Summer 5-26-2017

Performance in Sharing Economy: Evidence from Room-Sharing Service

Jiang Wu
School of Information Management, Wuhan University, China, jiangw@whu.edu.cn

Minne Zeng
School of Information Management, Wuhan University, China

Karen L. Xie
Daniels College of Business, University of Denver, USA

Performance in Sharing Economy: Evidence from Room-Sharing Service

Jiang Wu[1*], *Minne Zeng*[1], *Karen L. Xie*[2]
[1]School of Information Management, Wuhan University, China
[2]Daniels College of Business, University of Denver, USA

Abstract: Under the rapid development of sharing economy, performance is important for the prosperity of this innovative commercial model. However, the performance in sharing economy is less discussed in the academic field. Revenue and occupancy rate are widely applied as two ideal measures of performance in hospitality market. This study tries to fill the research gaps with both two measurements. Based on cue utilization theory, we explored the influence of listing cues and host cues on performance of listings and hosts in a representative Chinese room-sharing platform--XiaoZhu.com. The findings indicate that both listing and host cues have significant effects on performance. It's expected that this study discusses a number of implications and makes contributions for researchers and practitioners.

Keywords: Short-term rental; performance; occupancy rate; revenue; cues; sharing economy

1. INTRODUCTION

The widespread adoption of Internet technology has changed the way of trading. The decreasing transaction costs associating with trading and social connection lead to a development of an innovative commercial model，which is labeled as "sharing economy". It involves a transfer from ownership to access to material goods and services [1, 2]. Through integrating usable resource, service providers allow other people to rent or use products and services at a relatively budget price [3]. Strangers are connected together to build networks on online platforms, creating many opportunities for individuals to trade their idle resources [4]. Various industries have flourished in sharing economy, such as hospitality (e.g., Airbnb and XiaoZhu), transportation (e.g., Uber and DiDi) and clothing (e.g., Rent the runway). Room-sharing service is a representative service in hospitality marketplace. Platforms under this service enable individuals to share their usable but unused rooms or places with renters for a fee or other compensation. Hosts provide private home-stay facilities as well as personnel service for renters who live in rooms or spaces temporarily. Platforms with this service are gaining much popularity in the tourism marketplace. Airbnb for instance, the users of it spent nearly $56 million every year in San Francisco [5].

Despite the rapid development of the room-sharing service, the academic research on this topic is still in its infancy. Previous research has concentrated mainly on the conceptual level rather on the characteristics of sharing economies. The existing studies are most about users' behavioral intention based on the survey of questionnaires [6, 7]. However, there lacks empirical analysis of hosts and rooms in room-sharing service. Particularly, empirical evidence regarding performance in this services is sparsely reported. Faced with increasingly competitive hospitality market, hosts and marketers need the information to analyze performance to engage and target users [8-10]. Including financial and operational parts, the observed performance can raise the enthusiasm of hosts and marketers. In hospitality research, performance of hotel is widely verified to be influenced by online information, such as review, hotel location and type [8, 10, 11]. Because of information asymmetry, potential consumers make purchase decisions depending on the information displayed in room-sharing platforms [12]. They look through the description of listings (e.g., rooms and apartments) and hosts, choose their favorite listing and book it online. Consumers take advantage of online information to judge the quality of listings, evaluate perceived risk of listings and hosts [11]. However, the influence of online information on performance in room-sharing service is less analyzed in the academic field.

* Corresponding author. Email: jiangw@whu.edu.cn

In order to fill research gaps mentioned above, we empirically focus on listings and hosts in a Chinese room-sharing platform—XiaoZhu.com and explored whether performance is influenced by online information (i.e., cues) based on cue utilization theory. This paper makes both theoretical and practical contributions. First, this study is the first attempt to explore occupancy and financial performance in room-sharing service. The occupancy rate and revenue for a listing in XiaoZhu are applied as the measurement of performance in our study. Second, this study extends the literature based on the cue utilization theory. It is helpful to associate with cue utilization theory with sharing economy theoretically. Prior studies only concentrate on the effect of hosts or rooms, therefore, this study enriches and extends the behavior analysis of the sharing economy as well. Practitioners including entrepreneurs and hosts are very interested in their performance for more commercial development [13]. Hence, it is also expected that this research can provide a number of practical implications for them.

