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Signaling Peer Trust in Accommodation-sharing Services: Effects

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Abstract: Online P2P accommodation-sharing has been a rising sub-market of sharing economy in recent years. However, the trust issues still exist because of information asymmetry and economic risks. Based on signaling theory, we argue that the traveler-host demographic similarity and host review volume both foster traveler's trust-building. By an empirical study, we found that the traveler-host age similarity and education similarity have a significant positive effect on listing sales. Furthermore, it is found that the host's review volume moderate the relationship of age and education similarity of traveler-host on listing sales. The findings take the initiative to verify the effect of traveler-host demographic similarity in sharing economy, which contributes to the accommodation-sharing literature theoretically and provides practical guidelines for developing trust.

Keywords: accommodation-sharing, demographic similarity, online review

1.   INTRODUCTION

Over the past few years, as an emerging business model, the "sharing economy" has grown rapidly. According to PwC, the sharing economy market will grow to $335 billion by 2025 [1]. A rising sub-market of sharing economy is the area of peer-to-peer (P2P) accommodation-sharing services, which happens when a host rents an apartment or a room they own to travelers through a digital platform such as Airbnb. According to the iReseach report, it is estimated that the P2P accommodation-sharing trading volume of China will be $2.6 billion in 2018 [2]. The sharing economy in online short-term accommodation rental will still flourish in a long run. Although the P2P accommodation-sharing platforms provide direct interactions for travelers and hosts, the trust issues still exist. Since the suppliers and customers in P2P accommodation-sharing are both strangers, trust between them is the basis for trading and has a significant impact on consumer's decision-making [3]. Bacharach and Gambetta(2001) point out that trust can be regarded as a signaling problem[4], that is to say, trust can be developed on the basis of perceived cues or signals that indicate trustworthiness about individual's identity.

Previous literature has discussed the following signals about trust. On the one hand, the service provider's profiles such as demographics and other personal information exposed on sharing economy platforms can facilitate consumers' trust on them. In P2P accommodation-sharing platforms, trust can be enhanced by host's profiles, which serve as a means of identification [5] and a way to increase the sense of personal, sociable, human contact [6]. Accordingly, we consider that people who are similar in demographics (e.g. age, hometown, education) tend to trust each other more easily. On the other hand, the reputation system including online review and rating is expected to encourage trust among traders, given the potential risks in trading with strangers in P2P marketplaces [7]. Exposure to online reviews offers additional information about listings for travelers to measure its quality and fit their needs and preferences, which further drive their perceived trust. Based on above research, we propose that online reviews, as the other trust signal, can also facilitate trust of travelers to hosts and positively affect the listing sales. Meanwhile, online reviews represent the predecessor feedback about listings and hosts, while peer similarity among travelers and hosts are traveler's self-identification which can be

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substituted by predecessor feedback. Thus, we assert that there's a moderation relationship between the online review and the peer similarity of travelers and hosts.

In fact, little has been known about the specific effects of demographic similarities between travelers and hosts when compared to online reviews of hosts in sharing economy. This paper aims at answering the main effect and moderating effect of traveler-host demographic similarity and host's review volume on listing sales. Drawing on the signaling theory, we made an empirical study on an accommodation-sharing platform of China to address the research question.

2. LITERATURE REVIEW AND HYPOTHESIS

2.1 Signaling theory

Signaling theory is fundamentally concerned with reducing information asymmetry between two parties [8]. The primary elements of signaling theory consist of signaler, signal, receiver, and feedback [9]. In e-commerce, signaling is displaying of certain website features (signals) that carry information about an individual, product or firms from sellers (signaler) to buyers (receiver) and aim at motivating the buyer's behavioral intention (feedback). Signaling plays a significant role in resolving information asymmetries about the latent and unobservable quality of a product and evaluating the credibility and validity of a seller's qualities [10]. In the online P2P accommodation-sharing context, a traveler not only rents a listing but also literally purchasing the host's offline service. On the one hand, the review volume of a host received is a primary signaling cue indicating his/her popularity and trustworthy. On the other hand, as both traveler's and host's characteristics are important in P2P room-sharing transactions, a match of these characteristics can also be assumed to be important. Consequently, this study intends to integrate two focuses: demographic similarities and review volume. We are curious about the effect of two signals on listing sales and how they interact.

