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Do photos matter? the effect of hosts' facial features on customers' booking intentions in peer-to-peer accommodation: heterogeneity of host gender

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Abstract
This study aims to investigate the effect of hosts' facial features of different genders on customers' booking intentions on the Airbnb shared accommodation platform. A comprehensive model was built to analyze hosts' facial features in the United States (n = 105,084) through big data combined with an artificial intelligence facial recognition system. Results show that beauty, smile, aging, and wearing glasses positively affect customers' booking intentions. There is gender heterogeneity in the effect of hosts' facial features on customers' booking intentions. Compared to female hosts, smiling is significant for male hosts, and wearing glasses has a greater impact on female hosts. Host reputation somewhat weakens the positive effect of host facial features on customers' booking intentions, and the shared housing type strengthens the positive effect of facial features on customers' booking intentions. This study provides insights into customer decision-making that may be influenced by hosts' facial features.

Keywords Artificial intelligence · Facial features · Gender heterogeneity · Housing type · Host's reputation · Peer-to-peer accommodation

Introduction

Sharing economy has diversified from a social activity to a business model involving large-scale collaborative consumption and interactive online platforms, which is one of the economic models of the current society (Zhang et al., 2021). The sharing economy is increasingly playing an important role in boosting economic growth and employment in the service sector with the emergence of many customers and online platforms. P2P shared accommodation is a prime example of the sharing economy. As a leading P2P accommodation platform and a pioneer of the sharing economy, Airbnb operates in over 220 countries with 6 million listings worldwide. In Airbnb and other shared accommodation markets, trust is a critical factor due to the uniqueness of the products it provides, the few consumption experiences customers have, and the physical distance the product providers and customers have (Agag & Eid, 2019; Belarmino & Koh, 2020).

As service providers on the Airbnb platform, hosts provide customers with intangible accommodation services. Customers lack face-to-face communication with hosts during the booking decision process, and their perception of hosts comes from displaying personal information in hosts' online profiles, including hosts' profile photos and text descriptions. The theory of impressions suggests that people can form an impression of the person in a photograph simply from within one second of looking at it (Bar et al., 2006; Naylor, 2007) and influence subsequent behavior (Hassin & Trope, 2000; Naylor, 2007).

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Customer interest in host profile photos has been extensively studied (Ding et al., 2023; Ert et al., 2016; Jaeger et al., 2019). As the most prominent part of the overall image, facial image directly affects customer impression formation. The facial image is more reflected in facial features, and the facial features that can be recognized through available technologies include beauty (Li et al., 2022), facial trustworthiness (Jaeger et al., 2019), gender (Marchenko, 2019), smile (Jaeger et al., 2019; Jang, 2022), glasses (Banerjee et al., 2022), age (Ert & Fleischer, 2020), and others. The facial features in the host's photos were categorized into changeable aspects and relatively invariant aspects based on within-person variability (Sutherland et al., 2017). Among the changeable aspects include viewpoint and emotional expression, beauty, as the most prominent viewpoint feature is associated with more positive characteristics (Dion et al., 1972). A smile expresses positive emotions and signals of cordiality, sociability, honesty, pleasantness, and politeness (Bugental, 1986). Relatively invariant aspects include gender, age, and facial adornment items (glasses), with people commonly correlating experience and competence with age (Cleveland & Lim, 2007), and glasses-wearing hosts can be perceived as having positive qualities such as intelligence, reliability, and honesty (Fetscherin et al., 2020). These facial features directly influence customers' first impressions, but there are some gaps in research on the collaborative influences on customer behavior. On this basis, the gender of the host is given more importance as customers are faced with choosing an unfamiliar host to provide accommodation services in an unfamiliar environment, where there are some potential risks to customer safety. Customers prefer to book female than male hosts (Banerjee et al., 2022), and female hosts have a positive impact on perceived trustworthiness and attractiveness (Ert & Fleischer, 2020). The effect of host gender on customer choice has been evidenced, and research on how gender-specific host facial features affect customer choice has not been given attention. To fill these gaps, this study proposes the following two research questions:

> RQ1: How do hosts' facial features beauty, smile, age, and glasses affect customers' booking intentions in the shared accommodation industry?
> RQ2: Do hosts by gender show differences in the impact of facial features on customers' booking intentions?

In addition, the host's reputation can reduce customers' perceived risk and choice uncertainty and obtain more bookings (Liang et al., 2017), super host is the Airbnb platform's mark for hosts who provide quality services, and a sign that hosts have a good reputation. Existing research on the effects of host reputation has not only been in the direct effects of review numbers and ratings (Liang et al., 2017); but also shows a new tendency to investigate the mixed effects of host reputation between perceived trustworthiness and ratings (Barnes, 2021), as well as the effects of host reputation on facial attractiveness and consumers' booking intentions (Li et al., 2023). The moderating effect of host reputation on consumer behavior has been evidenced in the shared accommodation industry, but there is a gap in exploring the effect of host reputation on the relationship between host's facial features and customer behavior.

Existing studies have found differences in customer attention as a result of housing type (Ding et al., 2023; Han & Yang, 2021; Nicolau et al., 2023).The difference between booking an entire home/apt and a shared housing is whether needs to have face-to-face with the host, booking a shared housing is associated with more interaction and face-to-face communication with the host. That's why consumers expect a higher level of hosts' image, especially facial images when booking a shared housing. On this basis, it remains to be investigated whether positive qualities such as beauty, positive emotions, experience, reliability, and others identified in a host's photos attract more attention in customers' booking decision-making process when booking a shared housing.

From the above analyses, it can be found that when customers select housings, the host's reputation and housing type are also important references for customers' decision-making, in addition to the host's facial image. Housings satisfy accommodation needs and hosts with good reputations may reduce customers' high demand for hosts' facial images. Therefore, the relationship between hosts' facial image and hosts' reputation as well as housing type have to be considered comprehensively, and based on this, we propose the third research question:

> RQ3: How do the host's reputation and housing type moderate the effect of the host's facial features on customers' booking intentions?

In order to solve the above problems, this study uses massive Airbnb housing data to assist big data analysis through Baidu AI. Baidu AI open platform provides the world's leading voice, image, NLP, and other AI technologies, open dialogue AI system, and its deep learning-based AI face detection system generates AI information including host beauty score, facial expression, and other facial features. Based on first impression and emotional contagion theories, a comprehensive regression model is constructed to analyze the impact of hosts' facial features of different genders on customers' booking intentions, as well as the moderating effects of host reputation and housing type. This study enriches the literature on service providers' online profiles in the shared accommodation industry while providing some insights into how customers' booking decisions are influenced by hosts' facial features.