Literature review and hypotheses are introduced in Section 2. Cues are divided into listing cues (e.g., area and type) and host cues (e.g., the number of listings and orders). The data for analysis was collected by the crawler in October 2016 and November 2016 respectively. The specification of empirical setting and data are discussed in Section 3. Results and robustness check in Section 4 and 5, indicating that performance in room-sharing service are significantly affected by listing and host cues. Section 6 describes both discussions and implications. Finally, limitations and future directions are analyzed in Section 7.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Sharing economy and room-sharing service

The rapid development of Internet creates many opportunities for us to share and display our identity even without ownership [13]. The concept of sharing economy, as well as its activities, becomes more and more popular under this background. Sharing economy involves with dividing resource and things among relative strangers or acquaintance [14]. Scholars have discussed different terms in exploring the concept of sharing economy in different situation, such as in the access-based consumption [3]. For example, Botsman and Rogers pointed out that sharing includes traditional borrowing, bartering, renting, lending, swapping and gifting [2]. Different from many scholars, Belk put forward that it is the distribution and acquisition of resource integrated by people for the fee or compensation [14]. The Internet facilitates the transfer of access to goods and service, creating many ways of gift giving and commercial exchange. This internet-facilitated sharing includes sharing of material goods (e.g. rooms, cars and bicycles), virtual products (e.g. music and films) as well as intangible services [2].

Many platforms show up with the rising of sharing economy in the peer-to-peer marketplace. Especially in the hospitality industry, Airbnb and XiaoZhu are both very representative in the transaction-based online market. Resource shared in peer-to-peer rental platforms includes houses, apartments, rooms, tools, and kitchens [15]. Room-sharing platforms are monetary network hospitality because local people share their idle rooms with other strangers to live temporarily for some fees or compensations [6]. Stama [16] pointed out two outstanding difference between room-sharing platforms and other booking websites. First, various feedback system reduce information asymmetry in online environment. Second, transaction cost is largely reduced because of reusing free resource. Researches about room-sharing services are mainly related to renters or hosts. Liang analyzed the effects of perceived value and perceived risk on repurchase intention toward Airbnb [7]. UTAUT model with trust as well as perceived quality was discussed to explore motivational factors of behavioral intention to use Airbnb [16]. On the other hand, some scholars are interested in hosts in room-sharing. The experiment from Edelman and Luca indicates that racial information revealed from online host and house pictures have impacts on consumers' decisions [17]. More importantly, the host who is a professional agent acquires more orders than others [4].

However, there lack comprehensive studies on performance in sharing economy especially about room-sharing service, which is exactly what our study trying to full. Performance in hospitality research includes financial performance and profitability [18]. In the hotel industry, many reports about ideal measures of hotel performance and they can also be applied in room-sharing service. It is widely analyzed in lodging field that the occupancy rate is a general and regular measurement of performance [8-10]. Besides, profitability is also an appropriate measure of hotel performance [11]. Since sales are closely related to profitability, revenue is a precise indicator of profit levels [19]. Many scholars propose that occupancy rate is a reliable monitor and an effective substitute of financial performance [20, 21]. Therefore, occupancy rate and revenue are applied to measure performance in our study. Specific calculations of them are deeply explained in Section 3.

2.2 Cue utilization theory

After evaluating perceived quality of products, consumers can make consumption choice [11]. But it is difficult for consumers to assess quality objectively because of information asymmetry [12]. In order to make consumption decision, they are willing to try their best to search more specific information provided by commercial platforms as well as sellers. Promoted originally by Cox and developed by Olson and Jacoby, cue utilization theory is widely applied for analysis of determinants of consumers' decision in the commercial process [22]. Cues are the signal released from the coder and accepted from the decoder. They can be divided into extrinsic cues and intrinsic cues [23]. Similarly, a product includes many signals of its quality, which consists of extrinsic attributes and intrinsic attributes [24]. Extrinsic attributes are related with focal objects while intrinsic attributes are inherent to the fundamental of focal objects. Extrinsic cues are signals relating to marketing composition. They are consistent with extrinsic attributes of the product, including price, brand, reputation and so on [22, 24]. Therefore, orders, reviews and price in XiaoZhu can be regarded as extrinsic cues. On the other hand, intrinsic cues are inner characteristic of products (e.g., type, taste, color). They are more difficult to be observed compared with extrinsic. In the room-sharing platform, intrinsic cues include various listing information, such as listing type, area, and location. Cues bring predictive value and confidence value to consumers [22]. Both extrinsic and intrinsic cues are given in listing cues and host cues in XiaoZhu. According to cue utilization theory, extrinsic cues (e.g., review) increase confidence values and intrinsic cues (e.g., type, size) enhance predictive values. Consumers are preferred to use extrinsic cues when intrinsic brings low predictive and confidence values. However, they are intended to take intrinsic cues into more consideration if it includes high predictive and confidence values [22].

