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THE “BEAUTY PREMIUM” PHENOMENON: APPEARANCE DISCRIMINATION IN THE P2P MARKET

Hengyun Li[#], Ph.D.
School of Hotel and Tourism Management,
The Hong Kong Polytechnic University,
Hong Kong SAR, China
Email: neilhengyun.li@polyu.edu.hk

Danting Cai[#]
School of Hotel and Tourism Management,
The Hong Kong Polytechnic University,
Hong Kong SAR, China
Email: danting.cai@connect.polyu.hk

Gang Li, Ph.D.
School of Hospitality & Tourism Management,
University of Surrey
Guildford, Surrey, GU2 7XH, UK
Email: g.li@surrey.ac.uk

Mingming Hu*, Ph.D.
School of Business, Guangxi University;
Guangxi Development Strategy Research Institute,
100# East of Daxue Road, Nanning 530004;
Email: mingming.hu@gxu.edu.cn
Mobile Phone: +86 13877174602
Fax: +86 771 3232880
*Corresponding Author.

[#]The first and second authors contributed equally to this work and should be considered as co-first authors.

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None

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The "Beauty Premium" Phenomenon: Appearance Discrimination in the P2P Market

ABSTRACT: The online P2P accommodation market, including Airbnb, encourages accommodation hosts to upload profile photos. However, the inclusion of a profile photo may carry consequences such as appearance discrimination. Using secondary Airbnb data from Beijing, China, this study investigates the presence of the "beauty premium" in the relatively low-priced accommodation market and examines the extent to which consumers discriminate based on hosts' facial appearance from a supply perspective. Three experiments were conducted to respectively examine the impacts of hosts' facial beauty on customers' willingness-to-pay, boundary conditions, and underlying mechanisms. The findings emphasize the importance of hosts' visual self-disclosure in reducing appearance-based discrimination. By providing practical implications for P2P platform operators and accommodation hosts, this research contributes to a better understanding of appearance-based biases in the online accommodation market and reveals strategies for mitigating negative effects.

Keywords: appearance discrimination, visual self-disclosure, price, willingness-to-pay, peer-to-peer market

1. Introduction

Physical attractiveness, described as an aesthetically pleasing appearance, has been shown to offer economic, social, and psychological benefits in various contexts (Cryder et al., 2017). Hamermesh and Biddle (1994) identified a phenomenon called the "beauty premium," wherein employees of above-average attractiveness earn 10% -15 % more than workers whose attractiveness is below average. In an experimental labor market, Mobius and Rosenblat (2006) identified three mechanisms driving the beauty premium: confidence, capability, and social skills. Privileges brought by the beauty premium also exist in charity contexts: donors often choose beautiful recipients rather than those in genuine need (Cryder et al., 2017). In fact, appearance-based discrimination due to the beauty premium may subtly bias people's judgments and actions, even outside conscious awareness (Hosoda et al., 2003). Physical attractiveness has been found to elicit favorable treatment in a variety of contexts (Langlois et al., 2000). The advantages conferred by this "beauty premium" can in turn affect stakeholders' benefits.

Online peer-to-peer (P2P) markets, including platforms like Airbnb, have also shown evidence of appearance discrimination (Zhang et al., 2022). For example, Airbnb's booking system has identified digital discrimination online: users are inclined to choose potential hosts and guests based on race and sexuality (Edelman et al., 2017; Farmaki & Kladou, 2020), leading to unbalanced distributions of reservations and earnings (Zhang et al., 2022). On these platforms, although a seller's profile picture can enhance interpersonal relationships (Tussyadiah & Pesonen, 2016), limited textual or visual information can produce cognitive biases (Pino et al., 2020), with anonymity and lack of social censoring potentially contributing to biased judgments (Guan et al., 2015). According to the boundedly rational decision rule (Simon, 1972), stereotypes give rise to various forms of appearance-based discrimination. Edelman et al. (2017) noted that applicants with African-American names faced a higher likelihood of rejection than their counterparts with white-sounding names. In New York, black and non-white hosts have been shown to earn less than white hosts while providing similar accommodation services (Edelman & Luca, 2014). Although the literature has documented different forms of discrimination on P2P platforms, more remains to be discovered about facial beauty–based appearance discrimination.

Researchers have recently started to explore this phenomenon on Airbnb, with mixed findings regarding appearance discrimination's impact on listing prices (i.e., from a supply-side perspective). While Ert et al. (2016) found no observable effect of hosts' beauty on listing prices in Stockholm, Jaeger, Sleegers et al. (2019) discovered that facial beauty could generate price premiums in New York City. Although the literature has yielded some knowledge about facial beauty–based appearance discrimination on Airbnb, a comprehensive understanding has yet to be achieved, particularly concerning both the supply (i.e., Airbnb listing prices) and demand (i.e., consumers' willingness-to-pay, WTP) sides of the market. On this basis, the present study aims to investigate appearance-based discrimination in the peer-to-peer (P2P) accommodation market by drawing on dual process/system theory (Kahneman & Frederick, 2002; Kahneman, 2011). Dual system theory distinguishes between fast, intuitive thinking (System 1) and slower, analytical thinking (System 2). We argue that a host’s facial attractiveness can activate System 1 thinking, leading to more favorable intuitive judgments that manifest as a “beauty premium”. However, analytical System 2 thinking can help counteract this bias. Specifically, it is designed to explore the following questions: (1) does appearance-based discrimination exist in different P2P market segments (i.e., low-priced market vs. high-priced market) and does its impact differ in different market segments?; (2) what factors can alleviate appearance-based discrimination?; and (3) what is the internal mechanism behind it?

To answer these questions, we employ a multi-method approach. Using econometric modeling with secondary Airbnb data, we (1) analyze how hosts’ facial beauty affects Airbnb listings prices (i.e., from the supply-side); (2) compare how the effects vary between high- and low-priced markets; and (3) examine whether hosts’ visual self-disclosure may reduce appearance-based discrimination underpinned by the beauty premium. Then, we conduct online experiments to (1) test the impact of hosts’ facial beauty on consumers’ WTP (i.e., from the demand-side) across high- and low-priced markets, and (2) investigate whether hosts’ visual self-disclosure alleviates discrimination in the low-priced market and its underlying cognitive processes.

This study makes several key contributions. First, we identify important boundary conditions for the occurrence of the “beauty premium” in this context. Our findings reveal that the beauty premium effect only emerges when consumers use intuitive fast-thinking mode, which is prompted by lower priced listings. This explains conflicting findings in previous studies and establishes price as a pivotal moderator. Second, by examining both the supply-side (listing prices) and the demand-side (willingness-to-pay), we provide a more comprehensive insight into how host facial attractiveness influences pricing and consumer decisions in P2P accommodation. Third, we demonstrate that hosts' visual self-disclosure induces analytical processing in consumers, which mitigates appearance-based discrimination by counteracting intuitive biases about attractiveness. This identifies a novel strategy to override biased intuitive judgments with more thoughtful processing. We also uncover the underlying mechanism of perceived uncertainty reduction to explain how hosts' visual self-disclosure attenuates the beauty premium effect. With respect to the methodology, this study employs a multi-method design combining big data econometric analysis with experimental approaches. This methodological design provides a more robust understanding of how consumers process visual host information in P2P accommodation contexts.

2. Literature review and theoretical foundation

2.1 Consumer decision-making and the role of price in P2P accommodation markets

Bounded rationality theory (Simon, 1972) highlights the varying decision-making processes individuals employ based on their accessible information. Given the vast amount of information in P2P accommodation markets and the limited time and cognitive resources for processing, individuals often utilize cognitive shortcuts or heuristics. Dual system theory (Kahneman & Frederick, 2002; Kahneman, 2011) delineates two decision-making processes: the intuitive System 1 (i.e., fast-thinking) and the analytical System 2 (i.e., slow-thinking). The type of thinking system activated can influence consumer decision-making and susceptibility to biases (Kahneman, 2011). While System 1 is instinctual and influenced by experiences and stereotypes, System 2 is deliberate and cognitively demanding (Huang & Wang, 2019; Solaki et al., 2021).

In the P2P accommodation market, where the seller significantly impacts the service experience (Erl et al., 2016), customers' decisions hinge not only on product attributes but also on perceptions of the host's attributes. Price is a pivotal determinant in this dynamic, influencing the balance between quick, value-driven decisions and in-depth evaluations (Huang & Wang, 2019; Ren et al., 2021). With beliefs held firmly, price-sensitive customers, who are attracted to the P2P market due to cost-saving motives (Fagerstrøm et al., 2017), are more likely to use fast-thinking to make quick decisions based on perceived value (Ren et al., 2021). Conversely, when assessing high-priced offerings, customers lean towards applying slow-thinking. As such, appearance discrimination, rooted in the "beauty premium" may exert a stronger influence when intuitive System 1 thinking dominates, whereas analytical System 2 thinking may help counteract this superficial bias.

2.2 Beauty premium in P2P accommodation markets

Hosts on P2P accommodation platforms strategically include personal profile photos to mitigate anonymity-induced uncertainty, making their appearances visible to potential consumers (Chattopadhyay & Mitra, 2019). Such practices echo broader discussions about the sharing economy, where trust-building hinges on visual and informational cues (Mosaad et al., 2023; Dolnicar, 2019). This visibility provides consumers with touchpoints to form appearance-based judgments that influence their purchasing decisions (Pino et al., 2020). Furthermore, Li et al. (2023) employ Stimulus–Organism–Response theory and mental imagery theory to illustrate how hosts' facial attractiveness and textual self-disclosure affect booking intentions and willingness-to-pay, underscoring the psychological process behind consumer preferences in online accommodations. Likewise, Li et al. (2022) utilize lay theories to demonstrate the dual impact of 'beauty premiums' and 'beauty penalties' in the P2P market, highlighting the nuanced effects of host attractiveness on listing performance.

The “beauty premium” posits that attractive individuals often receive preferential treatment (Li et al., 2019). From an interpersonal dynamics perspective, attractive individuals are believed to foster more positive emotions (Lemay et al., 2010). Historically and evolutionarily, aesthetic appeal has been an indicator of good genes and health (Thornhill & Gangestad, 1999). This belief naturally leads to the “halo effect” (Thorndike, 1920), wherein a beautiful face creates a positive overall impression. Those blessed with this advantage often exhibit heightened self-confidence, as attractive people are believed to reap greater rewards from their appearances (Li et al., 2019). The phenomenon of appearance-related superiority occurs spontaneously (Čekrlija et al., 2023), resulting in a self-serving cognitive bias. This favorable bias becomes a self-reinforcing cognitive aspect (Bertini et al., 2020), underpinning the implicit personality theory, which posits that people rapidly judge attributes like sociability and credibility based on appearances (Bar et al., 2006).

In line with research across social psychology, labor markets, and digital online platforms, facial beauty evaluations are recognized as a facet of appearance discrimination, dubbed the "beauty premium" (Li et al., 2019). Such judgments can permeate various decision-making processes, leading to systemic biases against those considered less attractive (Jaeger, 2020). In consumer behavior, leveraging the principle of "what is beautiful is good", customers might inherently favor attractive hosts, bestowing upon them additional positive attributes. This bias potentially inflates the perceived value of a listing, especially when decisions are driven by intuitive and emotional factors. Conversely, a more analytical decision-making approach minimizes the sway of surface-level elements like host attractiveness (Mody et al., 2021).