Therefore, this study is structured as follows: Literature review describes the theoretical background and research framework as well as the present state of AI on facial feature recognition, the effect of facial features on customers' booking intentions, heterogeneity of hosts' gender, the moderating effect of host reputation and housing type. Methodology describes the data sources and processing, explaining the variables and constructing the comprehensive model. Results shows data analysis and hypothesis testing. Discussion section compares the results of this study in relation to the existing literature, theoretical implications, managerial implications and presents the limitations and future research directions. Conclusion section summaries the study.

Literature review

Theoretical background and research framework

First impression theory suggests that when people are exposed to something, they form a first impression of it which influences subsequent judgments about it (Hassin & Trope, 2000; Naylor, 2007). The first impressions formation of people is often acquired through the visual appearance of a face, distinguished from offline environments, people in online environments influence the viewer's perception by recognizing the visual attribute content (facial features) in a photo (Bacev-Giles & Haji, 2017; Ert & Fleischer, 2020), which consequently influences the viewer's impression of the person in the photograph. A photograph, which appears quite temporarily in a person's vision, people can also form a first impression of the person in the photograph (Bar et al., 2006; Naylor, 2007; Willis & Todorov, 2006) and influence subsequent behaviors. Products and services offered by service providers who are perceived to be more trustworthy and attractive carry a premium (Barnes & Kirshner, 2021) and are more likely to be chosen by customers (Yang et al., 2022).

Emotional contagion theory suggests (Hatfield et al., 1993) that people unconsciously and automatically imitate the emotional expressions of others, whether the subject is positive or negative emotion, the experimenter produces an emotion similar to the subject's emotion value (Kramer et al., 2014). In online environments, people's emotions are generated from visually recognized information in text and photos (Herrando et al., 2022; Ouyang & Wang, 2022). Smiling is believed to express more positive emotions (Ert & Fleischer, 2020; Li et al., 2021). Customers experience more positive effects when they interact with positive service providers (Pugh, 2001). Such contagious (or transferable) positive emotions are thought to contribute to increased customer satisfaction with service providers and service quality (Pugh, 2001). Smile or not is one of the salient facial features, a photo of a smiling person is more likely to be trustworthy and gain a competitive advantage in customer online choices (Ert & Fleischer, 2020).

The physical distance between customers and hosts during the booking decision-making process on Airbnb means that customers are unable to have face-to-face contact with hosts, while profile photos provided by hosts can create a first impression of hosts for potential customers (Ding et al., 2023). Customers subconsciously form an impression of the host based on the facial features of the person in the photo, which continues to play a role in subsequent communications, influencing the customer's booking decision.

The first impression theory and emotional contagion theory provide us with precise theoretical support, and in conjunction with the three questions of this study, we attempt to construct a research framework to answer the above questions. The first objective of this study is to examine the effects of a host's facial features beauty, smile, age, and glasses on customers' booking intentions. The second objective is to explore the host's facial features of different genders on the profile of customers' booking intentions. The third objective is to test whether host reputation and housing type moderates the effect of facial features on customers' booking intentions, and if so, how? The research framework is shown in Fig. 1.

Artificial intelligence assisted recognition of facial features

Big data is widely used by scholars to explore practical problems because it is not affected by sampling bias or limited representativeness in traditional statistical methods (Li et al., 2018). In view of the huge amount of data, the traditional way of data analysis will consume a lot of labor costs, machine learning, and artificial intelligence to assist big data for analysis are widely used in the academic field (Gunarathne et al., 2022; Troncoso & Luo, 2022; Zhang et al., 2018). AI techniques based on deep learning algorithms are developing rapidly, especially in processing large numbers of pictures, and are being used extensively for pattern recognition and classification in photo research (Ma & Sun, 2020). Many information sciences (IS) studies have identified and recognized the importance of pictures in web environments (Cyr et al., 2007), with picture studies focusing on the effect of picture color (Yu et al., 2020), number of pictures (Bufquin et al., 2020).

Facial recognition techniques in photo information are a subset of computer vision AI used to develop systems for recognizing faces. By providing application programming ports on open-source platforms, users can deploy machine learning applications without having to collect data or train their own models. Based on the recognition of facial key points information of photographs to obtain facial features data, Baidu has now increased the number of key points for face recognition from 72 to 150, which is recognized as a leading open-source platform for the accuracy of the data it obtains. Existing studies have identified facial features through AI systems mainly including beauty, smile,

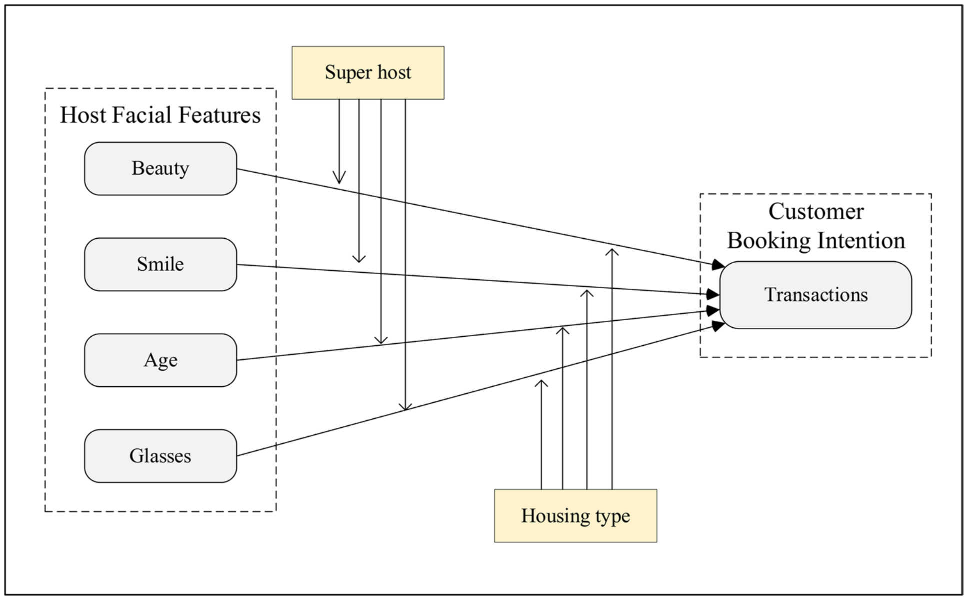


Fig. 1 Research model

age, gender (Yang et al., 2022), emotion (Jang, 2022), race (Gunarathne et al., 2022), length-to-width ratio of the face (Zhang et al., 2021), glasses (Banerjee et al., 2022), skin condition (Ouyang & Wang, 2022), among others, to explore the impact on product prices (Zhang et al., 2021), customer decision-making (Yang et al., 2022), and other aspects of the industry, including tourism (Yang et al., 2022), healthcare (Ouyang & Wang, 2022), and accommodation (Jang, 2022; Zhang et al., 2021).