With more cues about product characteristic and reputation information, the possibility that consumers buy the product or service also increases [25]. Perterson and Merino indicate that online information exerts influence on consumers' behavior, then affecting sales of product [26]. Unlike specific products, service is intangible and abstract. Consumers depend more on description and reviews to decrease uncertain risks caused by information asymmetry, especially in the online environment. On the other hand, quality uncertainty from consumers may hinder commercial activities from operating successfully. Therefore, sellers and platforms are willing to decrease potential buyers' uncertainty by giving more introduction and description[26, 27].

2.3 Hypotheses development

In C2C e-commerce market, consumers prefer to obtain more information about the product and the seller to decrease the information asymmetry [28]. The listing is the product and host is the seller for consumers in room-sharing service. As room-sharing service is a peer-to-peer commercial model, product information (e.g., listing cues) and service-providers' information (e.g., host cues) are both displayed in online platforms. Listing cues are information about rooms, while host cues include information about personal attributes and other characteristics. Zhang et.al proposed that in tourism website, online cues consists of hotel characteristic, consumer review, and recommendation information [29]. There are numbers of information displayed in room-sharing platforms. Specifically, host cues are attributes of a host, such as acceptance rate and confirmation time for the orders, the number of listings and orders; listing cues are description of a room, including area, listing type, the number of reviews and amenities for a room.

As mentioned above, occupancy rate and revenue are measurements of performance in our study. As the major indicators of performance in hospitality industry, occupancy rate demonstrates hosts' availability while revenue indicates the profitability [25]. Many reports reveal that occupancy rate and revenue are positively influenced by a numbers of hotel characteristics and information in the field of accommodation [27] [30]. Similarly, we also hypothesize that performance in room-sharing service are related to information (i.e., cues) displayed in online platforms. The information of product presented in platform has effect on consumers' purchasing willingness through trust building [31]. In hospitality research, hotel occupancy rate is affected by information of hotel, such as size and average room rate [30]. Orders and popularity are significantly influenced by hotel information [27].Therefore, listing cues (e.g., area, listing type, the number of reviews and amenities) may also influence performance in room-sharing service. Area indicates the specific location of a room; listing type includes whole apartment and a single room. Amenities are the number of facilities in this room. Therefore, the hypotheses are proposed,

H1a Occupancy rate in room-sharing service is affected by area in listing cues.

H1b Occupancy rate in room-sharing service is affected by listing type in listing cues.

H1c Occupancy rate in room-sharing service is affected by the number of reviews in listing cues.

H1d Occupancy rate in room-sharing service is affected by the number of amenities in listing cues.

H2a Revenue in room-sharing service is affected by area in listing cues.

H2b Occupancy rate in room-sharing service is affected by listing type in listing cues.

H2c Occupancy rate in room-sharing service is affected by the number of reviews in listing cues.

H2d Occupancy rate in room-sharing service is affected by the number of amenities in listing cues.

On the other hand, researches about online information indicate that consumers' decisions are significantly influenced by review information about sellers in hospitality industry [29, 32]. Consumers' purchasing intention are closely related to sellers' information especially in room-sharing service. As Ert et al propose, renters make decision depends on host attributes (e.g., photos) [33]. Therefore, occupancy and financial performance (i.e., occupancy rate, revenue) may be affected by host cues (e.g., acceptance rate, confirmation time, the number of listings and orders). Acceptance rate to the order, and the number of listings and orders represent host's ability of offering room-sharing service. Confirmation time is the respond time to renters, indicating the efficiency and politeness of a host. Therefore, we hypothesize that,

H3a Occupancy rate in room-sharing service is affected by acceptance rate in host cues.