2.2 Demographic similarity

The effects of demographic similarity on trust in P2P transactions are valued and equivocal. According to the homophily theory and similarity-attraction theory [11], similarity is "the degree to which pairs of individuals who interact are similar with respect to certain attributes, such as beliefs, values, education, social status, etc." [12]. The homophily theory was first developed in social network verifying that individuals are inclined to make friends and socialize with people to whom they consider similar. Then the homophily theory was applied in marketing when considering the role of consumer's similarity on their decision-making. Take the example of online review, when consumers perceive the demographic similarity with reviewers, they express more trust and are more likely to be persuaded [13]. Based on the homophily theory, we propose that demographic similarity, conceptualized as the similarity between travelers and hosts in demographic dimensions such as age, hometown, and education, influence consumers' decision-making by providing a means of identification [5] and a way to increase the sense of personal, sociable, and human contact [6] in the P2P accommodation-sharing context. The demographic similarity shortens the social distance between two parties and makes interaction among travelers and hosts easier and less challenging. The following hypothesis is thus developed:

H1: The traveler-host demographic similarities (the similarity of age, H1a; the similarity of hometown, H1b; the similarity of education, H1c) will positively affect listing sales.

2.3 Review volume and demographic similarity
2.3.1 Review volume and listing sales

As noted above, another major factor influencing hospitality or tourism performance is the number of

reviews, which has been proved by literature [14]. We summarize the influence of review volume on listing sales from following aspects. First, since the online rating of listings on room-sharing platform has the J-shaped distribution [15] and nearly 95% of Airbnb properties boast an average user-generated rating of either 4.5 or 5 stars[16], which means the lack of variance makes the online rating miss enough information value for travelers comparing to the number of reviews. Second, as an information source, one of the basic functions of online reviews is to provide information to travelers who have little prior knowledge about the listings [17]. Therefore, review volume determines how much information can obtain. The higher review volume, the more uncertainty of consumers can be reduced from peer evaluation. Neirotti (2016) point that the number of reviews has positive and significant moderation effect on revenue growth in hospitality industry [18]. In line with this empirical evidence, we hypothesize:

H2: The review volume of hosts received will positively affect listing sales.

2.3.2 Combining review volume and demographic similarity

Studies combining review volume and demographic similarity are surprisingly rare. We assert that online reviews and demographic similarity are both cues for consumers to evaluate the offering's quality although working in two different ways. The demographic similarity is the degree of a traveler's similarity perception to a host, which belong to the traveler's self-identification. Meanwhile, review volume of hosts received represents the predecessor's feedback to the listing and host. More reviews, more information may contain. Studies have shown that there is a substitution effect between self-identification and predecessor' feedback [13]. When demographic information is ambiguous, review volume can play an important role in compensating for information lack in the online environment and providing helpful cues for consumers to make decisions. Therefore, we expect the review volume of hosts received to be the primary source for trust and to show a stronger effect than demographic similarity with regard to the formulation of trusting beliefs and trusting behavior like making a reservation. Hence, we assert the impact of demographic similarity to depend on the review volume of hosts received, leading to the hypothesis:

H3: The review volume of hosts received moderate the effect of traveler-host demographic similarities (the similarity of age, H3a; the similarity of hometown, H3b; the similarity of education, H3c) on listing sales.
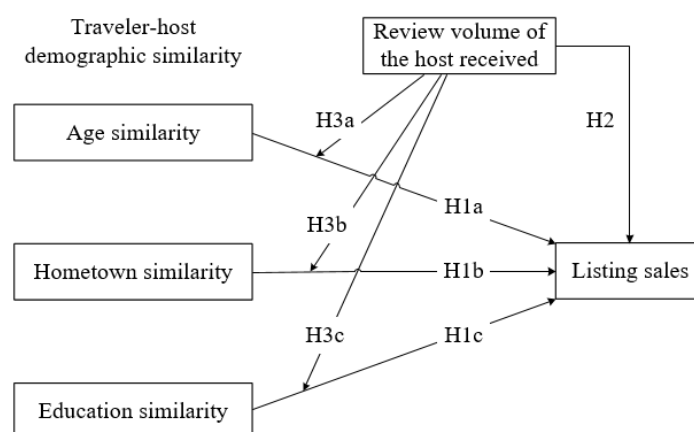