The effect of host facial features on customers' booking intentions

Airbnb platform provides customers with diverse and convenient services, and the functionality of service providers' online profiles has attracted extensive attention from scholars (Barnes & Kirshner, 2021; Li et al., 2022; Peng et al. 2020; Yang et al., 2022). Hosts, as Airbnb service providers, are encouraged by the platform to upload personal photos as profile photos, which allow customers to make decisions based on the personal information disclosed in the host's profile.

Early scholars believed that gender, educational background, age, and work experience were important factors affecting individual income in the labor market, while physical characteristics are not correlated with individual income (Loh, 1993). The prior study creatively found that the income of beautiful people is 3%-5% higher than that of plain people, while the income of ugly people is 5%-10% lower than that of plain people (Hamermesh & Biddle, 1994). The beauty premium is common in behavioral and labor economics and there are corresponding theories to explain it. Beautiful things are more likely to be appreciated by people, and which is often the case in the decision-making process. This stereotype of beauty premium represents a concept of "beauty is good" (Dion et al., 1972), namely, beauty can increase others' inference that "the beautiful host has positive qualities". And these inferences have real social and economic benefits for those who are beautiful. In other words, other things being equal, beautiful people are acknowledged as perceived to have more desirable positive traits such as knowledge, compassion, and humor (Eagly et al., 1991). On this basis we propose H1:

H1: Host with higher beauty scores have a positive impact on customers' booking intentions.

Emotional contagion theory (Hatfield et al., 1993) has been used to explain and understand the impact of service providers' facial expressions. According to the theory, people unconsciously and automatically imitate the emotional expressions of others. Facial expressions within host photos in online service environments influence the formation of the customer's first impression. Smile is considered to be the most salient facial expression and positively associated with emotional expression (Li et al., 2021). Smiling signals cordiality, sociability, honesty, pleasantness, and politeness (Bugental, 1986), and a big smile makes people feel warm and enthusiastic and is perceived as more trustworthy and attractive, which consequently influences customer behavior (Ert & Fleischer, 2020; Wang et al., 2017). Customers generate positive emotions when interacting with positive service providers (Pugh, 2001), which perceived as having better service quality (Pugh, 2001), and more likely chosen by customers (Ouyang & Wang, 2022). As a result, people are more likely to be favored to communicate and interact with people with positive emotions during choices, we propose H2:

H2: Host with smile have a positive impact on customers' booking intentions.

Among people's personal characteristics, age is the most obvious and public characteristic. Notably, age is considered the most noteworthy personal characteristic by which customers can perceive service providers, form attitudes, or react in some ways to service providers. "The older you are, the worse you are" is an age-based stereotype. However, many studies have challenged stereotypes and correlated age with experience and ability (Cleveland & Lim, 2007), suggesting that older people are more capable and experienced. Considering it requires an accommodation in unfamiliar environments, which involves the trust of customers towards the service provider, the perceived risk significantly affects the customers' booking intentions when choosing the housing listings provided by shared accommodation platforms online (Baldick & Jang, 2020; Mao et al., 2020). The photos of elder age hosts are perceived as more trustworthy, reducing customers' perceived risk and making them more likely to be chosen (Ert & Fleischer, 2020). Based on this, we argue that elder age hosts are more likely to be chosen by customers, proposing H3:

H3: Elder-aged host have a positive effect on customers' booking intentions.

Whether wearing glasses is one of the facial features that can be visibly recognized in a profile photo. The content of customers' perceptions of facial features in hosts' photos affects customers' first impressions, which continue to play a role in subsequent behaviors (Hassin & Trope, 2000; Naylor, 2007). Existing research in the shared accommodation industry has shown that hosts wearing sunglasses hinders the formation of customer trust in the host and reduces customers' booking intentions (Banerjee et al., 2022). However, there are still scholars who validate the wearing of glasses as perceiving positive qualities such as intelligence, reliability, and honesty, and males who wear glasses are perceived as less threatening, are perceived by customers to be more trustworthy and are more likely to be chosen (Fetscherin et al., 2020). Existing studies have shown that the shape of glasses has also been associated with positive attributes such as warmth and competence (Okamura & Ura, 2019), and based on this, we propose H4:

H4: Host with glasses have a positive effect on customers' booking intentions.

Heterogeneity of host gender

Host gender is recognized by the profile photo, customers are more likely to booking female than male hosts (Banerjee et al., 2022), female hosts have a positive impact on perceived trustworthiness and attractiveness (Ert & Fleischer, 2020), and the effect of host gender on customers' booking intentions has been demonstrated. In this study, based on the effect of hosts' facial features on customers' booking intentions, we explore whether there are differences in the effect of hosts' facial features on customers' booking intentions by host's gender.

Existing research suggests that females are more susceptible to beauty stereotypes than males, which is also contributes to the fact that females are more susceptible to injustice, prejudice, and social pressure (Muth & Cash, 1997). On this basis, the beauty premium has been shown to be more significant for females than males, and the result has been confirmed in several regions, including China (Yang et al., 2022), and European countries (Patacchini et al., 2014). The gender heterogeneity in the effect of facial features age, smile, and whether wearing glasses on customer decision-making has been verified in the tourism industry (Yang et al., 2022), during the customer booking stage, a smiling, young, and wearing glasses male tour guide is more likely to be chosen by the customer while these facial features do not have a significant effect on females. Based on this, we argue that there is gender heterogeneity in the effect of hosts' facial features on customers' booking intentions and propose H5:

H5: Gender heterogeneity in the effect of hosts' facial features on customers' booking intentions.