H3b Occupancy rate in room-sharing service is affected by confirmation time in host cues.

H3c Occupancy rate in room-sharing service is affected by the number of listings in host cues.

H3d Occupancy rate in room-sharing service is affected by the number of orders in host cues.

H4a Revenue in room-sharing service is affected by acceptance rate in host cues.

H4b Revenue in room-sharing service is affected by confirmation time in host cues.

H4c Revenue in room-sharing service is affected by the number of listings in host cues.

H4d Revenue in room-sharing service is affected by the number of orders in host cues.

3. METHODOLOGY

3.1 Empirical setting: XiaoZhu.com

XiaoZhu is a room-sharing platform connecting hosts with unoccupied rooms with renters who need to live in rooms temporarily. Hosts provide their empty rooms, houses or apartments as well as descriptions of listings in XiaoZhu.com. Consumers browse the information in website, communicate with hosts and choose to book their ideal accommodations. Founded in 2012, XiaoZhu is a famous room-sharing platform in China, experiencing great advance in room-sharing marketplace. Until 2016, there have been more than 100,000 listings in more than 300 cities around China. More than 3 million renters used the service before.

As a peer-to-peer platform, not only listing information but also host information are displayed in XiaoZhu. Listing information is shown in listing pages, including price, area, room type (e.g., single room, whole apartment), reviews, amenities and so on. Host information consists of total orders, comments, dairies, response rate, confirm time to renters and so on. In our study, information on listing pages are regarded as listing cues, while description from host pages are host cues. Orders including listing, renter, check in date and check out date are also displayed in host pages. Every listing in an order provides a link to its listing page. The specific description of order benefits us to explore the listing and host cues' influence on performance in room-sharing service. The representative example of orders is shown in Figure 1.

Figure 1. Example of order records in host page

3.2 Data and variables

Listings in the area of Beijing and their host pages were crawled in XiaoZhu.com, ranging from May 1, 2016 to October 1, 2016. In order to capture at least one month of complete data for analysis, five-month period data was collected by the crawler in October, 2016 and November, 2016 respectively. At first, available listings in Beijing were searched by the crawling procedure. Then listing details such as area, listing type (i.e., single room, whole apartment, sofa, and beds), reviews, amenities (e.g., kitchen, living room, balcony) were recorded through each link to a certain listing. Following the link to each host page, the crawler finds out host and order details lastly. Host details include his or her total numbers of listings, reviews, the number of dairies, order records, etc. Order records were analyzed to calculate occupancy rate and revenue which measure performance. Occupancy rate is the number of days occupied divided by the total number of available days monthly for the listing [8-10]. Therefore, occupancy rate is calculated as

$$OccupancyRate = NumDaysOcuppied \,/\, NumDaysAvailable \qquad (1)$$

NumDaysOcuppied is the number of days occupied for a listing. *NumDaysAvailable* is the number of days offered for a listing during a period, which is calculated by days of a month in our study. Revenue is defined as the income of a listing and is tested as

$$Revenue = NumDaysOcuppied * Price \qquad (2)$$

Revenue is the revenue for a listing during a month, which is calculated by multiplying *NumDatsOcuppied* and *Price*.

The sample consists of 852 different listings from 287 unique hosts in Beijing. Since there are very few sofas and beds in XiaoZhu, we mainly focus on two listing types (i.e., whole apartment and single room) in our analysis. The description and summary statistics of all variables are explained in Table 1.

