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Hey Host, Do Communicate with Guests: Empirical Evidence from Airbnb

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Abstract

Despite a wide practice of e-market sellers communicating with their consumers, little attention is given to how the practice affects consumers' purchase decision process. Based on the text analysis of 10,479 accommodation cases obtained from Airbnb, we empirically examine the relationship between the sellers' communication efforts and the wish-listing behaviors of guests. We find that the wish-listing is positively associated with the communication efforts of a host, such as (1) the feedback volume, (2) tailored messages and personalized contents, and (3) contingent responses to guest reviews. We discuss the theoretical and practical implications of the study.

Keywords: Communication Efforts, Feedback, Purchase Decision Process, Text Analysis
JEL Classifications: C01, D83, L81

Ⅰ. Introduction

Most e-market platforms allow consumers to share their shopping experience through a review system. A plethora of efforts have been devoted to understanding how online reviews or ratings affect the purchase decision of potential consumers by reducing information asymmetry between sellers and consumers, and building consumers' trust in sellers (see the review papers, King et al. 2014 and Beldad et al. 2010).

Despite a great deal of past research on the online review, our knowledge is more or less limited to how the reviews or ratings of consumers affect the purchase decision of other consumers. Little

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is known about how sellers' past action in a review system, such as their response to consumer reviews or comments, which is visible to potential consumers, affects their purchase decision process. Although there are a few studies examining the effect of sellers' feedback on negative consumer reviews (Karatepe 2006; Liao 2007; Skarlicki et al. 2004), most of them are survey-based, which might be limited in investigating ongoing interactions between sellers and consumers.

Although the seller-consumer interaction has not drawn much attention from research communities, it is widely recognized as an important factor that might affect consumers' platform usage or purchase decision in practice. In the case of Airbnb, for example, its active communication channel between guests and hosts is the main reason for guests to revisit the platform (Tussyadiah 2015). Further, social factors such as host feedback are reported to be more influential in choosing an accommodation rather than physical factors such as room size and type (Heo et al. 2015). Echoing this, online hotel reservation platforms such as TripAdvisor have renovated their website to implement a new feedback system, which allows hotels or guest houses to provide feedback on the reviews of past customers. As such, customers can make purchasing decisions not only based on reviews and ratings by other customers but also seller feedback on their reviews (Casalo et al. 2015).

As per our discussion above, our primary research questions are: (1) Do the communication efforts of sellers indeed play a role in consumers' purchase decision process? and (2) If so, how do they affect? To answer the questions, this study captures the dimensions of sellers' communication efforts (which is termed as 'interactivity') and empirically examine how each dimension is related to the purchase intention of consumers. Based on the analysis of guest review and host feedback on Airbnb, we show that the guests' wish-listing is positively associated with the communication efforts of a host. Specifically, we find that the wish-listing increases with (1) the communication volume by a host, (2) tailored messages and personalized contents provided by the host, and (3) contingent responses by a host to guest reviews.

Our findings provide theoretical and practical implications by empirically demonstrating the significant role of sellers' communication efforts in consumers' purchase decision. The contribution of the study also lies in providing insights on how to communicate with consumers to better nurture their purchase intention.

Ⅱ. Communication Efforts and Purchase Intention

The interactivity is the exchange of sequential messages and implies the relevance of the later message to the previous messages (Rafaeli and Sudweeks 1997). It also means the extent to which a speaker and a listener respond to each other's communication needs (Ha and James 1998; Newman et al. 2004).

The interactivity has been conceptualized in different ways across literature

(McMillan and Hwang 2002; Song and Zinkhan 2008; Wu and Wu 2006). For example, Dholakia et al. (2001) conceptualize it with six components—user control, responsiveness, real-time interaction, connectedness, personalization, and playfulness—, whereas Wu and Wu (2006) describe it with three components—user control, responsiveness, and personalization. McMillan and Hwang (2002) view two-way communication (which is communication volume), user control, and time as its key dimensions. Alba et al. (1997) highlight only two—the response time and response contingency.

We focus on the communication volume, response contingency, and personalization, which are common components of interactivity, to examine the effects of seller communication efforts on the purchase intention. The communication volume of the seller refers to the amount of information flow from a seller to a consumer (McMillan and Hwang 2002). Response contingency refers to how relevant a seller responds to a consumer (Alba et al. 1997, Dholakia et al. 2001). Both the communication volume and response contingency are critical in building trust in sellers (Ridings et al. 2002, Wu and Chang 2005), which is positively associated with the purchase intention (Lagace et al. 1991, Wu and Chang 2005). In addition, the personalized message could further promote the purchase intention. Given that customers are heterogeneous, tailored messages would better suit consumers' needs, and thus, more effectively build their trust in sellers than mechanic responses with the same contents (Komiak and Benbasat 2006).