This principle is also observed in the P2P accommodation market. Evidence indicates that appearance-based judgments can influence purchasing decisions, leading to systemic biases against less attractive hosts (Jaeger, 2020). Barnes and Kirshner (2021) later discovered that beauty and trust each had a strong positive effect on Airbnb accommodation prices. While recent research has begun unraveling the role of beauty in platforms like

Airbnb, results have been mixed regarding how appearance discrimination affects listing prices (see a summary of the relevant literature in Appendix A). For instance, while Ert et al. (2016) found no observable effect of hosts' beauty on listing prices in Stockholm, Jaeger, Sleegers et al. (2019) discovered that facial beauty could generate price premiums in New York City. In an attempt to shed light on this complex phenomenon, this study integrates the theory of dual system theory, aiming to elucidate this dynamic further, focusing on both the supply and demand facets of the market.

2.3 Suppy-demand dual perspective of hedonic pricing in P2P accommodation markets

Determining listing prices on P2P platforms is primarily the purview of hosts, many of whom are non-professionals (Ren et al., 2021). Understanding the determinants of pricing can optimize profitability and performance (Wang & Nicolau, 2017). While research has examined pricing determinants from either the demand (Chattopadhyay & Mitra, 2019) or supply perspectives (Barnes & Kirshner, 2021), this dual perspective remains underexplored.

Positioning theory (Ries & Trout, 2001) emphasizes product value perceptions in shaping pricing strategies. Hosts' pricing strategies are thus closely intertwined with consumers' perceptions. Hedonic pricing theory (Hartman, 1989) further illuminates how factors like property features and host characteristics can determine a listing's price (Lorde et al., 2018; Wang & Nicolau, 2017). From a supply perspective, attractive hosts might charge higher prices because their facial beauty is seen as desirable and people are inclined to offer a higher monetary value in exchange for these attributes. Accordingly, hosts with strong self-perceived physical attractiveness may overestimate the value of their offerings (Jiang et al., 2021), aligning with the beauty premium argument (Cao et al., 2020).

From a demand perspective, hedonic pricing captures a consumer's willingness-to-pay for perceived incremental differences that either enhance or detract from a product's intrinsic value. Among various factors, host attributes emerge as one of the most important considerations. Customers may be inclined to pay more for perceived favorable features of hosts that align with their preferences (Tussyadiah, 2016). Consequently, appearance discrimination may surface when host-related factors (e.g., their facial beauty) come into play and influence listing prices. In P2P accommodations contexts, hosts typically base their pricing decisions on their subjective assessments of customers' perceived value and preferences (Hill, 2015). By considering positioning and hedonic pricing theories, scholars can develop a more holistic sense of the dynamics that inform pricing strategies in this market.

3. Development of hypotheses

3.1 Beauty paradox in the divergent Airbnb market

3.1.1 Fast-thinking resulting in beauty premium in the low-priced market

Price is a pivotal determinant in P2P accommodation markets, as customers prioritize cost-effectiveness (Chattopadhyay & Mitra, 2019). Price can thus tier consumers into distinct groups. Those targeting the lower-priced segment are inclined towards fast, intuitive decision-making (System 1) (Kahneman, 2011; Ren et al., 2021). Instead of an exhaustive evaluation, consumers frequently lean on salient cues like seller attributes (e.g., facial beauty) to discern product value.

The beauty premium finds its roots in the "what is beautiful is good" stereotype, profoundly influencing fast decision-making (Dion et al., 1972). The appearance-driven perceptions can amplify perceived value, convincing consumers that an item is worth paying more for (Dion et al., 1972; Nisbett & Wilson, 1977). The underlying rationale is individuals' instinctual, rapid evaluations of others based on attractiveness, especially prominent during intuitive decision-making processes where facial cues are paramount (Jaeger, Evans et al., 2019). This phenomenon suggests that host beauty may affect the perceived value of a listing, particularly in a low-priced market, where heuristic-driven decisions dominate. This persuasion colors one's perceived value of accommodation, which may vary from the offering's authentic value. Therefore, the beauty premium, originating from impressions and feelings governed by stereotypes (e.g., what is beautiful is good), could be more prominent in this fast-thinking style (Solaki et al., 2021). In this case, a good-looking host might enjoy a higher beauty premium and thus increase customers' WTP. As such, the following hypothesis is proposed:

Hypothesis 1: *In the low-priced Airbnb market, face beauty plays a significant role in supply and demand decisions on price. Specifically, (a) hosts' facial beauty positively influences listing prices (i.e., hosts with higher facial beauty tend to charge higher prices), and (b) Customers are willing to pay higher prices for accommodations whose hosts have beautiful faces.*

3.1.2 Slow-thinking in the high-priced market

Dual system theory posits that consumers adopt slower, analytical thinking (System 2) for high-priced purchases, focusing on comprehensive value assessments (Kahneman, 2011; Ren et al., 2021). This suggests a more thorough decision-making process in slow-thinking mode. As Ozanne et al. (2019) noted, attractiveness holds greater weight in scenarios characterized by limited information or heuristic processing. Conversely, Amaldoss et al. (2011) suggested that individuals within the upscale market segment place a higher emphasis on the quality of products. As such, for significant investments like pricier accommodations, consumers, operating in a slow-thinking mode, may tend to weigh other factors more heavily, such as accommodation quality, available amenities, and previous reviews. This deliberate and analytical approach effectively diminishes the influence of the host's appearance on their decision-making process. Given this, it can be inferred that customers may be less influenced by hosts' facial attractiveness when dealing with high-priced accommodations. Thus, we posit the following hypothesis:

Hypothesis 2: *In the high-priced market, hosts' facial beauty does not have a significantly positive impact on supply or demand decisions on price. Specifically, (a) hosts' facial beauty does not influence listing prices, and (b) Customers are not willing to pay higher prices for accommodations whose hosts have beautiful faces.*

3.2 Moderating effect of visual self-disclosure

Drawing upon dual system theory, the engagement in analytical slow-thinking (System 2) has the potential to mitigate the biases originating from more intuitive, rapid judgments (System 1) (Kahneman, 2011; Ren et al., 2021). In the context of Airbnb host profiles, visual cues such as facial beauty likely trigger quick, System 1-driven evaluations, while information from visual self-disclosure demands more nuanced, System 2-driven evaluations. Therefore, we posit that a host's visual self-disclosure can catalyze more deliberate consumer processing, tempering innate biases like the beauty premium.

Goffman's (1959) self-presentation and impression management theory suggests that people present themselves in a manner consistent with their desired image. Within this paradigm, hosts might use visual self-disclosure to project approachability and trustworthiness. This aligns with Jourard's (1971) conceptualization of self-disclosure as a behavior that unveils personal information, which has been identified as a mechanism to attenuate prejudice and discrimination (Kite & Whitley, 2016). Such disclosure refines one's digital identity, curtailing the uncertainties that arise from online anonymity (Chattopadhyay & Mitra, 2019). In the P2P context, hosts' self-disclosure plays a pivotal role in shaping guests' trust perceptions and purchase intentions (Ma et al., 2017). Studies have shown that online identities are often disclosed through either implicit cues (e.g., user-uploaded photos) or explicit cues (e.g., users' self-descriptive text) (van der Heide et al., 2012). van der Heide et al. (2012) contended that photographs (implicit cues) particularly influenced social orientation judgments. Broeder and Crijns (2019) found that the level of hosts' self-disclosure in personal profile photos affected users' booking intentions by shaping trust. In this study, we measure Airbnb hosts' visual self-disclosure through (1) the prominence of the facial area in their profile image, and (2) the intensity of happiness expressed therein.

Airbnb personal profiles act as conduits for self-disclosure. Consumers navigate through provided cues—visibility, eye contact, and facial demeanor—to discern sellers (Broeder & Crijns, 2019). Such facial cues provide crucial information for individuals to infer others' personality and trait impressions (Barnes & Kirshner, 2021). Given the intrinsic human predilection to prioritize facial perceptions (Peng et al., 2020), a more expansive facial area in profile images provides richer cues, facilitating a more rounded perception and attenuating uncertainties (Tidwell & Walther, 2002). This reduces the disproportionate emphasis on attractiveness, thus moderating appearance-based biases.

Positive facial expressions, particularly smiles, are perceived as benevolent stimuli, inducing a leniency effect (LaFrance & Hecht, 1995) that may consequently diminish appearance biases. Research indicates that smiles cultivate a "warm glow" effect (Carr et al., 2017), which can ameliorate the circumstances and dilute the influence of appearance biases. As Schwarz and Clore (2003) suggested, facial expressions can act as information reservoirs. A smile might offer insights into an individual's character, conveying hospitality and warmth, and further mitigating biases rooted in appearance. Given these considerations, the following hypotheses are postulated:

Hypothesis 3*: Hosts' visual self-disclosure negatively moderates the positive effect of hosts' facial beauty on supply and demand decisions on price in the low-priced Airbnb market. Specifically*, *(a) a larger facial area in the host's profile photo can attenuate the impact of facial beauty, and (b) a higher degree of happiness expressed in their profile photo can weaken the impact of facial beauty.*

3.3 Internal mechanism: Perceived uncertainty

Perceived uncertainty delineates subjective impressions of ambiguity, rooted in fragmented or inconclusive data (Ma et al., 2022). In P2P contexts, this uncertainty can pertain to questions about hosts' credibility, capability, and dependability, or about the quality and safety of the services on offer (Yan & Gong, 2023). The uncertainty reduction theory argues that individuals inherently seek to minimize uncertainties in interpersonal interactions, fostering clearer communication and predictability (Berger & Calabrese, 1974). Diminishing uncertainty augments consumers' purchasing confidence. Zinko et al. (2020) stated that enhanced information transparency can decrease uncertainty and amplify WTP (Hong & Pavlou, 2014). This effect is accentuated in P2P, where seller-provided information is paramount (Bazarova & Choi, 2014). In P2P accommodations, individuals meticulously sculpt their online presence, aiming to project a desired image during interactions (Nieto García et al., 2020).

On Airbnb, a host's profile image becomes a visual testament to their preparedness, exuding confidence and dependability (Walther & Parks, 2002). An image with a larger facial area diminishes perceived uncertainties, offering more visual data to gauge the host's character and reliability. Research on emotion and social cognition has shown that positive facial expressions, such as happiness, are associated with approach-related behaviors, cooperation, and trustworthiness (Todorov et al., 2008). A happy expression conveys a host's positive disposition and augments perceived warmth, fostering a sense of security for customers (Van Kleef, 2009). This convergence of cues diminishes the outsized role attractiveness plays in decisions, leading to a diluted beauty premium. Hence, we formulate:

Hypothesis 4: *Perceived uncertainty negatively mediates the interaction effect of hosts' facial beauty and hosts' visual self-disclosure on customers' WTP. Specifically, (a) a larger facial area in a host's profile photo attenuates the impact of facial beauty on WTP via reduced perceived uncertainty, and (b) a happy facial expression in a host's profile photo attenuates the impact of facial beauty on WTP via reduced perceived uncertainty.*

Figure 1 provides a visual representation of our research framework.

[Insert Figure 1 Here]

4. Methodology and results

Our empirical method incorporated multiple quantitative approaches and information sources, including econometric modeling using Airbnb field data and three online experiments. Combining methods and data sources can generate robust results while mitigating the inherent weaknesses of singular methods (Su et al., 2022). We leveraged the strengths of each approach and compensated for its limitations. Econometric modeling with a large field dataset provided high external and ecological validity (i.e., high realism) (Roethke et al., 2020). Online experiments presented robust evidence of a causal link between facial beauty and consumers' WTP while demonstrating high internal validity due to effective control measures. We could thus verify the causality and generalizability of the hypothesized relationships.