Table 1. Variable Description and Summary Statistics

Dimensions	Variable	Definition	Mean	SD	Min	Max
Dependent variable	*OccupancyRate*	Number of days occupied divided by number of days offered in one month	0.48	0.57	0	1
	Revenue	Total income from renting a listing in one month	5741.49	5850.79	0	77500
Independent Variable (Cues of listing)	*Area*	Area of a listing in square meters	49.19	53.55	4	800
	ListingType	whole apartment = 1, single room = 0	0.52	0.50	0	1
	CommentNumber	Number of comments for a listing	3.83	1.54	0	15
	Amenities	Total numbers of bedroom, living room, bathroom, kitchen, balcony	6.56	2.34	2	21
Independent Variable (Cues of host)	*AcceptRate*	Number of reservation requests received versus number of acceptance to these requests given by a host	0.85	0.14	0	1
	ConfirmTime	Number of minutes that a host confirms the reservation request of the renter	5.27	4.24	0	71
	ListingNumber	The number of listings owned by a host	9.37	9.30	1	39
	OrderTotal	Total numbers of orders owned by a host	349.13	430.84	0	2002

3.3 Regression model

The estimation is to investigate how performance (i.e., occupancy rate, revenue) is influenced by cues of listing and host in room-sharing service. Two groups of OLS regression models were taken to analyze the effect among them. Specific models are shown in Equation 3 and 4 respectively.

$$\text{OccupancyRate} = \alpha0 + \alpha1 \textit{Area} + \alpha2 \textit{ListingType} + \alpha3 \textit{CommentNumber} + \alpha4 \textit{Amenities} + \alpha5 \textit{AcceptRate} + \alpha6 \textit{ConfirmTime} + \alpha7 \textit{ListingNumber} + \alpha8 \textit{OrderTotal} + \varepsilon \quad (3)$$

$$\textit{Log}\,(\text{Revenue}) = \beta0 + \beta1 \textit{Area} + \beta2 \textit{ListingType} + \beta3 \textit{CommentNumber} + \beta4 \textit{Amenities} + \text{B}5 \textit{AcceptRate} + \beta6 \textit{ConfirmTime} + \beta7 \textit{ListingNumber} + \beta8 \textit{OrderTotal} + \varepsilon \quad (4)$$

Revenue (skewness = 6.38) with skewed normal distribution is taken log transformation. Cues of listing include area, listing type, the number of comments and amenities. Cues of host consists of accept rate, confirm time, the number of listings and orders for the host.

4. RESULTS

Multicollinearity was checked among all variables in the model by computing values of variance inflation factors (VIFs). The results of VIFs were between 1.528 and 2.590, which were smaller than threshold score of 10 [34]. It suggests that multicollinearity is not a problem in our study. Table 2 is to test H1 and H3. The first column of coefficient only includes the influence of listing cues. Variables of *CommentNumber* and *Amenities* show significant effect on occupancy rate (α=0.119, p=0.000; α=0.042, p=0.008), indicating that H1c and H1d is supported. The occupancy rate increases with more numbers of comments and more facilities. However, *Area* (α=-0.001, p=0.317) and *ListingType* (α=0.027, p=0.114) do not influence occupancy rate importantly, indicating that H1a and H1b are rejected. The second column of coefficient contains effects of both listing cues and host cues. The coefficients and significance for listing cues are similar to column 1. As for host cues, the acceptance rate to orders (β=0.517, p=0.000), the confirmation time (β=-0.037, p=0.026), the number of listings, orders (β=0.022, p=0.043; β=0.093, p=0.000) strongly influence occupancy rate, meaning that H3a-H3d are well verified.

Table 2. Estimation Result of Cues of listing and host on Occupancy rate (Model 1)

Dependent Variable: Occupancy rate				
	Coefficient	Standard Error	Coefficient	Standard Error
Area	-0.001	0.001	-0.001	0.001
ListingType	0.027	0.013	0.016	0.076
CommentNumber	0.119***	0.013	0.071***	0.016
Amenities	0.042**	0.012	0.033**	0.013
AcceptRate			0.517***	0.142
ConfirmTime			-0.037*	0.016
ListingNumber			0.022*	0.003
OrderTotal			0.093***	0.002
(Constant)	0.397**	0.142	0.451***	0.227
Observations	852		852	
R^2	0.472		0.525	
Adjusted R^2	0.469		0.513	

Note: *** p<0.001, ** p<0.01, * p<0.05

Estimation results of cues of listing and host on Revenue are shown in Table 3. From first and second column of coefficient to see, most of listing cues (i.e., *ListingType*, *CommentNumber* and *Amenities*) have positive effects on listing revenue in a month, indicating that H2b-H2d is supported. However, revenue is not influenced by area, thus, H2a is rejected. Higher acceptance rate to reservations brings more revenue for the host (β=0.058, p=0.003). The number of listings and orders owned by a host have positive impacts on revenue too (β=0.113, p=0.000; β=0.034, p=0.007). Therefore, H4a, H4c and H4d are supported. While *ConfirmTime* does not show significant effect (β=-0.001, p=0.325), meaning that H4b is not supported.