Moderating effects of super host and housing type

Customers subconsciously form a first impression when they see a host's profile photo when booking a housing on Airbnb platform. The effects of host reputation on perceived trust and customer behavior have been validated (Han et al., 2019; Li et al., 2023; Liang et al., 2017; Zhang et al., 2018), and the super host reputation badge is the Airbnb platform's affirmation and endorsement of host performance in conjunction with hosts' past behaviors, and is a demonstration of providing customers with more responsive feedback and better service. Super host reputation badge is positively correlated with the number of reviews and ratings (Han et al., 2019; Liang et al., 2017), which will increase the demand for housing, super host reputation reduce customers' uncertainty in the decision-making process, enhances perceived credibility, strengthen the positive impression of hosts, and positively influences customers' booking intentions.

On this basis, we argue that there is a moderating effect of super host reputation on the relationship between facial features and customers' booking intentions. Super hosts strengthen the positive effect of beautiful, smiling, elder age, and glasses-wearing hosts on customers' booking intentions, and we propose a series of H6.

H6 Super host moderates the effect of facial features on customers' booking intentions.
H6a Super host strengthens the impact of host with higher beauty scores on customers' booking intentions.
H6b Super host strengthens the impact of host with smile on customers' booking intentions.
H6c Super host strengthens the impact of elder-aged host on customers' booking intentions.
H6d Super host strengthens the impact of host with glasses on customers' booking intentions.

Differences in housing types lead to variations in customer attention (Ding et al., 2023; Dogru et al., 2020; Han & Yang, 2021; Nicolau et al., 2023). Entire home/apt implies possessing the entire space of the whole house, whereas shared housing implies sharing part of the space with host or other customers, which involves the degree and frequency of the customer's contact with the hosts. Compared to entire home/apt, shared housing implies more contact and frequency with the host, generate more interactions (Ruan, 2020), and a more deliberate decision on the choice of the host during the customer's booking process. On this basis, we argue that there is an effect of housing type on the relationship between hosts and customers' booking intentions.

Based on emotional contagion theory (Hatfield et al., 1993) and first impression theory (Bar et al., 2006; Naylor, 2007) as well as people's desire for beautiful things, we argue that when customers booking a shared housing need to have face-to-face contact with the host, and customers are more prone to choose housings offered by beautiful, expressing positive emotions, and perceiving more trustworthy hosts. That is, shared housing strengthens the positive influence of beautiful, smiling, elder age, and glasses-wearing hosts on customers' booking intentions, thus we propose a series of H7.

H7 Housing type moderates the effect of facial features on customers' booking intentions.
H7a Shared housing strengthens the impact of host with higher beauty scores on customers' booking intentions.
H7b Shares housing strengthens the impact of host with smile on customers' booking intentions.
H7c Shared housing strengthens the impact of elder-aged host on customers' booking intentions.
H7d Shared housing strengthens the impact of host with glasses on customer booking intentions.

Methodology

Data collection and pre-process

Data for this study was extracted from housing attributes listing data on the Airbnb platform and the analysis of photos by Baidu's AI technology, the world's leading artificial intelligence service platform.

Housing attributes listings from Airbnb

The housing attributes listings data for this study was extracted from Airbnb, the world's largest short-term accommodation platform. Since its establishment in the United States in 2008, Airbnb has been operating worldwide in over 220 countries and territories and is committed to providing customers with a "home on the road". As the origin of Airbnb, the United States has become the most popular destination for Airbnb worldwide, and investigating the data of its popular city listings has certain promotion significance for other regions and cities. When considering booking housing, the customer makes decisions by comparing the publicly available information about the housing's attributes. The housing attributes include the following:

Host's individual dimension: the URL of host's profile photo (the photos of the host upload), reputation (whether the host is a super host), and registered listings.

Housing information dimension: the housing type (whether the housing is an entire home/apt or shared housing), the housing could offer how much the bedroom, bathroom, accommodation, and the available number of amenities (including cooking, parking, gym, and so on). The housing price, review ratings, and the number of reviews.

Airbnb housing attributes listings data is publicly available for download from insideairbnb.com, which is available under the Creative Commons Universal (CCU 1.0) Public Domain Dedication license and has been widely used for academic research (Barnes & Kirshner, 2021; Thomsen & Jeong, 2021). The data was downloaded in December 2022, and the web crawl code in Python was used for the Airbnb.com information supplement. The host profile photos according to the URLs obtained from insideairbnb.com download through MATLAB. We apply data on listings in ten popular US cities including Boston, Chicago, Denver, Los Angeles, New Orleans, New York City, San Diego, San Francisco, Seattle, and Washington DC. The data included all 105,084 housing listings.

Facial features database through Baidu AI

Photos can convey richer information than text, and first impression theory suggests that people can form an impression of a photograph by seeing it for just a few milliseconds influencing their subsequent behavior (Hassin & Trope, 2000; Naylor, 2007). The face is one of the most widely used and important physical attributes in human biometric systems and also the foremost place to be noticed in avatar photos. Based on deep learning algorithms, we use artificial intelligence to further extract the information from photos. This approach has been applied broadly to research in the tourism (Yang et al., 2022) and hospitality (Jang, 2022; Zhang et al., 2021) industries.

Baidu AI is a comprehensive and open-source AI platform. Based on Baidu's professional deep learning algorithm and massive data training, the face recognition algorithm has been evaluated in several most authoritative public competitions (FDDB, WIDERFACE). The accuracy of face recognition in LFW evaluation is up to 99.77%. Compared with other face recognition analysis models, the accuracy of Baidu AI has been verified (Chaudhuri, 2020; Yang et al., 2020) and used in academic paper research. Baidu's face recognition system is based on a massive dataset of a total of 200 million images from 2 million individuals all over the world and can effectively recognize the gender, age, and face shape of people in images (Yang et al., 2022). By deploying the platform's open Application Programming Interface (API), it can rapidly locate and detect face frames and identify 150 key points of facial features and contours including cheeks, eyebrows, eyes, mouth, nose, etc. It also identifies a variety of facial attribute information in the picture, including age, gender, expression, emotion, mask, face shape, head posture, whether close eyes, whether wear glasses, and face quality information.

