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Face recognition of profile images on accommodation platforms

Xianwei Liu [a], Chunhong Li [b], Juan Luis Nicolau [c], Meini Han [a]

[a] School of Management
Harbin Institute of Technology
92 West Dazhi Street, Harbin, China
E-mail: liuxianwei@126.com
E-mail: hanmeini@sina.cn

[b] School of Tourism Management
Sun Yat-Sen University
Guangzhou, China
E-mail: lichunhong2010@163.com

[c] Pamplin College of Business
Virginia Tech
Blacksburg, VA 24061, USA
E-mail: jnicolau@vt.edu

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Abstract: Visual information plays a critical role on peer-to-peer (P2P) accommodation platforms from the side of both consumers and service providers. Recent studies (rely heavily on traditional manual identification) have found that attractive hosts possess advantages in alluring potential guests and charging high prices, highlighting the beauty premium effect from the perspective of hosts. Are attractive guests more likely to receive better service from their hosts, thus producing a beauty premium effect from the perspective of guests? To answer this undocumented research question, we collect data from Airbnb accommodations listed in Los Angeles, New York, and Orlando in the US. By virtue of deep learning techniques, face recognition, and text-mining, our empirical results reveal a beauty premium effect from the perspective of guests that attractive guests are more satisfied with their accommodations and receive more interactions from hosts. These findings illustrate the application of face recognition in the context of P2P accommodation platforms and provide direct implications for the operation of accommodation platforms.

Keywords: visual information, attractiveness, beauty premium, satisfaction, Airbnb

1. Introduction

Sharing economy has evolved from social activities to business models involving massive collaborative consumptions and online platforms. A huge number of consumers and emerging online platforms make sharing economy increasingly important in promoting economic growth and employment in the service industry. Peer-to-Peer (P2P) accommodations like Airbnb is a pioneer in the field of sharing economy (Arvanitidis et al., 2020; Kuhzady et al., 2020). Compared with other products or services in sharing economy, P2P accommodations involve more interactions between guests and hosts (Ramos-Henríquez et al., 2021; Baute-Díaz et al., 2020). Research has shown that beauty premium (i.e. judging people by their appearance so that a better physical appearance contributes to the belief of a person being better) exists in many contexts, such as job hunting (Leckcivilize & Straub, 2020), wages (Mobius & Rosenblat, 2006) and also in peer-to-peer accommodations. Ert et al. (2016) revealed, through an experiment, that attractive hosts are more likely to be chosen over less attractive ones; that is, attractive hosts possess advantages in alluring potential guests. Stemming from Ert et al.'s (2016) work, Jaeger et al. (2019) further showed that more attractive hosts charge higher prices for their apartments. In fact, Barnes and Kirshner (2021) linked host images with an enhancement in reputation and perceived trustworthiness, and in this line, Jin et al. (2017) found, in the context of online peer-to-peer lending, that certain degree of dishonesty on the part of borrowers is, to some extent, more "tolerable" the more attractive they are. These studies provided empirical evidence of beauty premium from the perspective of hosts.

In the theoretical framework of beauty premium, physical attractiveness plays an important role in shaping consumer decision-making and service efficiency in the context of P2P accommodations (Li et al., 2021). Research has shown that physically-attractive people are more confident and have good communication and social skills (Mobius & Rosenblat, 2006). In line with this literature, and looking at the prism from the other side, we pose the following research question: Are attractive guests more likely to receive better service from their hosts, thereby producing a beauty premium effect from the perspective of guests? Beauty premium could be bidirectional in accommodation: on the one hand, attractive hosts (service providers) may be more popular among potential guests; and on the other hand, attractive guests may receive more interactions and better service from the hosts. In short, we argue that the positive effect of beauty premium should function on both sides (hosts and guests). We base this argument on the idea that, as social uncertainty takes place in P2P accommodation (Xu et al., 2021), trust is a need for both parties—hosts and guests. Given that a person's face is a relevant source of social information (Zebrowitz et al., 1996) and the human brain has specific areas that are stimulated for facial recognition and perception (Tsao et al., 2003), we propose the alluded bidirectional beauty premium. Extant studies have mainly focused on the beauty premium effect from the perspective of service providers (hosts), thus this research fills this gap and aims to examine whether the beauty premium effect functions from the perspective of guests.