Table 3. Estimation Result of Cues of listing and host on Revenue (Model 2)

Dependent Variable: Log (Revenue)				
	Coefficient	Standard Error	Coefficient	Standard Error
Area	-0.001	0.001	-0.001	0.001
ListingType	0.230***	0.059	0.258***	0.058
CommentNumber	0.083***	0.011	0.072***	0.017
Amenities	0.021*	0.010	0.026*	0.010
AcceptRate			0.058**	0.050
ConfirmTime			-0.001	0.004
ListingNumber			0.113***	0.025
OrderTotal			0.034**	0.013
(Constant)	2.783***	0.087	2.791***	0.162
Observations	852		852	
R^2	0.499		0.505	
Adjusted R^2	0.493		0.502	

Note: *** p<0.001, ** p<0.01, * p<0.05

5. ROBUSTNESS CHECK

Robustness check was conducted to alleviate model endogeneity and bias. Price is a key factor in building a rational commercial market for the balance of demand and supply. As Edelman and Luca pointed, price demonstrates digital discrimination and performance between black and non-black hosts in Airbnb marketplace [17]. Therefore, we take price of the listing as the dependent variable to check the model robustness. Like revenue, price (skewness = 7.12) with skewed normal distribution is also taken log transformation. The robustness check result is shown in Table 4. Most listing cues have significant effects on the price of the listing (i.e., *ListingType*, and *Amenities*). The price of an apartment is higher than that of a single room, demonstrating that price is decided by listing type (β=0.647, p=0.000). It is also affected by amenities (β=0.030, p=0.017). With respect to host cues, the accept rate to orders influence price positively (β=0.132, p=0.000). Results are similar to the estimation results in Section 4, supporting the consistency of the estimated model.

Table 4. Robustness Check

Dependent Variable: Log (Price)				
	Coefficient	Standard Error	Coefficient	Standard Error
Area	0.001	0.000	0.001	0.000
ListingType	0.647***	0.037	0.650***	0.036
CommentNumber	0.007	0.000	0.002	0.007
Amenities	0.030*	0.007	0.026*	0.007
AcceptRate			0.132***	0.096
ConfirmTime			-0.006	0.002
ListingNumber			0.004	0.002
OrderTotal			0.001	0.000
(Constant)	4.577***	0.064	4.658***	0.103
Observations	852		852	
R^2	0.533		0.607	
Adjusted R^2	0.531		0.602	

Note: *** p<0.001, ** p<0.01, * p<0.05

6. DISCUSSIONS AND IMPLICATIONS

Based on cue utilization theory, this study proposed, surveyed and tested models about influential factors to performance of a listing. An empirical study was conducted to explore whether performance in room-sharing service are affected by listing cues and host cues. Performance is quantified as occupancy rate and revenue monthly for a listing [8, 30]. Listing cues include many attributes of a listing, such as area, listing type (i.e., whole apartment, single room), amenities and its reviews. Host cues are information about a host, including the accept rate to orders, confirm time to orders, the number of listings, orders owned by him or her. Two regression models were conducted to check our hypotheses. Results indicate that occupancy rate and revenue are significantly by many listing cues and host cues. Specifically, occupancy rate is affected by listing cues (i.e., *CommentNumber*, *Amenities*) and host cues of *AcceptRate*, *ConfirmTime*, *ListingNumber*, *OrderTotal*, while revenue is influenced by *ListingType*, *CommentNumber*, *Amenities* in listing cues and *AcceptRate*, *ListingNumber*, *OrderTotal* in host cues.