We downloaded all the URLs of the host's photos of the housing listing into a folder through MATLAB and converted the images into BASE64 encoding in JPG format. By writing a Python program to guide the API of Baidu's face recognition system to encode processed photos for face recognition. Obtain specific recognition information about beauty, smile, age, whether wearing glasses, etc. Based on a vast amount of existing data trained on the images we provide. The extracted information is collated into Excel. Identify and delete 27,961 photos that cannot be detected by the system due to the distortion of photo pixels, resolution, and other reasons. We eliminated 13,040 data with incomplete housing information or valid comments, and finally 64,083 listings of remaining effective data.

Figure 2 shows the facial recognition results from the Baidu AI facial recognition system based on identifying 150 key points marked by Baidu AI. A virtual portrait was generated by the author via http://www.artbreeder.com.

Variables and models

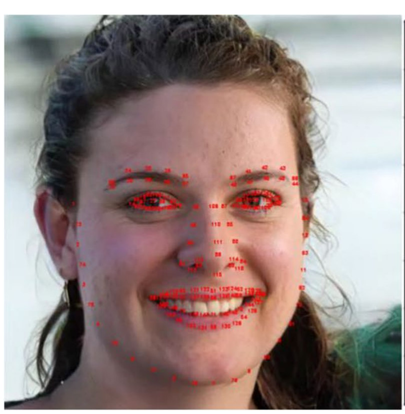
Variables

The dependent variable in this study is customers' booking intention; the Airbnb platform does not display the exact number of bookings for housing listings but only allows reviews from customers who have completed the transaction. The number of reviews has been considered as a proxy for online transactions (Ye et al., 2009) and this study standardized the number of reviews as shown in Eq. (1):

$$Booking\ Intention = Ln(Numberofreviews) \tag{1}$$

The independent variables in this study are the host's facial features, with specific data obtained through Baidu's API. The results returned by beauty and age are numeric variables. The beauty score varies from 0 to 100. The score represents the degree of beauty, the higher the score, the more beautiful the individual, and standardized processing (Logarithm with base "e"). Smile and glasses return results as binary variables, with "0" representing non-smile (non-glasses) and "1" representing smile (glasses).

The moderating variables in this study are the host's reputation and housing type. Whether the host is a super host, "1" for super host and "0" for non-super host. Whether the housing is an entire home/apt, "1" for the entire home/apt, and "0" for shared housing.



Face Recognition Result	
Identify Status	Success
Beauty	49
Expression	Smile
Age	33
Glasses	None
Gender	Female
Face shape	Round

Fig. 2 An example of face recognition by AI facial recognition system on Baidu

The categorical variable in this study is host's gender, obtained through the Baidu API, which is "0" for males and "1" for females. The control variables are the housing price and the available number of amenities. The specific is shown in Table 1.

Models

The purpose of this study is to investigate the effect of hosts' facial features on customers' booking intentions and to verify the moderating effects of super host and housing type. On this basis, we explore the heterogeneity of hosts' gender, which means the differences in the effect of male and female hosts' facial features on customers' booking intentions. Combined with the framework of this study, it is as follows: the comprehensive regression model (2) was constructed, and M1-M3 explored the effect of hosts' facial features on customers' booking intentions and the effect of male and female hosts' facial features on customers' booking intention, respectively. Comprehensive regression model (3) was constructed, and M4-M8 tested the moderating effect of super host on the relationship between hosts' facial features and customers' booking intentions. Comprehensive regression model (4) was constructed, and M9-M13 tested the moderating effect of the type of housing on the relationship between hosts' facial features and customers' booking intentions. The comprehensive regression model is constructed as follows:

$$\begin{aligned} Booking\ Intention = {} & \beta_0 + \beta_1\ Beauty + \beta_2\ Smile + \beta_3\ Age + \beta_4\ Glasses \\ & + \beta_5\ Price + \beta_6\ Amenities\ +\ \varepsilon \end{aligned} \tag{2}$$

$$\begin{aligned} Booking\ Intention = {} & \beta_0 + \beta_1\ Beauty + \beta_2\ Smile + \beta_3\ Age \\ & + \beta_4\ Glasses + \beta_5\ Price + \beta_6\ Amenities \\ & +\ \beta_7\ (Superhost)\ +\ \beta_8\ (Superhost\ \times\ Beauty) \\ & +\ \beta_9\ (Superhost\ \times\ Smile) \\ & +\ \beta_{10}\ (Superhost\ \times\ Age) \\ & +\ \beta_{11}\ (Superhost\ \times\ Glasses)\ +\ \varepsilon \end{aligned} \tag{3}$$

$$\begin{aligned} Booking\ Intention = {} & \beta_0 + \beta_1\ Beauty\ +\ \beta\ _2\ Smile\ +\ \beta_3\ Age \\ & +\ \beta_4\ Glasses\ +\ \beta_5\ Price\ +\ \beta_6\ Amenires \\ & +\ \beta_7\ (Housingtype)\ +\ \beta_8\ (Housingtype\ \times\ Beauty) \\ & +\ \beta_9\ (Hosingtype\ \times\ Smile) \\ & +\ \beta_{10}\ (Housing\ type\ \times\ Age) \\ & +\ \beta_{11}\ (Housing\ type\ \times\ Glasses)\ +\ \varepsilon \end{aligned} \tag{4}$$

where β_0 is the intercept term; β_1 to β_{11} are the coefficients of interest variables, and ε is the error term.

Results

Data analysis

Table 2 shows the descriptive statistics of all the variables in this study through SPSS 26 for data analysis. The beauty score in the virtual portrait example used for this study was 49, standardized to 3.892, which is higher than the average beauty score of 3.660, representing a moderately high level. The correlation between the variables was analyzed

Table 2 Descriptive statistics for variables

Variables	Obs	Min	Max	Mean	Std.Dev
Booking Intention	64,083	0	7.17	2.931	1.675
Beauty	64,083	1.988	4.514	3.660	0.415
Smile	64,083	0	1	0.680	0.467
Age	64,083	18	76	33.610	7.923
Glasses	64,083	0	1	0.200	0.402
Gender	64,083	0	1	0.450	0.498
Super host	64,083	0	1	0.370	0.484
Housing type	64,083	0	1	0.700	0.459
Price	64,083	10	10,000	193.230	267.676
Amenities	64,083	1	106	32.5	14.699