4.1 Study 1: Secondary Airbnb data modeling

4.1.1 Data collection

Airbnb.com is a popular platform for P2P accommodations. We used data from listings and hosts on Airbnb in Beijing, China. Information was obtained from Inside Airbnb, a non-commercial and autonomous assortment of data and tools demonstrating how Airbnb is being used globally.

The sample for our study comprised all accommodation listings from Airbnb.com in Beijing, encompassing 36,864 listings across 16 administrative regions. We collected data on May 27, 2020, including the attributes of the listings and host information. The average price of the listings was 709 CNY. To specifically study appearance discrimination against Airbnb hosts (i.e., beauty premium), we narrowed our focus to properties that featured a single face in the host's profile picture. The final sample included 9,736 listings after filtering out those containing (a) empty host self-descriptions, (b) English-language self-descriptions (i.e., to avoid language bias when extracting topics from hosts' self-descriptions), (c) no face or more than one face in a host's profile picture, (d) a host listing count (i.e., number of listings) of 0, (e) no bathroom or bedroom, and (f) a nightly price of 0 CNY or larger than 1,200 CNY. The listings' price distribution appears in Figure 2. The median listing price is 400 CNY (about 60 USD). According to the distribution of the listing prices, we focused on the relatively low-priced Airbnb market in this study. We used the median listing price level to identify relevant listings (<400 CNY per night; 5310 listings).

[Insert Figure 2 Here]

4.1.2 Variable operationalization

To investigate the extent of appearance discrimination against Airbnb hosts, focusing on listing prices, and to test whether and to what extent hosts' self-disclosure may reduce such discrimination, 23 variables were included in this study (see Appendix B). Key variables and their measurements are introduced below.

Dependent variable. The listing price was taken as the dependent variable (DV). Price information was extracted from the Airbnb property level dataset available on Inside Airbnb (http://insideairbnb.com/).

Independent variable. Hosts' facial beauty was the independent variable (IV), generated through the API service provided by Face++ (www.faceplusplus.com) by inputting the host's profile picture. Links to hosts' profile photos were extracted from Inside Airbnb. The service returns a "beauty score" from male and female perspectives, ranging from 0 to 100, with 100 denoting the highest facial beauty and 0 denoting the lowest.

Moderating variable. Host visual self-disclosure, as represented in the profile photo, served as the moderating variable. This was quantified through two metrics: (1) the degree to which the facial expression conveyed happiness and (2) the proportion of the face covered within the host's profile picture.

Control variables. Control variables included hosts' characteristics, room-related features and services, and hosts' textual self-description, in line with the past literature (e.g., Wang & Nicolau, 2017). Appendix C provides details of control variables.

4.1.3 Model specification

We sought to investigate the influence of hosts' facial beauty on the prices of corresponding Airbnb listings as well as the moderating effect of hosts' visual self-disclosure. Hedonic price models (Hartman, 1989), which have been applied to assess consumers' valuations of specific variables, were therefore employed. The hedonic price function (Rosen, 1974) and implicit marginal price can be written as

$$P = P(z, \varepsilon)$$

$$p_z = \frac{\partial P}{\partial z} = \frac{\partial P(z, \varepsilon)}{\partial z}$$

where P is the observed price of an Airbnb listing; z is the variable vector that affects the price; ε is the residual term; and p_z (the derivative of P with respect to z) is the unobserved marginal price, which mirrors the relative importance of a variable in a consumer's decisions.

The hedonic price models, including our baseline model (M-1) and the main regression model containing the variables of interest (M-2-1 and M-2-2), are specified as follows:

$$Price_i = Constant + \sum_k \beta_k Control\ variables_{ik} + error_i \qquad \text{(M-1)}$$

$$Price_i = Constant + \alpha_1 Beauty_i$$
$$+ \sum_k \beta_k Control\ variables_{ik} + error_i \qquad \text{(M-2-1)}$$

$$Price_i = Constant + \alpha_{11} Beauty_i + \alpha_{12} Happiness_i$$
$$+ \alpha_{13} Facial\ area_i + \alpha_{14} Beauty_i * Happiness_i$$
$$+ \alpha_{15} Beauty_i * Facial\ area_i$$
$$+ \sum_k \beta_k Control\ variables_{ik} + error_i \qquad \text{(M-2-2)}$$

where i represents the Airbnb listing. The host's characteristics, the host's self-description, and room-related features and services listed in Appendix B served as control variables in this model.

We then specified models for robustness checks. First, a semilogarithmic regression model, which is common in the literature (e.g., Wang et al., 2019), was used to specify the hedonic price model as a robustness check. In the semilogarithmic regression model, the natural logarithm of the listing price (*LNPrice*) served as the DV (M-3). Second, we used a dummy variable, *Happiness_dummy*, as an alternative measure of the facial expression of happiness (M-4). If happiness (compared with a neutral facial expression or one of surprise, sadness, disgust, anger, or fear) was the main emotion expressed in a host's face, then *Happiness_dummy* was coded as 1 and 0 otherwise. Third, we took *Smiling* as another alternative measure of the facial expression of happiness (M-5); it is a continuous variable (0–100) generated through the API service on Face++. Fourth, we substituted the facial expression of happiness with a categorical variable *Smiling_dummy* (M-6). Based on *Smiling*, we divided our sample into two categories: if the score of *Smiling* was equal to or greater than 50 (i.e., the probability of smiling≥50%), then the variable was coded as 1 and 0 otherwise.

Furthermore, we used 302 CNY (low-priced market covering one-third of all listings) and 522 CNY (low-priced market covering two-thirds of all listings) as additional thresholds to divide the sample into low-priced and high-priced Airbnb markets. We then re-estimated Model 2 as a robustness check (see Appendix D).

4.1.4 Results of field Airbnb data modeling

After the model diagnostic check, the heteroskedasticity robust standard error method (Atkinson et al., 2016) is used for model estimation. Estimation results for (M-1) and (M-2) are listed in Table 1 for the low-priced Airbnb market. The variance inflation factors for all variables were less than 2, indicating the absence of a severe multicollinearity problem. Compared with (M-1), (M-2-1) included the IV (i.e., hosts' facial beauty), while (M-2-2) added moderating variables (i.e., *Happiness* and *Facial area* of hosts' profile photos). We added hosts' characteristics, hosts' self-description, as well as room-related features and services (see Appendix C) as control variables. Estimation results were consistent between (M-1) and (M-2) for the selected markets.

The estimation results in Table 1 show that facial beauty had a significant and positive effect on price in the low-priced Airbnb market [coefficient (M-2-1) = 0.191, p =0.024]. Compared with bad-looking hosts, good-looking hosts (i.e., based on the host's profile photo) tended to charge a higher price for a listing in the Airbnb market given an appearance-based superiority complex. Hypothesis 1a was thus supported from the supply perspective.

Estimation results for (M-2-2) also revealed the moderating role of two host visual self-disclosure variables, *Happiness* and portrait *Facial area*, in the low-priced Airbnb market. As shown in Table 1, for the selected market segment, a host's facial beauty exhibited a significant positive influence on the listing price. However, the above impact could be weakened by *Happiness* and *Facial area*, as indicated by significantly negative coefficients of the interaction terms between facial beauty and happiness (coefficient = -0.006, $p < 0.01$) and between facial beauty and facial area (coefficient = -0.046, $p < 0.01$). These results indicate that both the host's facial happiness degree and the facial area of the host's profile picture can help weaken the effect of facial beauty on the listing price. The findings suggest that while the intuitive System 1 might be drawn to facial beauty as a primary cue (a heuristic), additional visual cues such as happiness and facial area activate the analytical System 2, prompting deeper processing.

In the case of increased facial happiness, as indicated in Figure 3, the intuitive allure of beauty on a listing price is moderated in the low-priced Airbnb market. In addition to a feeling of trustworthiness, warmth, and positivity (Todorov et al., 2008), a happy face may reduce consumers' uncertainty by allowing them to evaluate those attributes alongside beauty. This deeper processing explains why the listing price ascends more gradually for hosts displaying a higher degree of happiness, even with increasing facial beauty.

Similarly, for the facial area, as visualized in Figure 4, a larger facial area in the host's profile picture could provide more information for consumers to process, thus transitioning them from a mere beauty heuristic to a more analytical evaluation. A larger face offers more detailed cues – be it expressions, features, or nuances – that System 2 uses for a more comprehensive assessment, thereby tempering the beauty premium. Therefore, Hypotheses 3a and 3b were supported.

Additionally, our results verified the roles of several room-related variables (e.g., location and property type) as Airbnb listing price determinants. This outcome accords with previous research (e.g., Chattopadhyay & Mitra, 2019). However, the effects of hosts' characteristics on Airbnb listing prices, such as Superhost status and whether the host had a verified ID, were insignificant. These findings echo those of Jaeger, Sleegers et al. (2019).

[Insert Table 1 Here]

[Insert Figure 3 Here]

[Insert Figure 4 Here]

4.1.5 Robustness check

To ensure the validity of our findings, we implemented four robustness checks: (1) a semilogarithmic regression model; (2) alternative measures of happiness using *Happiness_dummy*, *Smiling*, and *Smiling_category*; (3) separating the low- and high-priced markets by using new threshold values; (4) testing the moderating effect of the price level (high vs. low) on beauty in affecting a listing's price.

The results of the first two checks are presented in Table 2. For the third check, we separated the Airbnb markets based on two different threshold values: 302 CNY (comprising approximately one-third of all listings priced below 302 CNY per night, or 3674 listings) and 522 CNY (encompassing two-thirds of all listings priced below 522 CNY per night, or 7191 listings). Detailed findings for this separation are in Table D-1 of Appendix D.

When we extended our analysis to the full sample size (9,736 listings) and within the high-priced market using three distinct thresholds (302 CNY, 400 CNY, and 522 CNY), we found no presence of beauty premiums, as evidenced in Table D-2. The investigation into the moderating influence of the price level on beauty's effect on a listing's price is provided in Table D-3. This further reinforced our rationale for examining the beauty premium primarily within the low-priced market.

[Insert Table 2 Here]

4.2 Experimental design

Utilizing empirical Airbnb data, our secondary data modeling identified the beauty premium from the supply perspective and two visual factors that may reduce such appearance discrimination. Three online experiments were next conducted from a consumer demand perspective to further validate these results and understand how appearance discrimination can be mitigated. To avoid common method bias, data collection for the three experiments occurred at different times: the first experiment was conducted in June 2022, while experiments 2 and 3 were conducted in December 2022. This approach ensures the robustness and validity of our findings.

4.2.1 Study 2: Experiment 1

Design and subjects

We employed a 2 (host's facial beauty: good-looking vs. bad-looking) × 2 (price: low-priced vs. high-priced market) between-subjects design to examine whether beauty premium effects are limited to low-priced markets. Subjects were randomly assigned to one of four groups: (1) bad-looking host in a high-priced market (n = 62), (2) good-looking host in a high-priced market (n = 58), (3) bad-looking host in a low-priced market (n = 66), and good-looking host in a low-priced market (n = 68). A total of 254 effective responses were collected from China's largest consumer survey platform, wjx.cn. G*Power analysis determined the sample size, recommending a minimum of 232 participants to achieve a medium effect size (i.e., 0.25) with 90% power and a 5% false positive rate. The sample consisted of nearly equal proportions of men (49.6%) and women, with 57.5% aged between

18 and 30, and 42.5% older than 31. Most participants (81.8%) held a bachelor's degree or higher, and the majority (78%) had experience booking P2P accommodations online, with 87.4% holding positive attitudes towards such platforms. Appendix H provides detailed demographic information.