Figure 1.   Research model

3.   METHODOLOGY

3.1 Research context

To empirically test our research model shown in Figure 1, we collected data from *Xiaozhu* (xiaozhu.com), a

clone of Airbnb that has led to a peer-to-peer accommodation-sharing platform in China. The online accommodation-sharing platform *Xiaozhu* is activated in August 2012 and now offers 200,000 online listings in more than 300 domestic cities [19]. As one of the leaders in the accommodation-sharing market in China, it's worth making research on the real-world data generated from the platform to reveal the effects of demographic similarity of traveler-host and review volume of a host received and their interaction effect on listing sales. To fulfill the research requirement, the demographic information of travelers and hosts, review volume of hosts received, and listing sale history need to be obtained. Fortunately, *Xiaozhu*.com provides us all information we need.

3.2 Data and measures

Using an automated Python-based script, we developed a web-crawler to retrieve and collect information relating to all travelers, hosts, and listings. Our sample covers 104,416 listing sale history made by 65,543 unique travelers who stayed at 14,358 unique listings of 7,069 hosts in 18 cities between August 5, 2012, and September 16, 2016. The unit of analysis in our research is *Listing-Check in date*, which allows us to track every unique listing over multiple points of time. Our dependent variable, *Listing_cumOrder* is a numerical variable representing the cumulative number of listing sales. The independent variables are categorized into five dimensions, including *Traveler-host Similarities*, *Moderator*, *Traveler Control, Host Control, and Listing Control.* The specific variable definitions and descriptive statistics are listed in Table 1. The correlation values among explanatory variables are below 0.8 indicating that the estimation is unlikely to be biased by collinearity of variables.

Table 1.   Variable Definition and Summary Statistics

Dimension	Variable	Definition	Obs	Mean	SD	Min	Max
Dependent Variable	Listing_cumOrder	Cumulative number of orders that a listing received	104,416	13.93	17.96	1	172
Demographic Similarities	Age_sim	Dummy variable of whether a host and a traveler are born in the same age, with values of 1=yes, -1=no, and 0=either of age information of hosts or travelers is missing	104,416	-0.01	0.20	-1	1
	Hometown_sim	Dummy variable of whether the hometown of a host and a traveler are the same provinces, with values of 1=yes, -1=no, and 0=either of traveler's or host's hometown information is missing	104,416	-0.03	0.20	-1	1
	Education_sim	Dummy variable of whether a host and a traveler have the same education level, with values of 1=yes, -1=no, and 0=either of traveler's or host's education information is missing	104,416	0.00	0.22	-1	1
Moderator	Host_cumReview	Review volume of the host has received	104,416	34.22	49.38	0	471
Traveler Control	Membership	Number of days since a traveler registered on Xiaozhu	104,416	88.64	156.40	0	1528
	PhoneVeri	Dummy variable of whether a traveler provides verified phone number, with values of 1=yes and 0=no	104,416	1.00	0.05	0	1