Table 1 Definitions of variables

Variables		Definitions	Notes
Booking Intention	DV	Standardisation of the number of reviews	Range:$[0, +\infty)$
Beauty	IV	Standardisation of beauty scores	Range:$[0, +\infty)$
Smile	IV	Smile(= 1) VS.non-smile(= 0)	Virtual variable
Age	IV	Age of the host in the image	Count variable
Glasses	IV	Glasses(= 1) VS.non-glasses(= 0)	Virtual variable
Super host	MV	Super host(= 1) VS.non super host(= 0)	Virtual variable
Housing type	MV	Entire home/apt(= 1) VS shared housing(= 0)	Virtual variable
Gender	CV	Female(= 1) VS.male(= 0)	Virtual variable
Price	CTV	Listed price per night (U.S. Dollars)	Count variable
Amenities	CTV	Number of amenities	Count variable

DV: Development variable; *IV*: Indevelopment variable; *MV*: Moderating variable; *CV*: Categorical variable; *CTV*: Control Variable and the maximum value of the correlation coefficient between the super host and customers' booking intention was 0.377 which is less than 0.5 and the data can be used for subsequent analysis and research. The correlation coefficients between facial feature variables beauty, smile, age, and glasses and customers' booking intentions are significant, which can be further analyzed by regression analysis. The correlation coefficient between gender and customers' booking intentions is significant, indicating the value of this study in exploring the effect of facial features on customers' booking intentions from the perspective of the host's gender.

Main effects and gender heterogeneity on customers' booking intentions

Tables 3 show the empirical results of this study, the 2nd column M1 shows the results of the effect of host's facial features on customers' booking intentions, beauty ($\beta_1 = 0.227, p < 0.01$), smile ($\beta_2 = 0.047, p < 0.01$), age ($\beta_3 = 0.031, p < 0.01$), and glasses ($\beta_4 = 0.125, p < 0.01$) significantly positively affect customers' booking intentions, and H1, H2, H3, and H4 of this study are supported.

Table 3 also displays the results of subgrouping the housing listings by hosts' gender characteristics and examining the effect of host facial features across genders on customers' booking intentions. Among those, facial features of beauty, age, and glasses of both male and female hosts positively and significantly affect customers' booking intention, and for whether smile, the results show that compared with female hosts, only smiling male hosts positively and significantly affect customers' booking intentions.

During the customer booking decision process, there is a beauty premium for both male hosts ($\beta_1 = 0.229, p < 0.01$, M2) and female hosts ($\beta_1 = 0.215, p < 0.01$, M3), but the results of the coefficient equality test (Paternoster et al., 1998) for beauty (Z = 0.942, p > 0.1) are not significant, suggesting that beauty positively influences customer booking intentions for both male and female hosts. The results of the coefficient equality test (Paternoster et al., 1998) for age (Z = -3.536, $p < 0.01$) indicated that age has a greater impact on females compared to male hosts. The results of the coefficient equality test (Paternoster et al., 1998) for glasses (Z = -1.952, $p < 0.05$) show that the effect of wearing glasses has a greater impact on females than males hosts.

The effect of host facial features on customers' booking intentions varied by gender, and H5 was supported.

Table 3 Main effects and heterogeneity analysis results

Variables	M1	M2 Male	M3 Female
Direct effects			
Beauty	0.227** (0.007)	0.229*** (0.010)	0.215*** (0.011)
Smile	0.047*** (0.014)	0.050*** (0.018)	0.025 (0.023)
Age	0.031*** (0.001)	0.030*** (0.001)	0.035*** (0.001)
Glasses	0.125** (0.016)	0.082*** (0.020)	0.195*** (0.025)
Control			
Price	-0.000418***	-0.00037***	-0.00048***
Amenities	0.033***	0.034***	0.031***
Obs	64,083	35,021	29,062
R2	0.772	0.774	0.770

*$p < 0.1$; **$p < 0.05$; and ***$p < 0.01$

Moderating effects on customers' booking intentions

Tables 4 and 5 shows the results of moderating effects of super host and housing type on customer' booking intentions. The 3rd column M2 to the 7th column M6 of Table 4 verified the moderating effect of super hosts on hosts' facial features and customers' booking intentions.

In M4 to M7, the interaction between super host and host's beauty, smile, age, and glasses was added for analysis respectively, and compared with M1, the results and significance of host's beauty, smile, and age on customers' booking intentions were consistent. Interaction terms of super host with beauty ($\beta_8 = -0.395, p < 0.01$), super host with smile ($\beta_9 = -0.117, p < 0.01$), and super host with age ($\beta_{10} = -0.014, p < 0.01$) are significant on customers' booking intentions, respectively. Interaction terms of super host with glasses was not significant, and combine the results of M6, H6 was partially validated. Super host reputations in M4 to M6 significantly and positively affect customers' booking intentions, but the coefficients on the interaction terms with the independent variables are negative, suggesting that super hosts weakened the effects of host's beauty, smile, and age on customers' booking intentions, and M7 interaction terms of super host with glasses was not significant, thus not supported H6a-H6d.

The 3rd column M9 to the 7th column M13 of Table 5 validate the moderating effect of housing type on host's facial features and customers' booking intentions. Among them, M9 to M12 added the interaction terms of housing type (whether the housing is an entire home/apt or shared housing) and host's beauty, smile, age, and glasses for analysis, respectively, and the results and significance of the effects of host's beauty, smile, age, and glasses on customers' booking intentions were consistent in comparison with M1. The interaction terms of housing type with beauty ($\beta_8 = -0.419, p < 0.01$), housing type with smile ($\beta_9 = -0.236, p < 0.01$), housing type with age ($\beta_{10} = -0.024$,

Table 4 The first part of the regression results

Variables	M1	M4	M5	M6	M7	M8
Direct effects						
Beauty	0.227***	0.293***	0.250***	0.219***	0.256***	0.257***
Smile	0.047***	0.035***	0.066***	0.027**	0.024*	0.036**
Age	0.031***	0.024***	0.027***	0.032***	0.027***	0.028***
Glasses	0.125***	0.096***	0.105***	0.101***	0.089***	0.078***
Moderating Effects						
Super host		2.538***	1.178***	1.564***	1.087***	2.982***
Super host × Beauty		-0.395***				-0.392***
Super host × Smile			-0.117***			0.004
Super host × Age				-0.014***		-0.014***
Super host × Glasses					-0.044	0.035
Control						
Price	-0.00042***	-0.00037***	-0.00037***	-0.00037***	-0.00037***	-0.00037***
Amenities	0.033***	0.020***	0.021***	0.021***	0.021***	0.020***
Obs	64,083	64,083	64,083	64,083	64,083	64,083
R^2	0.772	0.795	0.794	0.795	0.794	0.795