In sum, we expect that a seller's communication efforts regarding the communication volume, response contingency, and the degree of personalization in seller feedback to consumer reviews would be positively associated with the purchase intention of consumers. We empirically examine our conjecture in the next section.

Table 1. Descriptive Statistics

Variable	Description	Mean	S. D.	Min	Max
ln(Price)	Accommodation price per night (log)	11.395	.672	9.260	16.257
ln(Wish list)	The total number of wish lists (log)	3.604	1.733	0	9.402
Star Rating	Average rating of guest reviews	3.468	2.149	0	5
Guest Reviews	The total number of guest reviews	26.576	49.928	0	512
Bedrooms	The number of bedrooms	1.149	.645	0	10
Photos	The number of photos on the web	13.925	11.024	1	100
Rent Type	Rent rooms = 0 or whole house = 1	.315	.464	0	1
Host Feedback	The total number of host feedback entries	2.763	10.095	0	264

Ⅲ. Empirical Approach

1. Data

We collected data from Airbnb (www.airbnb.com) with a customized web crawler. A total of 27,966 accommodations in various cities across multiple countries including the United States, the United Kingdom, Canada, and Australia were crawled from October 15, 2016, to October 25, 2016. We obtained their basic information such as location, house type, and price, along with guest reviews and host feedback. We also crawled how many times an accommodation was wish-listed, which is used as a proxy for the guests' purchase intention in our study. <Table 1> presents the description and descriptive statistics for the variables.

2. Measures and Empirical Model

Unlike the communication volume, which can be measured by the number of comments and responses by a host, measuring the other two dimensions－response contingency and the degree of personalization－is not straightforward.

To measure the response contingency, we adopt a semantic calculation based on Latent Semantic Analysis (LSA), which is a widely-accepted natural language processing technique. Specifically, we look at whether the topic of a review matches well with the topic of host feedback. Through a singular value decomposition, we reduce the dimensions of the words' relationship matrix and calculate the inter-document similarity between a review and its corresponding feedback (Landauer et al. 1998). One merit of using this semantic method is, even though a review and the feedback does not contain the exact same morphology, it can compute the similarity based on semantically similar words. We calculate the response contingency of each host by taking the average on the cosine similarity between a guest review (Gl_j) and host feedback (Hl_j) using the LSA technique. That is,

$$Topic\ consistency_i = average\left(\frac{\overrightarrow{Gl_j}\cdot\overrightarrow{Hl_j}}{|\overrightarrow{Gl_j}|\times|\overrightarrow{Hl_j}|}\right)_i$$

for each host i and each pair of guest review and host feedback j.

To measure the degree of personalization, we calculate the similarity between host feedback based on the Term Frequency (TF) - Inverse Document Frequency (IDF) analysis. TF is a measure of how often a particular word appears in a document. It is the ratio of the number of a particular word (w) to the total number of words in the document (d). IDF is a measure of how rare a particular word is in the entire document and is the ratio of the total number of documents (D) to the number of documents containing the particular word $(f_{w,D})$ (Huang 2008).

$$TF - IDF = f_{w,d} \times log(\frac{|D|}{f_{w,D}})$$

We regard each host feedback as a document and all feedback from the same host as an entire document. We vectorize the TF-IDF value of each word in a document and then calculate the cosine similarity between each document vector (W_{dj}) and entire document vector (WD). The average value of these cosine similarities is defined as a similarity within hosts. That is,

$$Similarity\ within\ hosts_i = average\left(\frac{\overrightarrow{Wd_j} \cdot \overrightarrow{WD}}{|\overrightarrow{Wd_j}| \times |\overrightarrow{WD}|}\right)_i$$

for each host i and each feedback j. For example, if a host simply and repeatedly writes feedback such as "thank you," the similarity value would be high, and conversely, if her feedback contains various words, the similarity value would be low.

Lastly, if the degree of personalization is high, the feedback would provide unique information which cannot be obtained from other feedback. To measure this, we regard the feedback of all hosts except a particular host as the entire documents and each feedback of the particular host as a document and calculate the cosine similarity between each document vector (A_{dj}) and entire document vector (AD) (that is the *similarity among hosts*). That is,

$$Similarity\ among\ hosts_i = average\left(\frac{\overrightarrow{Ad_j} \cdot \overrightarrow{AD}}{|\overrightarrow{Ad_j}| \times |\overrightarrow{AD}|}\right)_i$$