Sharing economy and room-sharing service gain much popularity and growth in recent years. The major contribution of this study is that it provides a practical evidence that performance is affected by listing cues and host cues. Both theoretical and managerial implications are revealed. In theoretical perspective, this study is the first attempt to explore occupancy and financial performance in room-sharing service. It's widely considered that high occupancy rate and revenue mean better performance for the hotel in hospitality market [8, 35, 36]. Therefore, the occupancy rate and revenue for a listing in XiaoZhu are also applied as the measurement of performance in our study. Second, the findings of this research also extend the application of cue utilization theory in the context of the sharing economy. As room-sharing platform is a peer-to-peer economic model, online cues are classified into listing cues and host cues in this research. The findings indicate that performance is closely related to online cues. Finally, this study enriches and extends the behavior analysis of the sharing economy. Though there are a few empirical researches on behavior analysis of Airbnb [4, 7, 17], most of them are concerned only on the hosts or rooms. Therefore, this study makes the implement with more systematic, integrated analysis of the effect of both host and listing cues.

The findings also reveal managerial implications especially for hosts who are eager to attract more consumers and increase their performance. Firstly, hosts are supposed to recognize what the key cues are for potential renters and then offer appropriate listings to satisfy consumers’ demands. The more abundant facilities in a listing, the more popular it is. It is also beneficial for hosts to increase host cues quality such as spending less time on order confirmation. In addition, comments are important factors to influence performance. Therefore, it is necessary to encourage renters to review more about listings and hosts.

7. LIMITATIONS AND FUTURE DIRECTIONS

There are some limitations needed to be recognized. First, the study only focus on a region market (i.e., Beijing), more cities and larger sample size need to be analyzed in the future. Second, the findings provide the perspective only to a specific room-sharing market, might not be appropriate for other service in sharing economy. Therefore, more analysis of the other service (e.g., transportation) can be conducted in the future.

ACKNOWLEGEMENT

This work was supported by grants from the National Natural Science Foundation of China (Grant Numbers: 71373194 and 71332001). It was also partly supported by “the Fundamental Research Funds for the Central Universities”.

REFERENCES

[1] Belk, R. (2010). Sharing. Journal of Consumer Research, 36(5), 715-734.

[2] Botsman, R., Rogers, R. (2010). Beyond zipcar: collaborative consumption. Harvard Business Review, 88(10).

[3] Bardhi, F., Eckhardt, G. M. (2012). Access-based consumption: the case of car sharing. Journal of Consumer Research, 39(4), 881-898.

[4] Li, J., A. Moreno, D.J. Zhang (2015). Agent Behavior in the Sharing Economy: Evidence from Airbnb. https://deepblue.lib.umich.edu/bitstream/handle/2027.42/116384/1298_Li.pdf?sequence=1&isAllowed=y.

[5] Geron, T. (2013). Airbnb and the unstoppable rise of the share economy. http://www. forbes. com/sites/tomiogeron/2013/01/23/airbnb-and-theunstoppable-rise-of-the-share-economy.

[6] Ikkala, T. , Lampinen, A. (2015). Monetizing Network Hospitality: Hospitality and Sociability in the Context of Airbnb. http://collaborativeeconomy.com/wp/wp-content/uploads/2015/04/Ikkala-T.-Lampinen-A.2015.Monetizing-Network-Hospitality-Hospitality-and-Sociability-in-the-Context-of-Airbnb.pdf.

[7] Liang, L.J. (2015). Understanding Repurchase Intention of Airbnb Consumers: Perceived Authenticity, EWoM and Price Sensitivity. Doctoral dissertation. Guelph: University of Guelph.

[8] Jeffrey, D., Hubbard N.J. (1994). A model of hotel occupancy performance for monitoring and marketing in the hotel industry. International Journal of Hospitality Management, 13(1): 57-71.

[9] Ingram, P.(1988). Organizational form as a solution to the problem of credible commitment: The evolution of naming strategies among U.S. hotel chains. Strategic Management Journal, 3(3): p. 1-10.

[10] Mattsson, J., Orfila-Sintes. F. (2014). Hotel Innovation and Its Effect on Business Performance. International Journal of Tourism Research, 16(4): 388–398.

[11] Jacoby, J., J.C. Olson, R.A. Haddock. (1971). Price, Brand Name, and Product Composition Characteristics as Determinants of Perceived Quality. Journal of Applied Psychology, 55(6): 570-579.