Table 5 The second part of the regression results

Variables	M1	M9	M10	M11	M12	M13
Direct effects						
Beauty	0.227***	0.284***	0.190***	0.098***	0.208***	0.189***
Smile	0.047***	0.067***	0.201***	0.052***	0.040***	0.104***
Age	0.031***	0.024***	0.0.030***	0.044***	0.031***	0.034***
Glasses	0.125***	0.107***	0.123***	0.112***	0.169***	0.122***
Moderating Effects						
Housing type		2.719***	0.357***	1.015***	0.219***	2.041***
Housing type × Beauty		-0.419***				-0.344***
Housing type × Smile			-0.236***			-0.050*
Housing type × Age				-0.024***		-0.017***
Housing type × Glasses					-0.062***	-0.033
Control						
Price	-0.000418***	-0.000487***	-0.00049***	-0.00049***	-0.00049***	-0.000488***
Amenities	0.033***	0.030***	0.031***	0.030***	0.031***	0.030***
Obs	64,083	64,083	64,083	64,083	64,083	64,083
R^2	0.772	0.775	0.773	0.774	0.773	0.775

*$p < 0.1$; **$p < 0.05$; and ***$p < 0.01$

$p < 0.01$), and housing type with glasses ($\beta_{11} = -0.062, p < 0.01$) are significant in affecting customers' booking intentions, as well as the results of M13 support the H7 of this study. The housing type in M9 to M12 positively and significantly affects customers' booking intentions, but the coefficients of the interaction terms with the independent variables are negative, suggesting that shared housing strengthens the effects of host beauty, smile, age, and glasses on customers' booking intentions in comparison to entire home/apt, which supports H7a-H7d.

Discussion

Distinguishing from the traditional hospitality industry, the shared accommodation industry provides different options for customers with short-term housing by having a direct connection between hosts and customers. Customers are faced with the choice of hosts while comparing housing listings. This study is based on housing data from the top ten cities in the United States on the Airbnb platform assisted by Baidu's AI to identify hosts' facial features in their profile photos and develop a comprehensive model to analyze the impact of hosts' facial features of different genders on customers' booking intentions, as well as the moderating effects of host reputation and housing type. Specific findings are as follows.

First, in terms of facial features and gender heterogeneity of hosts. Existing literature has mixed results on the existence of beauty premium, some argue that beauty has no effect on customer choice (Ouyang & Wang, 2022), some support the existence of an inverted "U" shape of beauty premium and beauty penalty on customers' booking intentions (Li et al., 2022), and this study supports the existence of a linear relationship (Yang et al., 2022). Existing research suggests that smiling is associated with positive emotional expression (Li et al., 2021), and it can be perceived as warmth and enthusiasm (Wang et al., 2017) which is more preferred to be chosen by customers (Ert & Fleischer, 2020; Ouyang & Wang, 2022). Based on this, this study further compares the heterogeneity of the effect of smiling by hosts genders on customers' booking intentions and finds that compared to female hosts, smiling male hosts significantly enhances customers' booking intentions. Some studies have linked age to competence, suggesting that elder age host photos are perceived to be more trustworthy in choosing shared housing accommodations, and this study supports that elder age host photos are more likely to be chosen by customers (Ert & Fleischer, 2020). In this context, we explore the gender heterogeneity of hosts' age, and the data suggest that elder age female hosts are more likely to be chosen compared to male hosts. Glasses as one of the visibly recognizable facial features in photos, there are differences in the effect of host photos whether wearing glasses on customers' booking intentions (Banerjee et al., 2022; Fetscherin et al., 2020), and we support the view that photos wearing glasses positively influence customers' booking intentions, distinguishing from existing research that suggests that males wearing glasses are more likely to be chosen by customers (Fetscherin et al., 2020), this study suggests that female hosts wearing glasses have a greater impact.

Second, in terms of the reputation of super host. In customers' booking decision-making process, super host reputation is conducive to reducing uncertainty, which is perceived as more trustworthy by customers and positively affects customers' booking intentions (Han et al., 2019; Liang et al., 2017; Zhang et al., 2018), and customers have a stronger demand for housing offered by super hosts. Although beauty, smile, age, and wearing glasses increase customers' booking intentions, host reputation weakens the effects of some positive facial features on booking intentions, such as beauty (Li et al., 2023), and the findings of this study correspond with Barnes, 2021 where facial trustworthiness was overestimated (Barnes, 2021), which broadens the existing research on host reputation weakening the reliance on hosts' facial attractiveness in customers' purchasing decisions (Li et al., 2023).

Third, in terms of different housing types. Housing type is one of the important housing attributes, and there are differences in the content of customers' concerns in selecting different types of housing (Han & Yang, 2021). Existing research suggests that shared housing implies more contact and interaction between the customer and the host (Ruan, 2020; Tussyadiah & Pesonen, 2016) compared to entire home/apt, thus customers are more conscious about their choice of host. The first impression of hosts' facial features on personal photos affects customer perceptions, which in turn affects customer choices (Barnes & Kirshner, 2021; Yang et al., 2022). This study shows that shared housing strengthens the positive facial features of hosts on customers' booking intentions, which echoes the results of Tussyadiah's (2016) study in which shared housing positively affects customer satisfaction through perceived social benefits such as interaction with hosts (Tussyadiah, 2016).

Theoretical implications

The theoretical implications of this study are mainly reflected in the follows. First, this study expands research on facial features of service providers (hosts). Existing research on service providers' facial features focuses on the beauty premium effect (Li et al., 2022; Yang et al., 2022), smile (Ert & Fleischer, 2020; Yang et al., 2022), glasses (Banerjee et al., 2022), age (Gunarathne et al., 2022; Jang, 2022; Marchenko, 2019), and others, separately or in combination with some of them. This study from changeable aspects, and relatively invariant aspects based on within-person variability (Sutherland et al., 2017) combines beauty, smile, age and glasses to analyze the effect on customers' booking intentions. On this basis, this study categorizes service providers in terms of their gender demographics to explore the differences in the effects of facial features on customers' booking intentions by gender and finds that compared to female hosts, the effect of smiling significant affects customers' booking intentions for male hosts. In addition, this study combines service providers' facial features with service quality (service provider's reputation) and housing type to comprehensively analyze the effects on customers' booking intentions, and further broadens the research on facial features of service providers.