2. Data and methodology

2.1. Data collection

We collect guest reviews and their profile images from Airbnb, the most popular P2P accommodation platform (Leoni, 2020). First, we retrieve the 10 most visited cities in the US according to WorldAtlas (2019). Second, we retrieve the number of guest reviews for the 50 most populous metropolitan cities in the US. Third, we select Los Angeles, New York, and Orlando which possess most guest reviews among the 50 most populous cities and rank top 4 in the 10 most visited cities in the US. Fourth, a Python-based crawler is developed to download the information of reviews posted in 2019 for all the Airbnb listings in these cities. Fifth, we keep the reviews written in English to ensure homogeneity and perform sentiment analysis, and only keep the reviews with a profile image and a recognizable face. To eliminate ambiguity, we only use the one face samples and delete the samples with missing data. Finally, 190,091 (Los Angeles), 166,492 (New York), and 80,755 (Orlando) samples remain.

2.2. Face recognition and variable construction

The independent variable of interest is the attractiveness of a guest. We utilize a deep learning algorithm (Liu et al., 2015; Schroff et al., 2015; Open source algorithm: face detection) to perform face detection and recognition of the profile image of each guest. Trained on LFWA (Labeled Faces in the Wild-a) dataset which contains about 130,00 labeled face images across different gender, age, and race (about 80% of these images works as the training set and the rest functions as the test set), this algorithm outputs various face attributes. In this study, we focus on the guest's attribute of attractiveness (the probability of whether a guest is attractive) which ranges from 0 to 1 . Figure 1 lists some examples of the outcome of this algorithm (for privacy reasons, the images in Figure 1 show public personalities). Figure 2 reports the accuracy of identification.

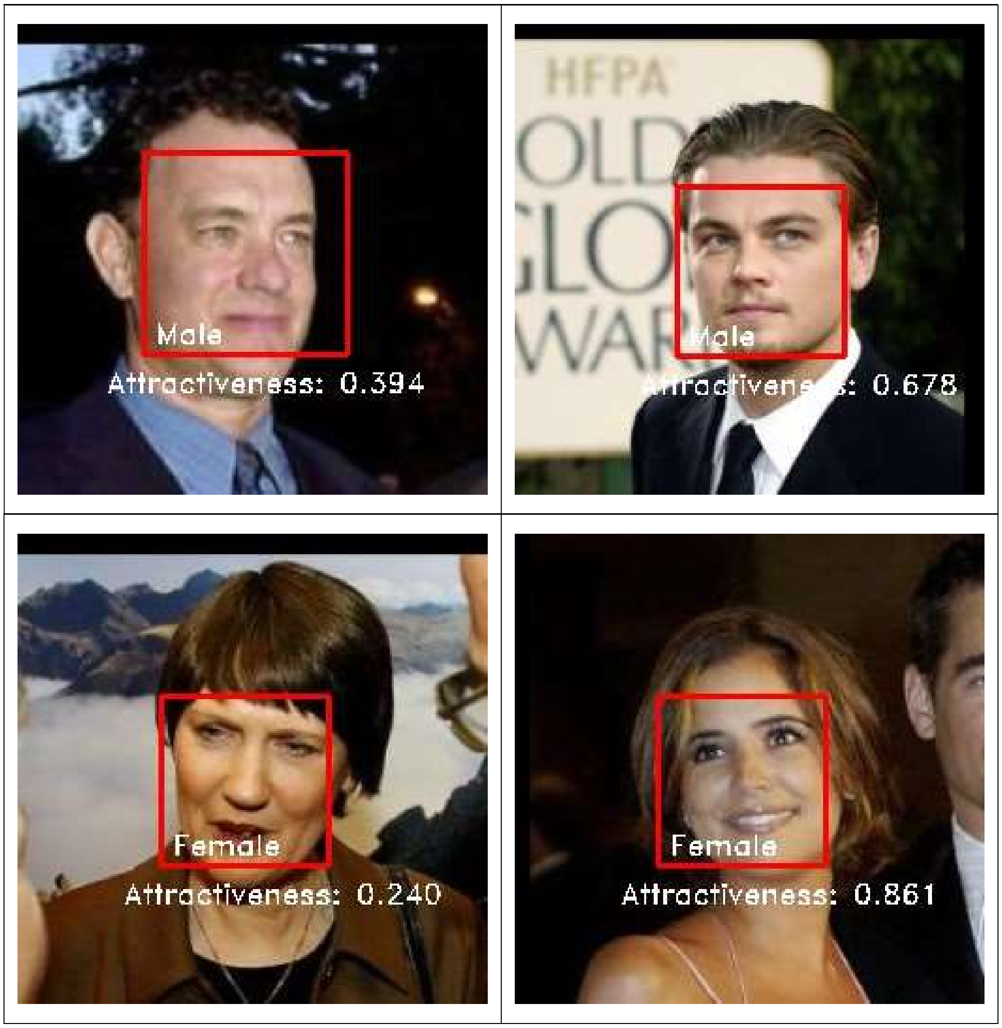

Figure 1. Samples of attractiveness outputted from face recognition.