Stimuli and procedure

To establish the context, participants were first asked to envision themselves planning a solo trip and considering various options for homestays on a P2P accommodation platform. They were then informed that they had located an accommodation that fit within their budget. However, they were not explicitly told if this accommodation belonged to a high-priced or low-priced market. Next, participants were about to review the host's information to determine their WTP.

Next we presented participants with scenarios where the reference nightly rate for the accommodation was either CNY 200 (low-priced market) or CNY 600 (high-priced market). Participants were told that the reference room rate per night was set at 200 CNY [or 600 CNY], and were asked to rate whether the price of the accommodation falls within a high or low price range. The median listing price from previously collected secondary data determined the CNY 400 cut-off point for high- and low-priced markets. Following this, two manipulation check questions regarding price were asked.

Participants were then exposed to host profile photos that were either rated as good-looking or bad-looking. These photos were consistently presented alongside fixed host attributes such as the host's name, registration date, and verified status (see Appendix E for face stimuli). Afterwards, participants were asked to indicate their WTP using a sliding scale. Following Marozzo et al.'s (2020) measurement, subjects could indicate a WTP price between 0 CNY and 1000 CNY (i.e., "Based on your impression of the host in the picture above, what is the most you would be willing to pay for the accommodation?").

Subsequently, realism check questions, manipulation checks regarding facial beauty, and questions concerning the authenticity and manipulation of the profile photo ("The host's profile picture looks authentic" and "The host's profile picture looks manipulated/edited.") were asked. To avert possible disruptions, subjects' familiarity ("The host looks like someone I know well") and perceived trustworthiness ("The host looks like a trustworthy person", "The host looks like they would not attempt to mislead others", "The host appears to be honest when dealing with others", Peng et al., 2020) with the host, past experiences with using P2P accommodation platforms, and attitudes toward using such platforms were gauged.

Lastly, the survey closed with demographic items. To ensure the quality of the participants' responses, several attention check questions were included in the experiment. For instance, one such attention check required participants to recall the reference price for the accommodation.

Experiment 1 results

Manipulation check. We conducted two checks to ensure proper manipulation. First, two items from Peng et al. (2020) were utilized to verify whether the hosts' facial beauty manipulation was successful. Items, "The host is very good-looking" and "The host has bad-looking appearance" (Cronbach's α = 0. 924), were scored on a 7-point scale anchored by "strongly disagree" and "strongly agree". The second item was a reverse-coded question.

An independent samples *t*-test revealed that subjects in the good-looking condition rated the host's facial beauty higher than those in the bad-looking condition ($M_{good\text{-}looking} = 5.45 > M_{bad\text{-}looking} = 2.89$; $t = 16.575$, $p < 0.001$). Therefore, the manipulation operated as intended.

Two 7-point Likert scale questions were employed to check the success of the manipulation of the market price for high- and low-priced markets: "To what extent do you think the price of the homestay in the situation is in the high-priced market?" ($M_{\text{high-priced}} = 5.77$, $M_{\text{low-priced}} = 2.21$; $t = 23.382$, $p < 0.001$), and "To what extent do you think the price of the homestay in the situation is in the low-priced market?" ($M_{\text{high-priced}} = 5.78$, $M_{\text{low-priced}} = 1.98$; $t = -25.933$, $p < 0.001$). Results showed that participants perceived the pricing conditions as intended.

WTP. Two independent samples *t* tests were performed, revealing a significant difference in customers' WTP between the high facial beauty condition and the low facial beauty condition ($M_{good\text{-}looking} = 278.76 > M_{bad\text{-}looking} = 187.45$; $t = 7.928$, $p < 0.001$) in the low-priced market, while no significant difference was found in the high-priced market condition ($M_{good\text{-}looking} = 525.31 > M_{bad\text{-}looking} = 523$; $t = 0.123$, $p = 0.902$) (see Figure 5). That is, participants were willing to pay a higher price for a P2P accommodation offering with a good-looking host only in the low-priced market. In addition, no significant differences emerged between participants in the experimental conditions in terms of gender [$\chi^2(1) = 0.523$, $p = 0.602$], income [$\chi^2(4) = 1.425$, $p = 0.157$] and P2P accommodation experience

[F(2, 196) = 0.902, $p = 0.369$]. The results showed that appearance discrimination affected consumers' WTP; Hypothesis 1b was hence supported from the customer demand perspective.

[Insert Figure 5 Here]

Hayes's PROCESS Model 1 was used to verify the moderating role of market price on the relationship between hosts' facial beauty and consumers' WTP. By employing bootstrapping ($n = 10{,}000$), a 95% confidence interval (CI) was generated for parameter estimates. Results revealed a noteworthy moderating effect ($F = 64.4797$, $p = 0.000$). No statistically significant impact was observed for hosts' facial beauty on consumers' WTP in the high-priced market ($\beta = -5.9259$, SE = 17.3581, 95% CI: [-40.1204, 28.2686]). However, a significant effect existed in the low-priced market ($\beta = 96.0186$, SE = 16.2294, 95% CI: [64.0476, 127.9895]). Figure 6 shows the moderating role of market price without (a) and with (b) control variables. A significant impact of facial beauty on WTP consistently appeared in the low-priced market.

[Insert Figure 6 Here]

4.2.2 Study 3: Experiment 2

Design and subjects

A 2 (host's facial beauty: high vs. low) × 2 (host's visual self-disclosure: large facial area vs. small facial area) between-subjects design was employed to investigate the interplay between host's facial beauty and visual self-disclosure (facial area). Subjects were randomly allocated to one of the following groups: (1) a good-looking host with a large facial area in the profile photo (n = 63), (2) a bad-looking host with a large facial area (n = 61), (3) a good-looking host with a small facial area (n = 67), and (4) a bad-looking host with a small facial area (n = 68). The experiment included 259 effective responses and had a medium effect size (i.e., 0.25) with 90% power. The gender distribution was roughly equal, and participants' demographic characteristics were assessed (see details in Appendix F).

Stimuli and procedure

Experiment 2 followed a procedure similar to Experiment 1 to assess subjects' WTP. Upon reviewing the lodging details, subjects were directed to the host's homepage and assigned to one of the four previously stated scenarios. Hosts' facial beauty was manipulated in the same manner as in Experiment 1, while hosts' visual self-disclosure (facial area) was altered based on the facial area depicted in their profile photo. High visual self-disclosure involved a larger facial area; lower visual self-disclosure involved a smaller facial area. Subjects were then prompted to respond to questions concerning perceived uncertainty, measured with four items on a 7-point Likert scale (α = 0.938; see details in Appendix F) adapted from Torkzadeh and Dhillon (2002). Building upon Peng et al. (2020), we inquired about participants' perceptions of the profile photo's authenticity and potential manipulation, as well as their perceived familiarity and trustworthiness of the host. Participants also provided information regarding their past experiences, usage frequency, and attitudes toward P2P accommodation platforms, in addition to their demographic details.

Experiment 2 results

Manipulation check. Two manipulation checks were completed. The first check aimed to assess the success of manipulating hosts' facial beauty using the same question as in Experiment 1. Findings revealed a significant difference between ratings assigned to the high facial beauty group and the low facial beauty group, with the former receiving notably higher ratings ($M_{\text{good-looking}} = 5.692 > M_{\text{bad-looking}} = 3.446$; $t = 17.514$, $p = 0.000$). The manipulation of hosts' visual self-disclosure (facial area) was assessed with the following question: "To what extent do you agree that a large portion of the host's profile photo shows the face?" (1 = *strongly disagree*; 7 = *strongly agree*). Subjects gave significantly higher ratings to hosts in the large facial area group versus those in the small facial area group ($M_{\text{large}} = 5.74 > M_{\text{small}} = 1.79$; $t = 35.209$, $p = 0.000$), showing that the manipulation of hosts' visual self-disclosure (facial area) was effective.

Moderation analysis. Viglia and Dolnicar (2020) recommended using SPSS with PROCESS add-ons to test mediation and moderation models. We employed Model 1 from Hayes's (2018) PROCESS procedure, utilizing 10,000 bootstrapping iterations, to validate Hypothesis 1b and examine Hypothesis 3a. The estimated results (Table 3) demonstrated a significant primary effect of hosts' facial attractiveness on consumers' WTP at a 95% confidence level ($\beta = 52.4331$, $p = .0000$). The moderating impact of hosts' visual self-disclosure (facial area) on facial attractiveness was negatively significant ($\beta_{B\times A} = -44.9056$, $p = .0012$). The host's facial area in the profile photo also exhibited a positive and significant impact on consumers' WTP at a 95% confidence level ($\beta = 34.1070$, $p = .0004$); that is, hosts with a larger facial area in their profile photos prompted consumers to pay more. Hypotheses 1b and 3a were therefore supported.

[Insert Table 3 Here]

Moderated mediation analysis. PROCESS Model 8 was applied with bootstrapping (10,000 samples) to examine the moderated mediating effect (Hayes, 2018). The IV was facial beauty; perceived uncertainty functioned as the mediator. Hosts' visual self-disclosure (facial area) acted as a moderating variable, and WTP served as the DV. As illustrated in Figure 7, the conditional direct effect of hosts' facial attractiveness on consumers' WTP was not significant when the facial area was small (β = -5.9295, p = .4407) but significantly negative when the facial area was large (β = -29.1098, p = .0002). A test for equality of the conditional direct effects in both groups revealed a significant difference between the low and high visual self-disclosure (facial area) groups ($\beta_{facial\ beauty \times facial\ area}$ = -23.1803, p = .0177). This outcome substantiates Hypothesis 3a.

The mediating effect via perceived uncertainty was stronger in the small facial area group (β = 58.3626, 90% CI: [45.5546, 70.3952]) compared with the large facial area group (β = 36.6374; 90% CI: [23.2807, 50.1243]). This finding reveals a difference between conditional indirect effects (index of moderated mediation = -21.7252, 90% CI: [-36.8811, -6.2436]). Additionally, a t-test result indicated that the bigger the face area shown in the profile photo, the less uncertainty perceived by the participants (M_{small} = 3.71> M_{big} = 3.20, t = -2.657, p < 0.01). The results support Hypothesis 4a, indicating that hosts' self-disclosure moderated the relationship between facial attractiveness and consumers' WTP via lower perceived uncertainty.

[Insert Figure 7 Here]

4.2.3 Study 4: Experiment 3

Design and subjects

This experiment aimed to examine the moderating effect of hosts' visual self-disclosure (facial expression) in the low-priced market. A 2 (host's facial beauty: low vs. high) × 2 (host's visual self-disclosure: happy expression vs. neutral expression) between-subjects design was adopted. The sample included 260 subjects with 90% power and a medium effect size based on G*Power analysis. Subjects were drawn from the same population as those in Experiment 1 and were randomly divided across four scenarios: (1) a bad-looking host with a neutral expression (n = 68), (2) a good-looking host with a neutral expression (n = 62), (3) a bad-looking host with a happy expression (n = 68), and (4) a good-looking host with a happy expression (n = 62). We summarized demographic information for participants in the three experiments (see Appendix G for details).