Second, this study expands the application of "first impression" theory and "emotional contagion" theory in the shared accommodation industry. It provides new empirical evidence on the influence of hosts' facial features in customers' booking decision-making process based on the integration of the "first impression" and the "emotional contagion" theory. The first impression of a host is generated by customers based on the content of their perceptions of the facial features in the host's profile photo (Barnes & Kirshner, 2021; Yang et al., 2022) when choosing a housing listing online. The aspiration for beautiful things leads people to associate beauty with positive things, and the existence of a beauty premium has been confirmed (Li et al., 2023; Yang et al., 2022). Smile as a salient facial expression is associated with positive emotions (Li et al., 2021), photos of smiling individuals perceive trust, warmth, and enthusiasm (Banerjee et al., 2022; Ert & Fleischer, 2020; Ouyang & Wang, 2022), and customers communicating with people who have positive emotions will contract positive emotions. Elder age and wearing glasses are perceived as less risky and more trustworthy (Ert & Fleischer, 2020; Fetscherin et al., 2020). These facial features create a positive first impression and act in customer subsequent behaviors (Hassin & Trope, 2000; Naylor, 2007).

Third, there is innovation in the research method. Unlike traditional interviews or questionnaires to obtain data, this study is based on a large amount of real-life host profile photo data to analyze the effect of facial features on customers' booking intentions, which reduces the data limitations due to the limited sample, and the results obtained are universal. On this basis, this study assists artificial intelligence technological to identify the facial features on the photos, and the validity of the results is recognized by the academic paper (Gunarathne et al., 2022; Troncoso & Luo, 2022; Yang et al., 2022; Zhang et al., 2018). At the same time, the analysis and recognition of picture information by machine learning and artificial intelligence provide reliable technical support for future empirical research.

Managerial implications

This study also provides the following managerial insights. First, the management of hosts' online profiles in the shared accommodation industry. Our study provides guidance on how Airbnb hosts can better present themselves through their online profiles for business competitive advantage. It is true that other efforts on the housing listings may diminish the limited effect of facial features, but with other basic conditions being similar, hosts' facial features can increase the customer's booking intentions somewhat. While uploading hosts' profile photos, for personal image, consider wearing glasses to enhance credibility (Fetscherin et al., 2020), by dressing up to be more experienced, friendly and trustworthy (Ert & Fleischer, 2020; Cleveland & Lim, 2007), as well as properly reshaped photos to enhance facial image and gain a competitive advantage (Yang et al., 2022). Hosts are advised to choose professional personal photos for uploading since good photos results will evoke a good first impression and enhance customers' booking intentions, and professional photos have better angles and light choices. A pair of glasses and a genuine smile can significantly enhance the image of an Airbnb host and increase the customers' booking intentions to some extent.

Second, shared accommodation platform management. Firstly, for circumvent over-embellishment of photos or upload other photos by hosts to attract customers and gain a competitive advantage, which results in photo distortion, Airbnb platforms can validate the degree of consistency of the host's photo with the ID card through artificial intelligence technology, aiming to help hosts establish credible housing information. Secondly, the Airbnb platform, in addition to encouraging hosts to upload real photos, requires regular replacement to ensure that the photos are recent, enhancing timeliness and reducing customer information asymmetry. Thirdly, in view of the effects of different hosts' facial features on customers' booking intentions, Airbnb platforms should consider how to eliminate such effects in developing their algorithms, including building a comprehensive word-of-mouth evaluation system for hosts, emphasizing reviews rather than personal photos, etc., aiming to provide a fairer competitive environment for all hosts. Finally, the platform only has screening for housing listings, but lacks screening for the host's dimension. The platform management should increase the screening for the host's information, including the host's reputation, the host's gender and so on. At the same time, artificial intelligence combining with customer behavioral data is used to make accurate recommendations to customers, promote customers' booking intentions and enhance the platform's operational efficiency.

Third, this study also contributes to the overall industry development of the sharing economy. Using a large amount of data from shared accommodation industry as an example, this paper investigates the role of hosts' facial features on customers' booking decision-making process, which provides some implications for service providers in the sharing economy industry. On this basis, the results of the moderating effects of the host's reputation and housing type between facial features and customers' booking intentions indicate the importance of reputation for a service provider. In order to gain an advantage in the customer choice process, service providers should gain a good reputation by continuously improving their service content and service attitude, which also applies to other sharing economy industries.

Limitations and future research

This study exists the following limitations which provide direction for our future research. First, although we applied a large number of datasets in reality, the source of datasets is limited to US housing listings on Airbnb, and in the future, we can consider examining datasets from different platforms, countries, and cultures to improve the generalisability of the results. Second, for host's facial features data was obtained only from one single

Baidu AI facial recognition system. In view of potential bias and other issues, future research can consider obtaining data through other mechanical learning approaches and human cross-validation, among others to cross-validate the validity of the data. was obtained through Baidu's AI facial recognition system. Third, this study uses the number of reviews as a proxy indicator for online transactions (Ye et al., 2009) to measure consumers' booking intentions, while there is a discrepancy between the number of reviews and actual online transactions since not all customers who have booked conduct reviews. Future research will focus on the correlation and discrepancy between the number of reviews and actual transactions to comprehensively measure the customers' booking intentions. Fourth, this study only considered the effect of host profile photos' facial features on customers' booking intentions. The photo is only one part of the host's profile, and future research analyses the effect of the description of unstructured textual information in host's profile, as well as the effect of gender-specific customers' booking intention by service provider's facial features.

Conclusion

This study identifies hosts' facial features in 105,084 housing data from 10 popular cities on the Airbnb platform through Baidu's AI facial recognition system and develops a comprehensive model to systematically analyze the causal relationship between hosts' facial features and customers' booking intentions. The results show that beauty, smile, age, and wearing glasses positively affect customers' booking intentions. There is gender heterogeneity in the effects of hosts' facial features on customers' booking intentions. Compared with male hosts, age and wearing glasses have a greater effect on female hosts; compared with female hosts, smiling significantly enhances customers' booking intentions for male hosts. On this basis, this research suggests that host reputation somewhat weakens the positive effect of host's facial features on customers' booking intentions. Furthermore, shared housing involves more frequent contact and interaction with hosts, which strengths the positive effect of hosts' facial features on customers' booking intentions.

Data availability The datasets generated and or analyzed during the current study are available from the corresponding author on reasonable request.

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