[12] Akerlof, G.A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. The Quarterly Journal of Economics, 84(3): 488-500.

[13] Belk, R.W.(2013). Extended self in a digital world. Journal of Consumer Research, 40(3): 477-500.

[14] Belk, R., You are what you can access: Sharing and collaborative consumption online. Journal of Business Research, 2014. 67(8): 1595-1600.

[15] Hawlitschek, F., Teubner, T., Gimpel, H. (2016). Understanding the Sharing Economy—Drivers and Impediments for Participation in Peer-to-Peer Rental. Hawaii International Conference on System Sciences, 4782-4791.

[16] Satama, S. (2014). Consumer adoption of access-based consumption services - case airbnb. Journal of Service Industry Management, 16(4): 357-72.

[17] Edelman, B.G. , M. Luca. (2014). Digital discrimination: The case of airbnb. com. Harvard Business School NOM Unit Working Paper, 14-54.

[18] Jeffrey, D. , R.R.D. Barden. (2001). Multivariate models of hotel occupancy performance and their implications for hotel marketing. International Journal of Tourism Research, 3(1): 33-44.

[19] Meidan, A. (2006). The Marketing of Tourism. Service Industries Journal, 4(3): 166-186.

[20] Evans, M., P. (1992). Mcdonagh, and L. Moutinho, The Coastal Hotel Sector: Performance and Perception Analysis. Built Environment, 18(1): 67-78.

[21] Jr, J.A.R. (1991). Variance analysis: Evaluating hotel room sales. Cornell Hotel & Restaurant Administration Quarterly, 31(4): 60-65.

[22] Richardson, P.S., A.K. Jain. (1994). Extrinsic and Intrinsic Cue Effects on Perceptions of Store Brand Quality. Journal of Marketing, 58(4): 28-36.

[23] Wheatley, J., J. Chiu, A. Goldman. (2015). Physical Quality, Price, And Perceptions of Product Quality: Implications for Retailers, 57(2): 100-116.

[24] Longstreet, P. (2010). Evaluating Website Quality: Applying Cue Utilization Theory to WebQual. Hawaii International Conference on System Sciences. IEEE Computer Society, 1-7.

[25] Dellarocas, C., X. Zhang, N.F. Awad. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. Journal of Interactive Marketing, 21(4): 23-45.

[26] Peterson, R.A., M.C. Merino. (2003). Consumer information search behavior and the internet. Psychology & Marketing, 20(2): 99–121.

[27] Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. Journal of Marketing, 70(3): 74-89.

[28] Kwahk, K.Y., X. Ge, J.M. Lee. (2012). The Effects of Use of Instant Messenger on Purchase Intention: The Context of Chinese C2C E-Commerce. Asia Pacific Journal of Information Systems, 22.

[29] Zhang, M., G.Y. Zhang, Y.E. Zuo-Liang. (2011). Exploring the Impact of Online Information on Hotel E-bookings--Based on the Analysis of the Data from Ctrip. Tourism Tribune, 26(7): 79-84 (in Chinese).

[30] Hung, W.T., J.K. Shang, F.C. Wang. (2015). Exploring the Determinants of Hotel Occupancy Rate : A Dynamic Panel Data Approach. Abstract of Economic Finance & Management Outlook, 1(1): 3.

[31] Liao, Y., L. Yi. (2010). The Influence of Information Presentation and Online Trust in the C2C Web Store Context. in International Conference on Management and Service Science. IEEE, 1-4.

[32] Qiang, Y., R. Law, B. Gu. (2009). The impact of online user reviews on hotel room sales. International Journal of Hospitality Management, 28(1): 180-182.

[33] Ert, E., A. Fleischer, N. Magen. (2016) Trust and reputation in the sharing economy: the role of personal photos in Airbnb. Tourism Management, 55: 62-73.

[34] O’Brien, R.M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. Quality & Quantity, 41(5): 673-690.

[35] Arnold, D. (1994). Profits and prices: a lodging analysis. Cornell Hotel & Restaurant Administration Quarterly, 35(1): 30-33.

[36] Malk, M., R.S. (1993). Schmidgall, Financial analysis of the rooms department. Bottomline, 8(6): 18-21.