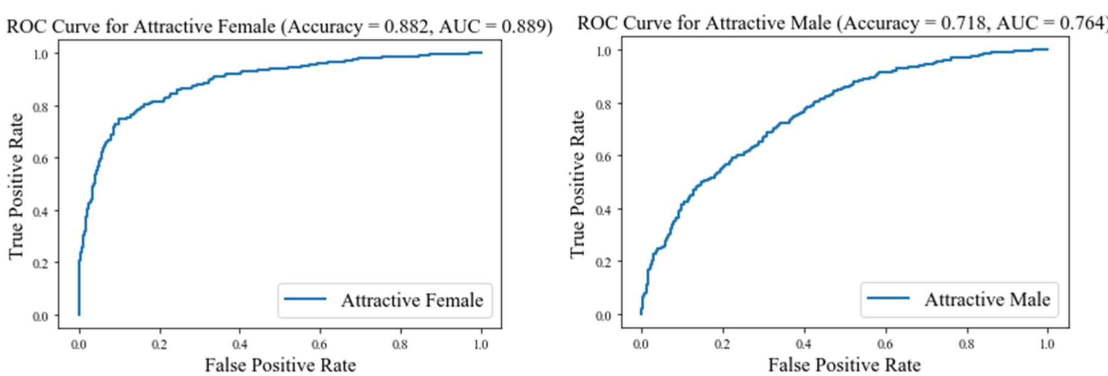

Figure 2. Accuracy of identification.

Two sets of dependent variables are employed in this study. First, guests satisfaction degree. We use guests' accommodation evaluations (rating score from one to five) on their orders to measure satisfaction degree (Liu & Law, 2019). This variable captures whether attractive guests are more satisfied with their accommodation experiences. We also conduct the Valence Aware Dictionary and sEntiment Reasoner (VADER) analysis to measure the sentiment of each review (Hutto, 2014), which ranges from −1 (most negative) to +1 (most positive). Second, potential interactions between guests and hosts. We apply the following text-mining to measure the potential interactions and services guests received from their hosts. First, we collect the name of the host for each house and develop a Python-based program to check whether the host name of a house is mentioned in its guest reviews (*Text_Host*). This is a dummy variable that equals to 1 if a review mentioned the host name of the accommodation, and 0 otherwise. Second, calculate the number of adjectives in each review (*Text_Adj*). These two variables could reflect the interactions between guests and hosts and the praise from the guests regarding the hosts' services.

We also employ several control variables (guest features) in the empirical analysis, measured through dummy variables where "yes" takes value of 1 and 0 otherwise: whether the address of a guest is in the United States, a guest is verified, a host is a super host, a guest's work unit and email are disclosed. The time interval between a guest's registration year and 2020 is also included to control for experience. We further include the house fixed effect to account for heterogeneity across houses and the month fixed effect to control for time-variant factors.

3. Results

3.1. Main results

Table 1 reports the regression results with house and month fixed effects using data collected from three cities. The coefficients of *Attractiveness* in columns 1-6 are all positive and significant at the 0.01 level, indicating that attractive guests are more satisfied with their accommodation and post reviews with more positive sentiment. Accordingly, we infer that attractive guests are more likely to receive better service or more interactions from hosts. To validate this inference, we use *Text_Host* and *Text_Adj* as dependent variables which measures the interactions between guests and hosts. The empirical results reported in Table 2 are highly consistent and show that attractive guests are more likely to mention and praise the host that accommodated them. This largely indicates that attractive guests received better service from the hosts and thus praise them when posting reviews. Compared with prior studies which mainly documented the beauty premium effect from the perspective of hosts in the context of P2P accommodations (Ert et al., 2016; Jaeger et al., 2019; Barnes and Kirshner, 2021), our results indicate that beauty premium also functions from the side of guests.

Table 1. Main results (rating and sentiment).

	Los Angeles		New York		Orlando	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*Rating*	*Sentiment*	*Rating*	*Sentiment*	*Rating*	*Sentiment*
Attractiveness	0.022***	0.052***	0.035***	0.050***	0.025***	0.052***
	(0.005)	(0.002)	(0.006)	(0.003)	(0.009)	(0.004)
Address	0.025***	0.006***	0.069***	0.001	-0.026***	-0.006**
	(0.003)	(0.001)	(0.003)	(0.001)	(0.006)	(0.003)
RegAge	-0.006***	0.005***	-0.006***	0.004***	-0.006***	0.004***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
SuperHost	-0.009	0.001	-0.003	0.003	-0.032	0.001
	(0.012)	(0.005)	(0.013)	(0.006)	(0.023)	(0.010)
Verified	0.014***	0.000	0.008*	0.003	0.012**	0.003
	(0.004)	(0.002)	(0.004)	(0.002)	(0.006)	(0.002)
WorkUnit	0.010***	0.012***	0.007*	0.012***	0.009	0.022***
	(0.003)	(0.002)	(0.004)	(0.002)	(0.007)	(0.003)
WorkEmail	0.012***	-0.001	0.012***	-0.003*	0.020***	0.002
	(0.004)	(0.002)	(0.004)	(0.002)	(0.007)	(0.003)
Constant	4.773***	0.760***	4.744***	0.770***	4.771***	0.754***
	(0.008)	(0.004)	(0.009)	(0.004)	(0.013)	(0.006)
House FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Obs.	190,091	190,091	166,492	166,492	80,755	80,755
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.190	0.169	0.189	0.173	0.246	0.219

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2. Main results (text).