	EmailVeri	Dummy variable of whether a traveler provides verified email, with values of 1=yes and 0=no	104,416	0.11	0.31	0	1
	SocialVeri	Dummy variable of whether a traveler provides verified social media account such as WeChat, with values of 1=yes and 0=no	104,416	0.22	0.41	0	1
Host Control	Hmembership	Number of days since a host registered on Xiaozhu	104,416	247.43	269.49	0	1492
	ReplyRate	Number of online replies of a host versus number of inquiries of online shoppers	104,416	0.95	0.08	0	1
	ConfirmTime	Average number of minutes a host takes to respond to a reservation request	104,416	5.26	10.48	0	598
	AcceptRate	Number of accepted reservations versus number of reservation requests	104,416	0.89	0.11	0	1
	NameVeri	Dummy variable of whether a host provides verified name, with values of 1=yes and 0=no	104,416	0.32	0.47	0	1
	NumList	Number of listings owned by a host	104,416	5.65	7.07	0	82
	Gender	Dummy variable of host gender, with values of 1=female and 0=male	98,574	0.65	0.48	0	1
Listing Control	Area	Area of a listing in square meter (m^2)	104,416	56.13	47.61	1	1200
	Bedroom	Number of bedrooms of a listing	104,416	2.09	1.19	0	21
	Livingroom	Number of living rooms of a listing	104,416	1.12	0.70	0	5
	Bathroom	Number of bath rooms of a listing	104,416	1.28	0.71	0	22
	Kitchen	Number of kitchens of a listing	104,416	0.91	0.31	0	11
	Balcony	Number of balconies of a listing	104,416	0.95	0.72	0	18
	Bed	Number of beds of a listing	104,416	1.82	1.15	1	21
	Price	Rate per night of a listing in Chinese Yuan	93,642	286.30	238.64	28	8000
	Category	Nominal variable of listing type, with 1=listing shared with the host (base category), 2=listing shared with other travelers, and 3=private listing	104,416	2.47	0.83	1	3

3.3 Model specification

The overall aim of this study is to examine how traveler-host demographic similarity and host's review volume influence and interact on listing transactions. Because our sample is panel data, the Hausman test was performed before empirical analysis to decide whether the fixed effect should be applied or the random effect in our model. The Hausman result shows that the fixed effect fits our model more. Although the fixed effect model drops the time-invariant explanatory variables in the regression, it is still considered an effective estimation method for controlling the unobserved heterogeneity. We use the ordinary least squares (OLS) regression with fixed effect estimations to examine our regression model as shown in equation (1).

$$Listing\_cumOrder_t = \alpha + \beta_1 Age\_sim + \beta_2 Hometown\_sim + \beta_3 Educaton\_sim + \beta_4 Host\_cumReview_{t-1} *$$
$$Age\_sim + \beta_5 Host\_cumReview_{t-1} * Hometown\_sim + \beta_6 Host\_cumReview_{t-1} * Education\_sim \qquad (1)$$
$$+ \Psi Traveler + \Phi LIST + \Gamma HOST + \varepsilon$$

4.   RESULTS

4.1 Empirical results

Collinearity check was performed to ensure the accuracy of estimation before analyzing the regression model. The collinearity indicator, variance inflation factors (VIF) values of all independent variables are below 5, which indicates there's no multicollinearity lie in our research model. We then ran the OLS model with fixed effect to analyze our model, as presented in Table 2.

The empirical result of our focal explanatory variables is presented in column 5 of Table 2. Time-invariant explanatory variables were dropped because of fixed effect. We can see that the empirical results of three traveler-host similarity variables partially support our hypothesis. To be specific, the *Age_sim* (β=1.037, *p=0.000*) and *Education_sim* (β=0.558, *p=-0.004*) show a significant and positive influence on listing sales. The travelers and hosts that were born in same age or educated to the same level can be more appealing to each other comparing to individuals that were not. Hence, H1a and H1c are supported. Differ from the above results, the *Hometown_sim* (β=0.313, *p=-0.133*) of travelers and hosts fails to have a positive effect on listing sales significantly, meaning that the travelers do not prefer the hosts who come from the same province, rejecting H1b. This may arise from traveler's motivation to accommodation-sharing platform, which largely includes the novelty-seeking and local information acquisition. Travelers tend to pursue unique and novel experience and get a deeper understanding of local customs, which foster them to reserve the local host's listings. In line with Hypothesis 2, we further find that the *Host_cumReview* positively influence the listing observations indeed (β=0.232, *p=0.000*). The more review volume of hosts received, the more trust that travelers build on hosts, the more reservations that travelers may contribute to. As expected in H3a and H3c, the *Review_age_sim* (β=-0.023, *p=0.000*) and *Review_education_sim* (β=-0.006, *p=-0.013*) pass the hypothesis test by showing a negative effect on listing sales, meaning that the review volume of hosts received can negative moderate the effect of traveler-host similarity of age and education on listing sales. That is, as the growth of host's review volume, the age and education similarities of traveler-host are less important in traveler's decision making. We further find that *Review_hometown_sim* (β=-0.002, *p=-0.489*) don't make significance on listing sales, indicating that there's no moderating effect between the review volume of hosts received and the hometown similarity of traveler-host. H3b was not supported.