Table 2. Examples of Host Feedback and Guest Reviews

Host ID	Host Feedback	Guest Review	Similarity
11169842	Thank you=)	The place was exactly as described in the listing! … There were tons of food and dessert places that are walking distance :) Victoria was able to accommodate our late arrival/ early check out as well. Highly recommend!	Within: .756 Among: .100 Topic: .036
	Thank you!!! I will be glad to see you again=)	Cute place in Koreatown. Walkable distance to shopping centers. Thanks, Victoria, I would stay here again if I visit Los Angeles again.	
10518631	It is listed in several places on my profile that there is a dog that lives in the house. I have had multiple guests show up fully aware that my dog lives here. Not sure why it was an issue in this situation.	It was our first stay in the US and we want to give it a positive opinion. Diane didn't mention anything about her dog though she did her best to keep him outside. …	Within: .484 Among: .042 Topic: .508
	Betty was a great guest! In response to the neighborhood not being close to dining: the neighborhood is residential and mixed-use and is very close to downtown which is the primary restaurant district in Oakland. ⋯	Diana made me feel right at home, … The location is not ideal for evening dining at the cafe just down the street closes at 4 pm. It would require a taxi or Uber to get out at night as I wouldn't feel comfortable walking after dark.	

for each host i and each feedback j. The measure is high, when a host writes feedback just like other hosts, but low when the feedback contains the unique information. <Table 2> shows a few examples of guest reviews, host feedback, and their similarity values.

With the measures developed above, we build our empirical model. We are interested in the role of communication efforts by hosts in fostering guests' accommodation intention. Our variables of interests are the feedback volume by a host, measured by the normalized counts of host feedback (*Host_feedback*), the response contingency, measured by the topic consistency between consumer review and host feedback (*Topic_consistency*), and the degree of personalization, measured by the similarity within and among host feedback (*Similarity_within_hosts, Similarity_among_hosts*). We also controlled for the review valence (*Star_rating*) and accommodation heterogeneity such as the number of bedrooms (*Bedrooms*), the type of rent (*Rent_type*), and price (*Price*). Our dependent variable is how many times the accommodation is wish-listed (*Wish_list*).

The following equation describes our model.

Ⅳ. Empirical Findings

After excluding the accommodations without any host feedback from the original sample, a total of 10,479 accommodations were used to estimate the parameters in our model. The Model (1) in <Table 3> summarizes the result.

The coefficient of *Host_feedback* is positive and significant, meaning that the wish-listing is positively associated with the normalized feedback volume by a host. Further, the coefficient of *Topic_consistency*, which is the measure for response contingency, is also positive and significant, suggesting that he wish-listing is positively associated with it. The coefficients of our two measures related to the degree of personalization, *Similarity_within_hosts*, and *Similarity_among_hosts*, are negative and significant, confirming that tailored messages might encourage the purchase intention.

When there is only one host feedback, the value of similarity within hosts is always one. To address the empirical concern, we rerun the model without such cases. A total of 6,849 remained accommodations were used for the robustness check and the results are shown in Model (2) in <Table 3>. The results are consistent with our main finding.

$$\begin{aligned} ln(Wish\ list)_i = \alpha &+ \beta_1 \times ln(Price)_i + \beta_2 \times Star\_rating_i + \beta_3 \times Guest\_reviews_i \\ &+ \beta_4 \times Bedrooms_i + \beta_5 \times Photos_i + \beta_6 \times Rent\_type_i + \beta_7 \times Host\_feedback_i \\ &+ \beta_8 \times Similarity\_within\_hosts_i + \beta_9 \times Similarity\_among\_hosts_i \\ &+ \beta_{10} \times Topic\_consistency_i \end{aligned}$$

Table 3. Regression Results

Variable	Model (1) Coefficient (Robust Std. Err.)	Model (2) Coefficient (Robust Std. Err.)
ln(Price)	.280 (.019)***	.314 (.023)***
Star Rating	.281 (.009)***	.152 (.023)***
Guest Reviews	.014 (.000)***	.013 (.000)***
Bedrooms	-.155 (.013)***	-.153 (.016)***
Photos	.008 (.000)***	.007 (.001)***
Rent Type	.628 (.022)***	.596 (.026)***
Host Feedback	.002 (.001)*	.002 (.001)*
Similarity within Hosts	-.363 (.035)***	-.882 (.077)***
Similarity among Hosts	-1.553 (.412)***	-1.556 (.472)***
Topic Consistency	.645 (.052)***	1.058 (.086)***
N	10479	6849
R^2	.636	.617

Notes: Our dependent variables is ln(Wish_list); Two-tailed tests, ***p<0.001, **p<0.01, *p<0.05

Ⅴ. Discussion and Conclusion

In this study, we investigate how the communication efforts of a seller work for the purchase intention of consumers. Based on the crawled data from Airbnb, we find that the wish-listing of guests is positively associated with the communication efforts of a host, such as (1) the feedback volume, (2) tailored messages and personalized contents, and (3) contingent responses to guest reviews.