Stimuli and procedures

As in Experiments 1 and 2, subjects were instructed to envision a scenario for booking lodging and were redirected to the host's homepage after reviewing the lodging details. Subjects were provided with manipulated information about the host, including different facial beauty and visual self-disclosure (facial expression: happiness) under each condition. The above-mentioned scenarios were randomly assigned. As in previous experiments, hosts' facial beauty was manipulated, and visual self-disclosure was altered according to hosts' expressed happiness. Hosts with high visual self-disclosure had a happy expression; those with lower visual self-disclosure had a neutral expression. The remaining procedures were the same as those in Experiment 2.

Experiment 3 results

Manipulation check. Two manipulation checks were completed. The first check used the same question as the previous experiments to evaluate the manipulation of hosts' facial beauty. An independent samples *t*-test revealed that good-looking hosts received significantly higher ratings than bad-looking hosts ($M_{\text{good-looking}} = 5.698 > M_{\text{bad-looking}} = 3.838$; $t = 13.284$, $p = 0.000$). The second check assessed the effectiveness of manipulating hosts' visual self-disclosure (facial expression: happiness) by asking subjects to rate the extent to which they agreed that the host's facial expression looked happy (1 = *strongly disagree*; 7 = *strongly agree*). Hosts displaying a happy facial expression received significantly higher ratings than those with a neutral expression ($M_{\text{happy}} = 6.53 > M_{\text{neutral}} = 1.93$; $t = 46.694$, $p = 0.000$). Hosts' visual self-disclosure (facial expression: happiness) was thus manipulated successfully.

Moderation analysis. PROCESS Model 1 with 10,000 bootstrapping iterations was applied to validate the beauty premium and the negative moderating effect of hosts' visual self-disclosure (happiness). The estimated results (Table 4) demonstrated a significant primary impact of hosts' facial beauty on consumers' WTP at a 95% confidence level (*β*

= 88.7376, p = .0000). The moderating impact of hosts' visual self-disclosure (happiness) on facial attractiveness was negatively significant ($\beta_{B\times H}$ = -62.0691, p = .0001). The host's facial expression in the profile photo also exhibited a positive and significant impact on consumers' willingness-to-pay at a 95% confidence level (β = 52.6745, p = .0000): hosts with happy expressions in their profile photos convinced consumers to pay more. Hypotheses 2 and 4b were accordingly supported.

[Insert Table 4 Here]

Moderated mediation analysis. We applied PROCESS Model 8 to examine the moderated mediating effect. The IV was facial beauty with perceived uncertainty as the mediator. Hosts' visual self-disclosure (happiness) was the moderating variable, and the DV was consumers' WTP. Data were bootstrapped using 10,000 resamples. The conditional direct effect of hosts' facial beauty on consumers' WTP was not significant when the profile photo displayed a happy expression (β = -.4478, p = .9614). However, it was statistically significant when the expression was neutral (β = 46.5408, p = .0000). Positive emotional cues in the host's profile photo (e.g., a happy expression) might attenuate the impact of facial attractiveness on WTP. A test of equality of the conditional direct effects between the neutral and happy facial expression groups revealed a significant difference ($\beta_{facial\ beauty\ \times\ happiness}$ = -46.9886, p = .0003), lending support to Hypothesis 3b.

The results further indicated that the indirect effect of a host's facial beauty on WTP through perceived uncertainty was notably stronger in the neutral expression group (β =

42.1968; 90% CI: [29.2575, 55.4020]) compared with the happy expression group (β = 27.1163; 90% CI: [16.8867, 38.8101]). The parity of conditional indirect effects (index of moderated mediation = -15.0806; 90% CI: [-28.5578, -.9486]) supported Hypothesis 4b. Further, a *t*-test result showed that the host with a happy expression received a lower score of perceived uncertainty compared to the host with a neutral expression (M_{netural} = 3.8135 > M_{happy} = 3.1923, t = -3,524, p = < 0.01). Therefore, perceived uncertainty negatively mediated the interplay between hosts' facial beauty and visual self-disclosure (happiness) on consumers' WTP. Figure 8 presents these results.

[Insert Figure 8 Here]

5. Discussion and conclusion

This study examined the extent of appearance discrimination (i.e., beauty premium) against hosts in the P2P accommodation market with a focus on listing prices and customers' WTP in low vs. high priced markets. Additionally, we tested whether and how hosts' visual self-disclosure may reduce appearance discrimination. A multi-method approach using online secondary data from Airbnb and experiments indicated that the beauty premium only occurs in lower priced listings, aligning with the dual system theory (Kahneman & Frederick, 2002). The high-priced market showed no significant impact of hosts' facial beauty on both Airbnb listing prices and consumers' WTP. Our robustness check did not demonstrate evidence of hosts' facial beauty positively influencing listing prices in the high-priced market. This finding may be attributed to consumers' increased cognitive elaboration when evaluating high-priced options (Gladstone et al., 2022). For lower-priced bookings, intuitive System 1 thinking dominates, increasing susceptibility to biases like favoring attractiveness. However, consumers use more careful, analytical System 2 thinking for higher priced listings (Huang & Wang, 2019; Ren et al., 2021), which attenuates superficial biases. This empirically demonstrates dual process mechanisms in a novel context.

We also determined that hosts' visual self-disclosure can reduce multiple effects of appearance discrimination in the low-priced P2P accommodation market in both secondary Airbnb data and experiments. This finding further enriches dual system theory by revealing self-disclosure as a strategy to elicit System 2 thinking and reduce attractiveness biases. More host disclosure reduced uncertainty perceptions and reliance on looks, consistent with the uncertainty reduction theory (Berger & Calabrese, 1974) and social information processing (Van Kleef, 2009). This supports dual system notions that analytical thinking attenuates intuitive biases.

Experiments 2 and 3 further revealed that perceived uncertainty mediated the alleviating effects of hosts' visual self-disclosure on consumers' decisions via facial area size (large vs. small) and facial expression (happy vs. neutral). The mediating role of perceived uncertainty was weaker when a host engaged in high visual self-disclosure, such as displaying a happy (vs. neutral) expression. This observation aligns with the uncertainty reduction theory (Berger & Calabrese, 1974). When hosts engage in high visual self-disclosure, such as displaying a happy expression, they provide more information for consumers to form impressions about their personality and trustworthiness. This increased information can reduce perceived uncertainty (Hong & Pavlou, 2014; Yan & Gong, 2023). This could also be supported by emotion as a social information model (Van Kleef, 2009) which suggests that emotional expressions, such as happiness, serve as social cues that influence interpersonal judgments and behaviors. A happy expression in a host's profile photo can convey warmth and positive intentions, which in turn can reduce perceived uncertainty by fostering trust and positive expectations about the host (Todorov et al., 2008). Consequently, consumers may rely less on superficial cues, such as facial beauty, and focus more on the disclosed information in their decision-making process.

Additionally, when a host's facial area was small (i.e., low visual self-disclosure), the indirect effect through perceived uncertainty was stronger than for hosts with a large facial area (i.e., high visual self-disclosure). Our findings support the notion that more visual information provides additional details about a host, based on which consumers can make inferences about the person's trustworthiness and reliability (Banerjee et al., 2022). Perceived uncertainty about the purchase process then declines (Walther & Parks, 2002). Conversely, a smaller facial area may make the host seem less confident and more secretive, leading consumers to feel more insecure.

5.1 Theoretical implications

This study contributes to the literature in several ways. First, existing research has acknowledged the existence of the "beauty premium" in various contexts (Ert et al., 2016; Peng et al., 2020). Our study offers nuanced insights by identifying the boundary conditions under which this premium operates within the P2P accommodation sector. This study draws on dual system theory to depict appearance-based discrimination and uncover the divergent consumers' responses to the "beauty premium" in low-priced and high-priced P2P accommodation markets. Contrary to broad assumptions, our findings indicate that the beauty premium is not omnipresent. Instead, it manifests specifically when consumers operate under intuitive fast-thinking, which is notably triggered by lower-priced listings. This discovery can potentially reconcile conflicting findings from earlier studies, emphasizing the critical role of price as a determining factor in the beauty premium's influence (Ert et al., 2016; Jaeger, Sleegers et al., 2019; Peng et al., 2020). This study provides empirical evidence to suggest that beauty-related visual stimuli intercept with price can trigger consumers' divergent information processing systems and lead to different purchase decisions.

Second, while some researchers have examined the implications of facial attractiveness on either the supply-side (Jaeger, Sleegers et al., 2019) or the demand-side (Barnes & Kirshner, 2021), our study bridges this gap. By concurrently analyzing both listing prices and consumers' WTP, we furnish a holistic understanding of the role host facial attractiveness plays in shaping pricing dynamics and influencing consumer decisions within the P2P accommodation realm. Ert et al. (2016) relatedly discovered that hosts who appeared more trustworthy in photos charged higher prices based on 175 Stockholm samples. Jaeger, Sleegers et al. (2019) discerned the attractiveness effects of hosts on Airbnb listing prices (supply perspective) based on 1020 Airbnb listing data from New York City. The present study contributes to this stream of literature by further clarifying price determinants related to host attributes (i.e., facial beauty based on hosts' profile photos) from both the demand (i.e., consumers' WTP) and supply perspectives (i.e., rental prices on Airbnb) with a larger sample (i.e., 9,736 listings) and a series of scenario-based experiments.

Third, previous works have recognized that consumers often rely on visual cues, such as attractiveness, to make decisions (Jaeger, Evans et al., 2019). This study makes an initial effort to examine the visual elements that could mitigate appearance-based bias in P2P markets, and find out what mechanisms are at work internally. Although self-disclosure has been deemed an effective way to reduce prejudice and discrimination (Kite & Whitley, 2016), scholars have yet to explore the role of visual self-disclosure—in reducing facial discrimination in online P2P accommodation contexts. We demonstrate that host visual self-disclosure (i.e., host's facial expression and facial area) can shift consumers from intuitive to analytical processing, thus neutralizing biases stemming from attractiveness. This outcome echoes earlier findings indicating that visual changes in one's appearance, even when subtle, can alter others' judgment (Ert et al., 2016). Furthermore, our findings go beyond merely identifying the importance of visual self-disclosure. We noticed that consumers' perceived uncertainty about the host mediated the role of such self-disclosure in their decisions. Thus, this study offers a nuanced understanding of the interplay between visual cues, social perceptions, and consumer behavior in the online P2P accommodation context with potential implications for other online marketplaces.

Fourth, methodologically, while prior studies in the domain often relied on singular methods, be it big data analysis (Peng et al., 2020) or experimental designs (Ert et al., 2016), our approach synergizes both to study the impact of facial beauty–based appearance discrimination on the accommodation market. Most research on facial beauty effects has involved experiments or small samples. These design attributes could compromise the findings' robustness and generalizability if a study does not include authentic user-generated data (Peng et al., 2020) or uses a small sample size (Jaeger, Sleegers et al., 2019). This fusion ensures a more robust and comprehensive understanding of consumer behavior in processing visual host information within P2P accommodation platforms. Furthermore, Ert et al. (2016) and Jaeger, Sleegers et al. (2019) recruited workers from MTurk to evaluate a limited number of hosts' facial beauty, which partly narrowed these studies' scale. Our work overcame this limitation by evaluating hosts' facial beauty through AI powered API services provided by Face++, a commercial algorithm that has been widely used to extract indicators from a large number of facial images (Edelman et al., 2017; Yang et al., 2020).

5.2 Managerial implications

This study offers actionable insights for various stakeholders within the P2P accommodation platform, for both individual hosts and platform operators.

