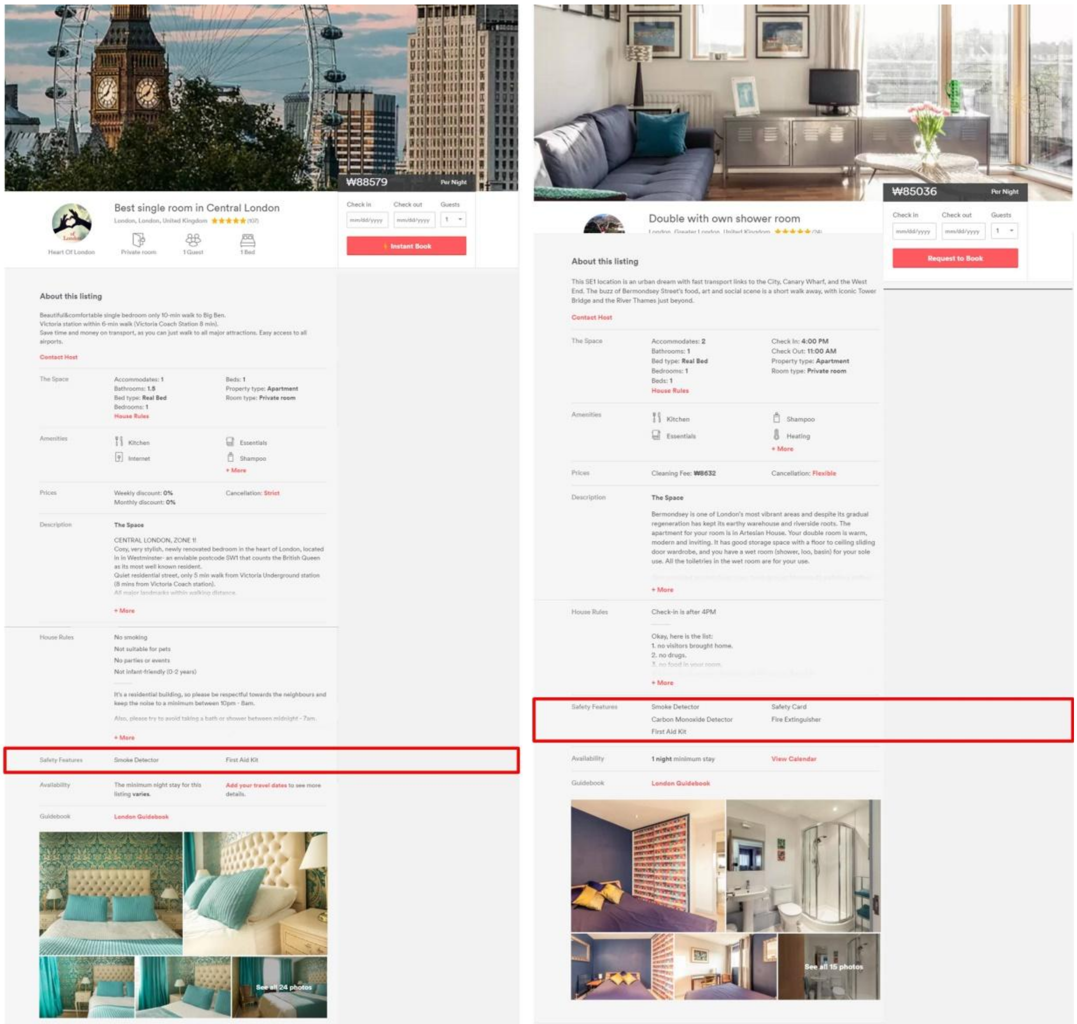
6. CONCLUSION AND DISCUSSION

This study aims to explore the influence relation between high scope cue and low scope cue in the sharing economy context based on cue utilization theory. In Airbnb, a representative example of the sharing economy businesses, two kinds of information cues signifying host reputation, a super host badge and an ID verification badge, are selected as high scope cues and other two kinds of information cues signifying product information, price and safety feature, are selected as low scope cues. Based on cue utilization theory and Airbnb's condition, the four hypotheses are suggested. In the data analysis, it is confirmed that the influence of price to perceived quality of accommodation is influenced by host reputation, but the influence of safety feature to perceived quality of accommodation is not influenced by host reputation.

About the first point, the assumption of cue utilization theory that the effect of low scope cue to people's attitude or behaviour can be affected by the valence of high scope cue is appeared to be able be applied to the sharing economy context. In other words, Airbnb users evaluate the accommodation quality quite differently according to the price range if the hosts have good reputation. Since the good reputation of host can increase the reliability of low scope cue, the low scope cue's impact to the recipients' perceptions can be significant.

About the second point, the assumption of cue utilization theory is appeared to be unable to be applied to the sharing economy context. Namely, Airbnb users make decisions, whether choose the accommodation place to stay or not, regardless of the number of safety features equipped in the place, even if the host has a good reputation. This result indicates that Airbnb users tend to under estimate the importance of safety information to make a decision. This can be attributed to Airbnb's website situation. Since a variety of information about the accommodation as well as the host is provided in one website page and in different size and location, the perceived importance of information can be different. In fact, the safety information is located in lower part of the website page and also has comparatively smaller size than other information, so it is easy to be overlooked, if the users were not check the webpage carefully. This situation is appeared in Figure 7.

Figure 7. The location and size of safety feature information in Airbnb webpage



This study has several implications theoretically and practically. First theoretical implication can be found in the contribution about the understanding of the sharing economy. Since this research investigates a certain issue in the sharing economy context, its value can be appreciated in the current situation, which is lack of substantial cases about the sharing economy. Second theoretical implication can be found in the development about the online information cues' influence relation. This research examines the inter relation among information cues based on cue utilization theory. Because the previous cases primarily focus on the relation between online information and online users behaviours, the study exploring the inter relationship between online information cue and other online information cue can be meaningful. The major theoretical implication is that this research results can be important basement for the future guideline to improve Airbnb website operation strategy. If the future research were performed by expanding the target information cues, the more extended understanding about the perceived importance of each information cue can be realized. If so, significantly helpful guidelines can be resulted from the research. This research becomes the basement for this possibility, so the practical implication can be found in this respect.

In case of limitations, two limitations can be referred. First, the problems caused by the data collection method, a web harvesting method, can be a limitation for this research. Generally, a low explanation power of variable or the possibilities of deceptive date are issued about a web harvesting method. To overcome this limitation, the future research should adopt more developed and effective data collection method. Second, the data used in the analysis are collected from the limited area, only from cities. Thus, the possibility of generalization of research results can be decreased. In this reason, future research should expand the data collection area to acquire the more effective and plausible results reflecting the sharing economy business significantly.

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