This study provides several implications. While the seller's role in a review system is under-examined, our findings suggest that it could be a critical factor for nurturing consumers' purchase intention. Not only the communication volume but also the relevancy and the degree of personalization play a significant role in promoting the purchase intention. Our analysis results also urge sellers to actively engage in the communication with their consumers. Further, the results suggest that e-market platforms should implement and facilitate a feedback system where sellers can effectively communicate with their consumers.

References

Alba, J., J. Lynch, B. Weitz, C. Janiszewski, R. Lutz, A. Sawyer et al. (1997), "Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces", *Journal of Marketing*, 61(3), 38-53.

Beldad, A., M. De Jong and M. Steehouder (2010), "How Shall I Trust the Faceless and the Intangible? A Literature Review on the Antecedents of Online Trust", *Computers in Human Behavior*, 26(5), 857-869.

Casalo, L. V., C. Flavian, M. Guinaliu and Y. Ekinci (2015), "Do Online Hotel Rating Schemes Influence Booking Behaviors?", *International Journal of Hospitality Management*, 49, 28-36.

Dholakia, R. R., M. Zhao, N. Dholakia and D. Fortin (2001, January), "Interactivity and Revisits to Websites: A Theoretical Framework", Conference Proceedings: American Marketing Association.

Ha, L. and E. L. James (1998), "Interactivity Reexamined: A Baseline Analysis of Early Business Web Sites", *Journal of Broadcasting & Electronic Media*, 42(4), 457-474.

Heo, Hoseok, Ji Ho Sung, Soonyoung Cha, Bo-Gyu Jang, Joo-Youn Kim, Gangtae Jin et al. (2015), "Interlayer Orientation-Dependent Light Absorption and Emission in Monolayer Semi- conductor Stacks," *Nature Communications*, 6.

Karatepe, O. M. (2006), "Customer Complaints and Organizational Responses: The Effects of Complainants' Perceptions of Justice on Satisfaction and Loyalty", *International Journal of Hospitality Management*, 25(1), 69-90.

King, R. A., P. Racherla and V. D. Bush (2014), "What We Know and Don't Know about Online Word-of-mouth: A Review and Synthesis of the Literature", *Journal of Interactive Marketing*, 28(3), 167-183.

Komiak, S. Y. X. and I. Benbasat (2006), "The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents", *MIS Quarterly*, 30(4), 941-960.

Lagace, R. R., R. Dahlstrom and J. B. Gassenheimer (1991), "The Relevance of Ethical Salesperson Behavior on Relationship Quality: The Pharmaceutical Industry", *Journal of Personal Selling & Sales Management*, 11(4), 39-47.

Landauer, T. K., P. W. Foltz and D. Laham (1998), "An Introduction to Latent Semantic Analysis", *Discourse Processes*, 25(2-3), 259-284.

Liao, H. (2007), "Do It Right This Time: The Role of Employee Service Recovery Performance in Customer-Perceived Justice and Customer Loyalty after Service Failures", *Journal of Applied Psychology*, 92(2), 475.

McMillan, S. J. and Jang-Sun Hwang (2002), "Measures of Perceived Interactivity: An Exploration of the Role of Direction of Communication, User Control, and Time in Shaping Perceptions of Interactivity", *Journal of Advertising*, 31(3), 29-42.

Newman, E. J., D. E. Stem Jr and D. E. Sprott (2004), "Banner Advertisement and Web Site Congruity Effects on Consumer Web Site Perceptions", *Industrial Management & Data Systems*, 104(3), 273-281.

Rafaeli, S. and F. Sudweeks (1997), "Networked Interactivity", *Journal of Computer Mediated Communication*, 2(4).

Ridings, C. M., D. Gefen and B. Arinze (2002), "Some Antecedents and Effects of Trust in Virtual Communities", *The Journal of Strategic Information Systems*, 11(3), 271- 295.

Skarlicki, D. P., R. Folger and J. Gee (2004), "When Social Accounts Backfire: The Exacerbating Effects of a Polite Message or an Apology on Reactions to an Unfair

Out- come", *Journal of Applied Social Psychology*, 34(2), 322-341.

Song, Ji Hee and G. M. Zinkhan (2008), "Determinants of Perceived Web Site Interactivity", *Journal of Marketing*, 72(2), 99-113.

Tussyadiah, I. P. (2015), "An Exploratory Study on Drivers and Deterrents of Collaborative Consumption in Travel". In I. Tussyadiah and A. Inversini (Eds.), *Information and Communication Technologies in Tou- rism 2015*, Springer, 817-830.

Wu, G. and G. Wu (2006), "Conceptuali- zing and Measuring the Perceived Interactivity of Websites", *Journal of Current Issues & Research in Advertising*, 28(1), 87-104.

Wu, J.-J. and Y.-S. Chang (2005), "Towards Understanding Members' Interactivity, Trust, and Flow in Online Travel Community", *Industrial Management & Data Systems*, 105(7), 937-954.