First, our study uncovers the pronounced beauty premium in the P2P accommodation market, specifically for lower-priced listings. Managers and hosts should be aware of the potential influence of attractiveness on property listing prices, but also recognize that this influence wanes in higher-priced markets. Furthermore, the duality of decision-making processes, as exemplified by dual system theory, has substantial implications for how consumers perceive value. Platforms can design their user interfaces in ways that nudge consumers towards more analytical thinking, particularly for high-priced listings, to ensure decisions are based on substantive factors rather than superficial ones.

Second, hosts, especially those in the lower-priced market segment, can combat appearance discrimination by engaging in higher levels of visual self-disclosure. Displaying more of oneself, especially with positive emotions like happiness, can steer the decision-making process away from mere facial attractiveness. Platforms like Airbnb might guide hosts on how to present themselves effectively, emphasizing the importance of genuine, happy, and large profile photos. In detail, platforms can offer training sessions or guidance materials for hosts, emphasizing the importance of visual-self disclosure. They could also redesign their interface to highlight hosts' profile photos and possibly even reward or prioritize those with higher levels of visual self-disclosure. Also, the platform can implement a host avatar review system: when a host uploads an avatar that does not meet guidelines (e.g., when the facial area is too small), the host can be asked to upload a revised version or an alternative photo. By adopting these strategies, appearance discrimination can be managed more effectively, promoting a more equitable marketplace.

Third, perceived uncertainty can be a significant hurdle in the P2P accommodation market. Our findings suggest that visual self-disclosure, particularly through positive facial expressions and larger profile photos, can alleviate such uncertainties. Hosts should be encouraged to use authentic, clear, and warm photos to help potential guests feel more comfortable and secure in their decision-making. Specifically, the platform can introduce in-app guidelines or photo suggestions during the photo upload process to guide hosts. For instance, specifying a standard facial disclosure ratio in hosts' profile pictures and encouraging them to use avatars showing happy expressions or showing examples of 'ideal photos' can be beneficial. By providing tips and best practices for creating engaging and authentic profile photos, hosts can improve their online presence and increase consumer confidence.

5.3 Limitations and future studies

This study has several limitations that present opportunities for future research. First, due to data availability constraints, we focused only on Airbnb listing prices and willingness-to-pay as outcome variables related to appearance discrimination. As more data become available, the impacts of appearance discrimination on other meaningful outcome variables (e.g., property occupancy and revenue) can be further explored. In addition, distinct customer segments may react differently to hosts' appearance discrimination in P2P accommodation platforms. It would be interesting to further explore the heterogeneity of various customer segments. Second, our sample included only listings in Beijing, China during the COVID-19 pandemic period. Cross-cultural comparisons before and after the pandemic are needed to assess generalizability across individualistic and collectivistic cultures. Third, we did not control for review ratings in our pricing model due to the very high volume (over 40%) of missing data for that variable in our dataset. This highlights an avenue for further research on how review behaviors differ across cultural markets. Fourth, only one host's profile photo was included in each experimental scenario. Follow-up studies presenting multiple photos could provide richer insight.

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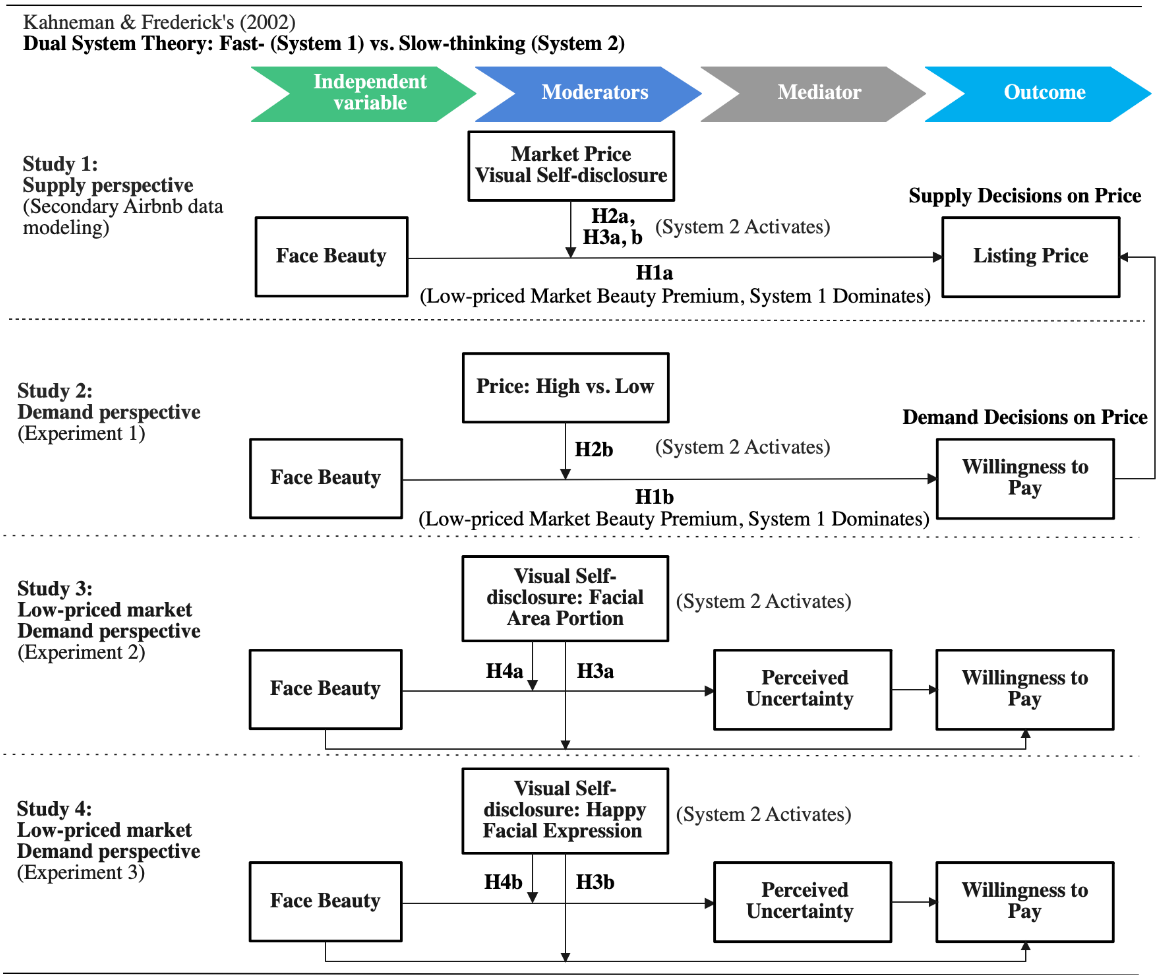