	Los Angeles		New York		Orlando	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*Text_Host*	*Text_Adj*	*Text_Host*	*Text_Adj*	*Text_Host*	*Text_Adj*
Attractiveness	0.079***	0.579***	0.084***	0.492***	0.073***	0.699***
	(0.004)	(0.046)	(0.005)	(0.052)	(0.007)	(0.073)
Address	0.005*	0.244***	-0.004	-0.169***	0.009*	0.091*
	(0.003)	(0.027)	(0.003)	(0.029)	(0.005)	(0.050)
RegAge	0.012***	0.192***	0.013***	0.167***	0.016***	0.239***
	(0.001)	(0.006)	(0.001)	(0.007)	(0.001)	(0.012)
SuperHost	0.014	0.047	0.029***	-0.056	0.019	0.353*
	(0.011)	(0.113)	(0.010)	(0.119)	(0.019)	(0.207)
Verified	0.013***	-0.068**	0.004	0.067*	-0.001	-0.053
	(0.003)	(0.034)	(0.003)	(0.034)	(0.004)	(0.044)
WorkUnit	0.025***	0.528***	0.022***	0.594***	0.041***	0.669***
	(0.003)	(0.033)	(0.003)	(0.037)	(0.006)	(0.066)
WorkEmail	-0.003	-0.078**	-0.008**	-0.090**	0.002	0.048
	(0.003)	(0.033)	(0.003)	(0.038)	(0.006)	(0.059)
Constant	0.476***	4.255***	0.543***	4.837***	0.396***	3.792***
	(0.007)	(0.067)	(0.007)	(0.080)	(0.011)	(0.106)
House FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Obs.	190,091	190,091	166,492	166,492	80,755	80,755
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.164	0.123	0.185	0.151	0.215	0.192

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4. Discussion

As the pioneer of sharing economy, P2P accommodation has become increasingly popular among consumers and created lots of job opportunities in business practice. The importance of P2P accommodation has attracted significant academic attention, wherein current studies have shown that the physical attractiveness of hosts plays an important role in pricing and alluring guests. Different from these studies, we explore the beauty premium effect from the side of guests.

Theoretically, this research is among the first to reveal the beauty premium effect from the perspective of guests in the context of P2P accommodations that physically attractive guests are more interactive and thus gain better services from hosts. Leveraging deep learning techniques, this study largely overcomes the shortcomings of an experimental setting (e.g., small sample, subjectivity, and laboratory effect). Moreover, our findings add knowledge to the application of deep learning and face recognition in online P2P accommodation platforms.

Practically, our findings offer important implications for P2P accommodation platforms and the service industry. Although P2P accommodation platforms like Airbnb have announced that “Moving forward, rather than displaying a potential guest’s profile photo *before* the booking is accepted, hosts will receive a guest’s photo in the booking process only *after* they’ve accepted the booking request” in October 2018 to fight bias and discrimination, this only works before check-in (Zhu, 2021). Our findings suggest that attractive guests may receive better service from hosts, a bias produced after check-in. Therefore, P2P accommodation platforms like Airbnb should consider making polices to fight bias and discrimination during accommodation. This is even more important because the host’s service attitude perceived by guests is critical (Lv et al., 2021) and distrust in P2P accommodations is a chief reason that consumers argue to avoid using such platforms (Del Chiappa et al., 2021).

5. Conclusion

In this study, we perform face recognition and text-mining using large-scale real samples collected from Airbnb. The empirical results reveal that attractive guests are more satisfied with their accommodation service and receive more interactions from hosts, suggesting a beauty premium effect from the side of guests. Despite the theoretical and practical implications of these findings, this study also has several limitations which deserve future research efforts. First, this study only collects data from cities located in the US, thus, whether our findings still hold in different cultures remains unknown. Therefore, collecting data from other destinations (e.g., the Asian and European market) to replicate the results presented in this study is indispensable. Second, the function of beauty premium may vary across gender, age, and other factors; hence, there is potential to research on the heterogeneity of beauty premium and its influence on consumer behavior.

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