Table 2.   Estimation results and robustness check

Independent variables	Model1	Model2	Model3	Model4	Robustness check
Dependent Variable: *Listing _cumOrder*					
Age_sim		-0.178	-0.266*	1.037***	1.395***
		(0.312)	(0.077)	(0.000)	(0.000)
Hometown_sim		0.433**	0.214	0.313	0.173
		(0.016)	(0.163)	(0.133)	(-0.530)
Education_sim		0.399**	0.260*	0.558***	0.594**
		(0.015)	(0.063)	(0.004)	(-0.018)
Host_cumReview			0.232***	0.232***	0.167***
			(0.000)	(0.000)	(0.000)
Review_Age_sim				-0.023***	-0.024***
				(0.000)	(0.000)
Review_Hometown_sim				-0.002	0.001

				(0.489)	(-0.651)
Review_Education_sim				-0.006**	-0.007**
				(0.013)	(-0.013)
Traveler control					
Membership	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PhoneVeri	2.629***	2.650***	1.974***	1.976***	2.252***
	(0.000)	(0.000)	(0.001)	(0.001)	(-0.002)
EmailVeri	1.891***	1.934***	1.332***	1.347***	1.627***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SocialVeri	-0.196**	-0.194**	-0.136**	-0.136**	-0.086
	(0.016)	(0.017)	(0.050)	(0.049)	(-0.377)
Host control					
Hmembership	0.059***	0.059***	0.029***	0.029***	0.047***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-3.569***	-3.590***	-3.148***	-3.138***	-5.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-square	0.465	0.465	0.612	0.612	0.628
Observations	88469	88469	88469	88469	50286

Note: $^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$

4.2 Robustness check

In our empirical model, we did not consider the effect of location city of listings on listing sales. Therefore, robustness check was performed to verify that the effect of traveler-host similarity and host's review volume on listing sales across the different cities. We kept the listings from the top three marketplace of *Xiaozhu*.com which is Beijing, Shanghai, and Chengdu as our robustness check sample, and ran our estimation model again to exclude the effect of cities on our empirical result. As shown in column 6 of Table 2, the estimation results are highly consistent with our main results, which further provide a strong evidence for our estimated results.

5. CONCLUSIONS

In this paper, we focused on the traveler-host demographic similarity and host's review volume and investigated their effect on listing sales. We addressed the research question by proposing detailed hypotheses concerning the relationship between the traveler-host demographic similarity, host's review volume, and listing sales. The OLS model with fixed effects was employed to empirically validate our research model. Results show that the traveler-host demographic similarity of age and education have a significant positive effect on listing sales. Further, the host's review volume presents a positive effect on listing sales and a negative moderating effect on the relationship between the demographic similarity of age and education and listing sales. Based on the results, both theoretical and practical implications were presented above. Although this paper offers important contributions to both theory and practice, the limitations still exist. First, the host's characteristic data in our dataset was acquired from the personal homepage of them. However, not all hosts of *Xiaozhu*.com have opened his/her personal page, which makes our dataset may not contain all hosts and their listings. Second, we use the host's review volume as a moderator variable. We argue that the review score and valence of hosts received are also important indicators to represent online reviews, which can be studied as future directions.

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