Figure 1. Research framework

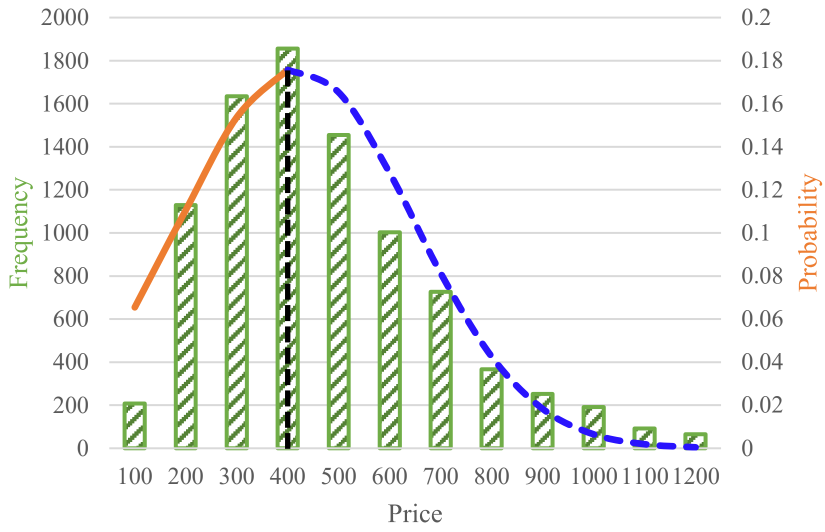


Figure 2. Price distribution of Airbnb listings

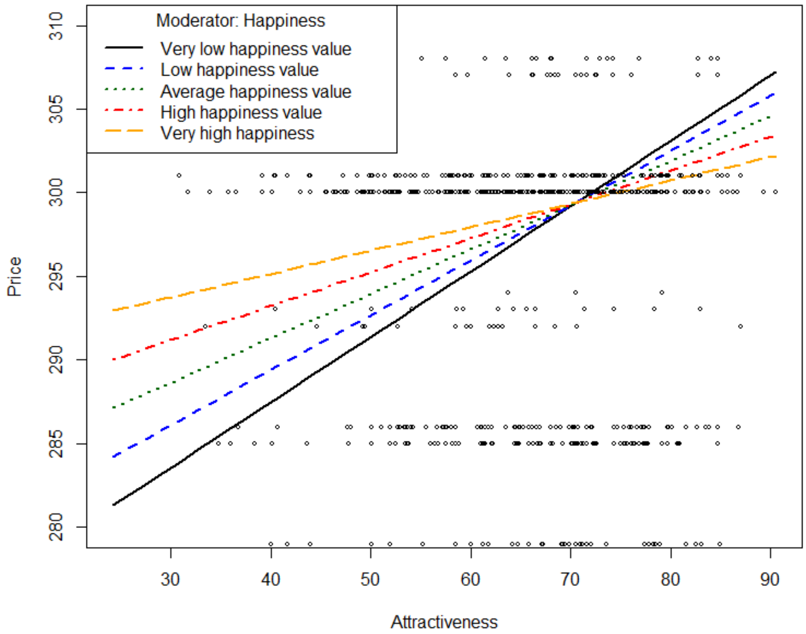


Figure 3. Moderating effect of *Happiness* on appearance discrimination

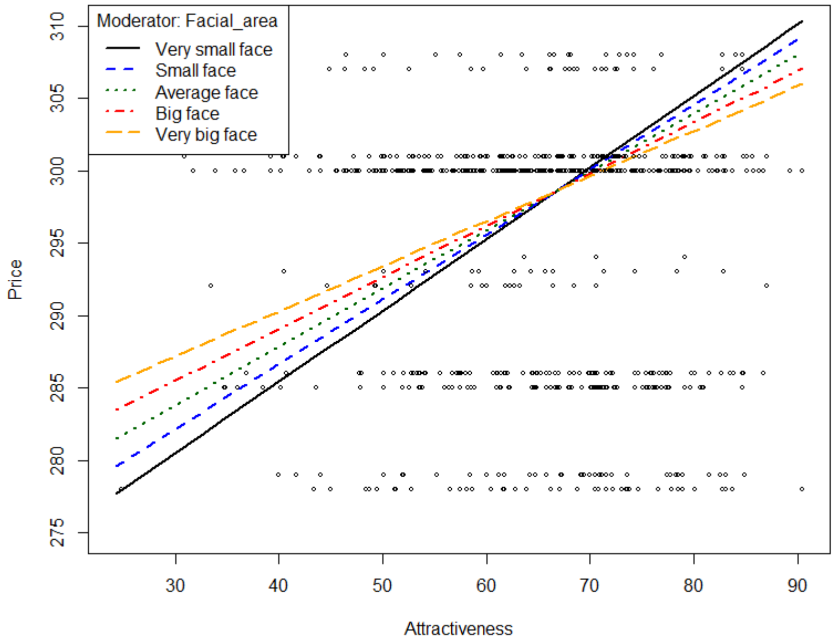


Figure 4. Moderating effect of *Facial area* on appearance discrimination

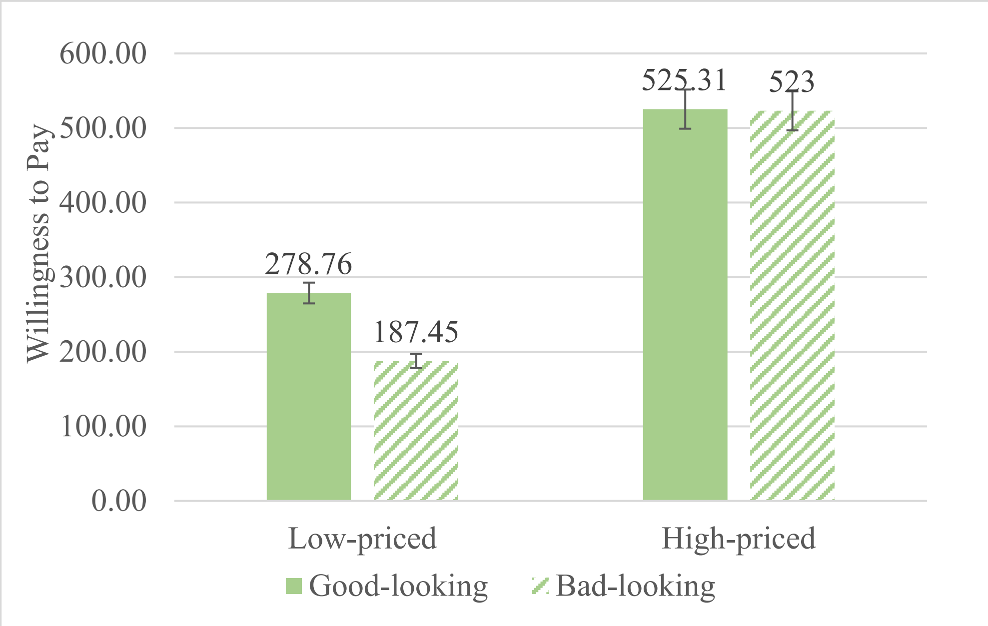
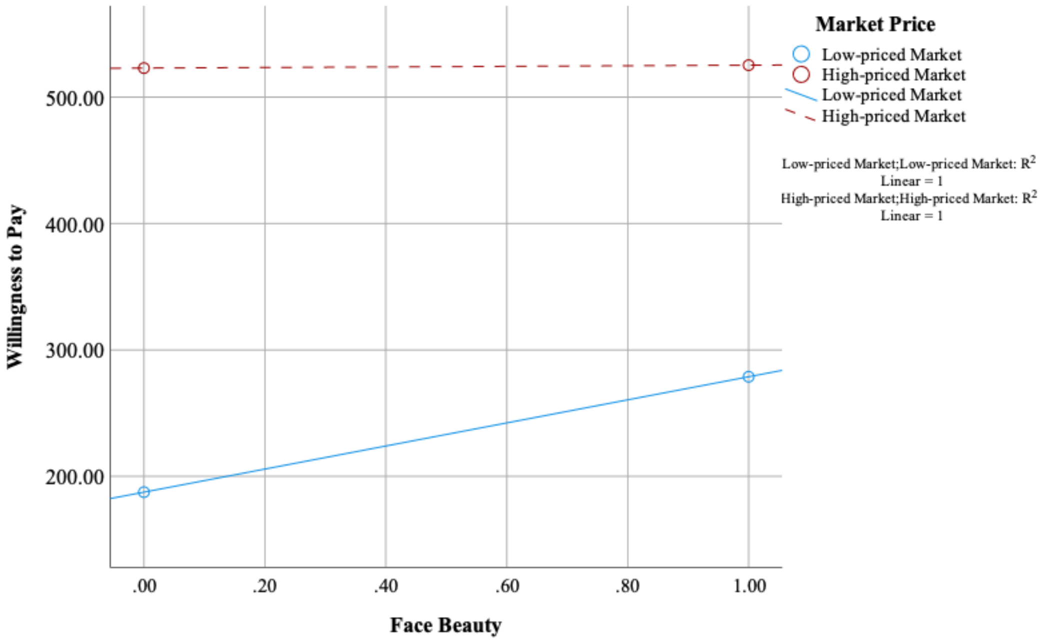
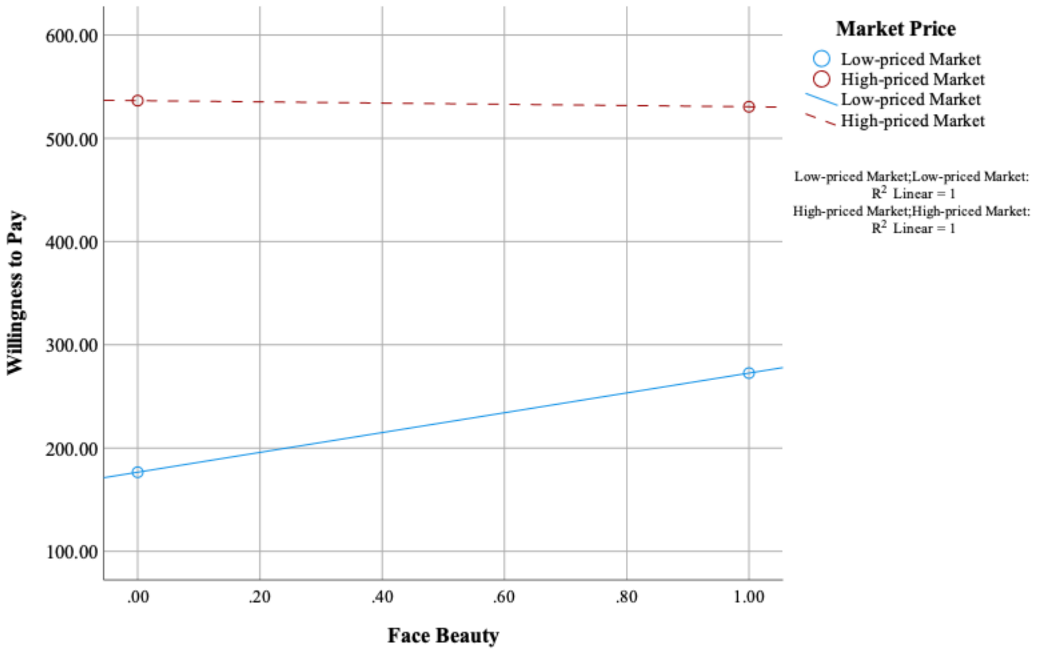


Figure 5. The impact of hosts' facial beauty on customers' WTP in different priced markets



(a) Without control variables



(b) With control variables

Figure 6. The moderating role of market price

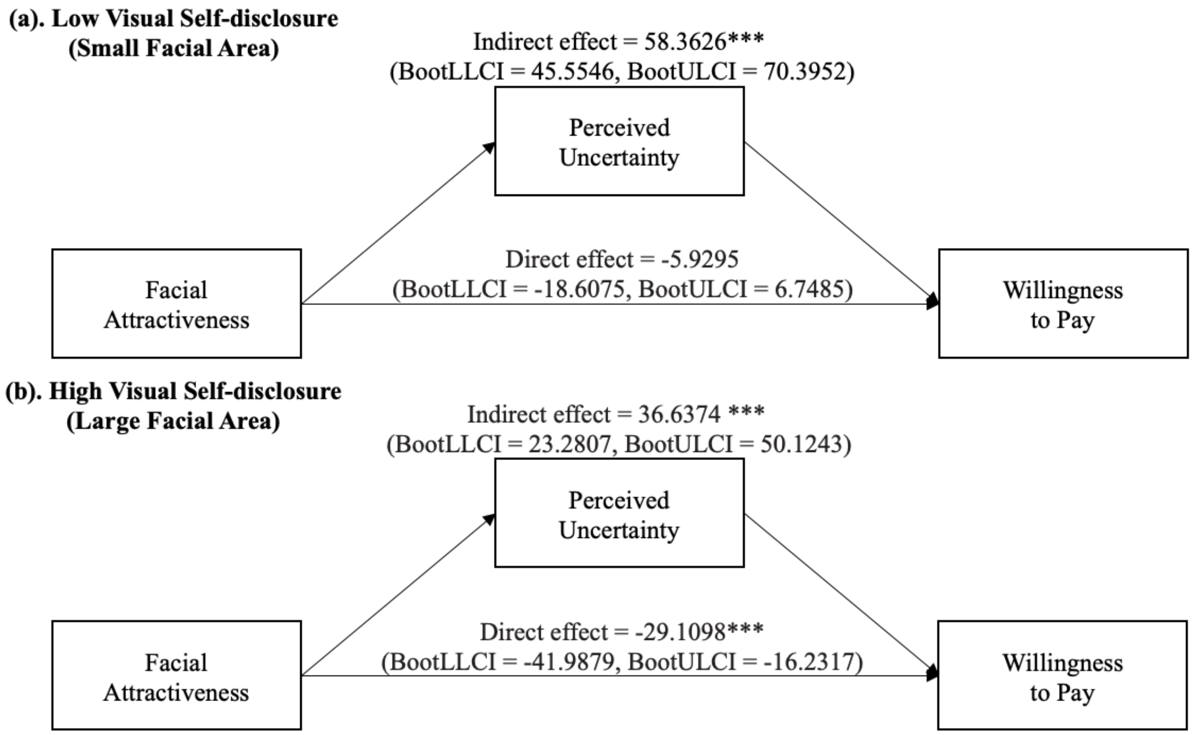


Figure 7. Moderated mediating effect of hosts' visual self-disclosure (facial area)

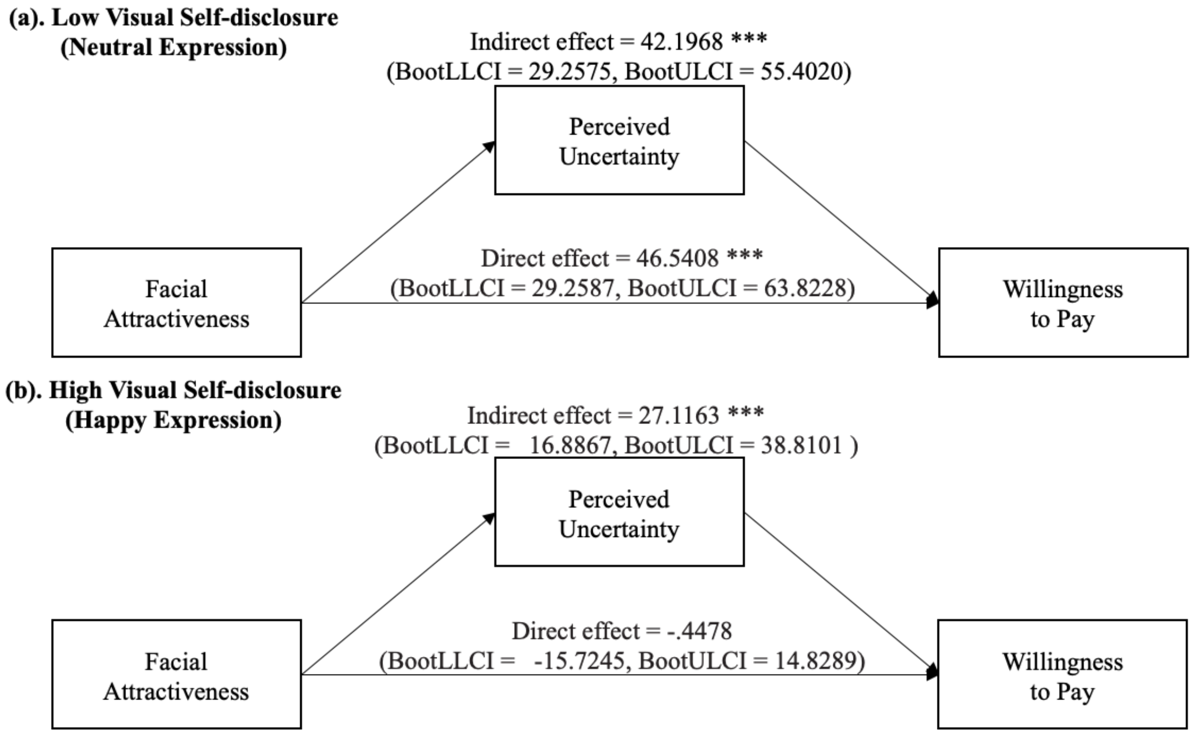


Figure 8. Moderated mediating effect of hosts' visual self-disclosure (facial expression: happiness)

Table 1. Estimation results for M-1 and M-2

	M-1			M-2-1			M-2-2		
	Coefficient		***p*-value**	**Coefficient**		***p*-value**	**Coefficient**		***p*-value**
Intercept	198.668	***	0.000	186.586	***	0.000	146.412	***	0.000
Beauty				0.191	**	0.023	0.794	***	0.000
Happiness							0.443	***	0.000
Facial area							3.041	***	0.006
Beauty×Happiness							-0.006	***	0.001
Beauty×Facial area							-0.046	***	0.007
Superhost_T	0.681		0.758	0.679		0.759	0.855		0.700
Identity_T	-3.134		0.237	-3.194		0.227	-3.231		0.220
Listing	0.316	***	0.000	0.303	***	0.000	0.294	***	0.000
Emotion	0.214	**	0.018	0.211	**	0.019	0.213	**	0.019
Length	0.010		0.512	0.008		0.608	0.007		0.662
Topics	2.660	***	0.000	2.725	***	0.000	2.737	***	0.000
Accommodates	0.690		0.309	0.751		0.269	0.664		0.327
Room_Private room	-82.707	***	0.000	-82.523	***	0.000	-83.294	***	0.000
Room_Shared room	-169.649	***	0.000	-169.658	***	0.000	-169.658	***	0.000
Bed_T	28.941		0.115	28.956		0.110	29.214		0.107
Wifi	12.268	**	0.014	12.269	**	0.014	12.826	**	0.010
Breakfast	8.476	**	0.040	8.195	**	0.047	7.635	*	0.065
Parking_others	15.467	***	0.000	15.232	***	0.000	14.736	***	0.000
Parking_paid	17.844	***	0.000	17.768	***	0.000	16.951	***	0.000
Instantbook_T	1.996		0.350	2.214		0.300	2.249		0.290
Cancellation_moderate	4.226	*	0.070	3.933	*	0.092	4.069	*	0.081
Cancellation_strict	8.660	***	0.001	8.182	***	0.002	8.630	***	0.001
Smoking_T	7.325	***	0.000	7.038	***	0.001	7.147	***	0.001
Property		Yes			Yes			Yes	
Location		Yes			Yes			Yes	
R-squared		0.4131			0.4136			0.4157	
Adjusted R-squared		0.4089			0.4094			0.4111	
Observations		5310			5310			5310	

Table 2. Robustness check results for M-3 to M-6

Dependent variable	M-3 *LNPrice* Coefficient		*p*-value	M-4 *Price* Coefficient		*p*-value	M-5 *Price* Coefficient		*p*-value	M-6 *Price* Coefficient		*p*-value
Intercept	4.976	***	0.000	153.063	***	0.000	151.416	***	0.000	158.107	***	0.000
Beauty	0.003	***	0.000	0.697	***	0.000	0.763	***	0.000	0.668	***	0.000
Happiness	0.002	***	0.002									
Happiness_dummy				29.706	***	0.007						
Smiling							0.355	***	0.004			
Smiling_dummy										23.345	**	0.032
Facial area	0.012	**	0.016	2.882	***	0.010	2.598	**	0.020	2.555	**	0.022
Beauty×*Happiness*	-2.39E-05	***	0.005									
Beauty×*Happiness_dummy*				-0.409	**	0.014						
Beauty×*Smiling*							-0.006	***	0.002			
Beauty×*Smiling_dummy*										-0.393	**	0.017
Beauty×*Facial area*	-1.81E-04	**	0.019	-0.043	**	0.011	-0.039	**	0.023	-0.038	**	0.025
Superhost_T	0.002		0.833	0.783		0.724	1.144		0.606	1.033		0.641
Identity_T	-0.017		0.162	-3.177		0.229	-3.414		0.196	-3.210		0.225
Listing	0.001	***	0.000	0.295	***	0.000	0.296	***	0.000	0.291	***	0.000
Emotion	0.001	**	0.017	0.210	**	0.020	0.217	**	0.016	0.216	**	0.017
Length	0.000		0.382	0.007		0.662	0.009		0.571	0.009		0.579
Topics	0.012	***	0.000	2.770	***	0.000	2.705	***	0.000	2.749	***	0.000
Accommodates	0.001		0.862	0.679		0.317	0.652		0.336	0.663		0.329
Room_Private room	-0.360	***	0.000	-83.245	***	0.000	-83.057	***	0.000	-82.859	***	0.000
Room_Shared room	-0.884	***	0.000	-169.741	***	0.000	-169.810	***	0.000	-169.729	***	0.000
Bed_T	0.118		0.205	29.095		0.109	28.798		0.115	28.273		0.121
Wifi	0.056	**	0.016	12.759	**	0.011	12.473	**	0.013	12.468	**	0.013
Breakfast	0.044	***	0.021	7.748	*	0.061	8.174	**	0.049	8.023	*	0.053
Parking_others	0.060	***	0.000	14.951	***	0.000	14.822	***	0.000	14.974	***	0.000

Parking_paid	0.069	***	0.000	17.180	***	0.000	17.236	***	0.000	17.333	***	0.000
Instantbook_T	0.015		0.122	2.274		0.285	2.063		0.332	2.063		0.333
Cancellation_moderate	0.022	**	0.038	4.090	*	0.080	4.268	*	0.067	4.130	*	0.077
Cancellation_strict	0.044	***	0.000	8.610	***	0.001	8.575	***	0.001	8.471	***	0.001
Smoking_T	0.035	***	0.000	7.150	***	0.001	6.780	***	0.001	6.843	***	0.001
Property		Yes			Yes			Yes			Yes	
Location		Yes			Yes			Yes			Yes	
R-squared		0.4407			0.4152			0.4154			0.4150	
Adjusted R-squared		0.4362			0.4105			0.4107			0.4103	
Observations		5310			5310			5310			5310	

Table 3. Impact of hosts' facial beauty and facial area on consumers' WTP

	Coefficient	***SE***	***t***	***p***	**LLCI**	**ULCI**
Constant	19.0391	35.3847	.5381	.5910	-50.6593	88.7375
Test effects						
Facial beauty	52.4331	9.6083	5.4570	.0000	33.5072	71.3590
Facial area	34.1070	9.5367	3.5764	.0004	15.3222	52.8919
Beauty × Area	-44.9056	13.6915	-3.2798	.0012	-71.8741	-17.9370
Covariates						
Authenticity	-5.5944	4.3499	-1.2861	.1996	-14.1624	2.9737
Manipulation	-4.1217	2.6525	-1.5539	.1215	-9.3465	1.1030
Trust	13.5475	4.2884	3.1591	.0018	5.1005	21.9945
Familarity	6.1647	2.6406	2.3346	.0204	.9635	11.3659
Experience	-15.8721	11.9803	-1.3248	.1865	-39.4701	7.7260
Frequency	9.4616	3.2545	2.9072	.0040	3.0510	15.8722
Attitude	1.8462	4.2178	.4377	.6620	-6.4618	10.1541
Gender	1.5585	6.7461	.2310	.8175	-11.7297	14.8466
Age	4.2552	3.9152	1.0868	.2782	-3.4567	11.9670
Education	4.9682	5.7321	.8667	.3869	-6.3226	16.2590
Income	8.2360	3.6573	2.2520	.0252	1.0322	15.4399

Note*: Model summary:* $R^2 = .4176$*;* $F = 12.4960$*,* $p = .0000$*; SE = Standard Error; CI = Confidence Interval.*

Table 4. Impact of hosts' facial beauty and happiness on consumers' WTP

	Coefficient	***SE***	***t***	***p***	**LLCI**	**ULCI**
Constant	220.1667	48.4752	4.5418	0.0000	140.1256	300.2078
Test effects						
Facial beauty	88.7376	11.5766	7.6652	0.0000	69.6226	107.8527
Happiness	52.6745	10.3568	5.0860	0.0000	35.5736	69.7754
Beauty×Happiness	-62.0691	15.1115	-4.1074	0.0001	-87.0208	-37.1175
Covariates						
Authenticity	-21.8505	4.8699	-4.4869	0.0000	-29.8915	-13.8095
Manipulation	-7.6115	3.1740	-2.3981	0.0172	-12.8523	-2.3706
Trust	13.4543	4.7670	2.8224	0.0052	5.5832	21.3254
Familarity	-5.6043	2.9122	-1.9244	0.0555	-10.4129	-.7957
Experience	-19.5401	16.7077	-1.1695	0.2433	-47.1274	8.0472
Frequency	6.6970	4.3047	1.5557	0.1211	-.4108	13.8049
Attitude	.8602	5.3039	.1622	0.8713	-7.8975	9.6178
Gender	8.6060	7.9352	1.0845	0.2792	-4.4964	21.7084
Age	-5.5653	3.9721	-1.4011	0.1625	-12.1238	.9933
Education	.0878	5.0250	.0175	0.9861	-8.2092	8.3849
Income	13.1689	3.7175	3.5425	0.0005	7.0307	19.3071

Note*: Model summary:* $R^2 = .3817$; $F = 10.6721$, $p = .0000$; *SE = Standard Error; CI = Confidence Interval.*

Appendix A. Summary of literature related to the outcomes of a host's facial attributes in tourism and hospitality research

Author (year)	Theory	Host attribute studied	Dependent Variable	Moderators	Mediators	Methodology	Conclusion
Li et al. (2023)	Stimulus–organism–response theory and mental imagery theory	• Facial: hosts' facial attractiveness; • Non-facial: hosts'reputation and host text-based self-disclosure	Booking intention and Willingness-to-pay	Hosts' reputation; Hosts' text-based self-disclosure	Perceived enjoyment; Perceived threat	Experimental design	Customers tend to favor and pay premium rates for accommodations offered by attractive hosts. This preference is driven by their anticipated stay experience (i.e., mental imagery of their future stay) and moderated by the host's reputation and level of personal disclosure.
Li et al. (2022)	Lay theories	• Facial: host attractiveness	Listing performance (rental rate multiplied by average price of listings)	Similarity	Perceived trustworthiness	Secondary data analysis and experimental design	Both 'beauty premiums' and 'beauty penalties' are observed. Overly attractive or plain hosts may reduce bookings, while those of moderate attractiveness enhance them. Trustworthiness mediates the relationship between attractiveness and booking decisions, with the similarity between host and customer further moderating this effect.

Barnes (2021)	Dangerous decision theory	• Facial: perceived attractiveness • Non-facial: superhost	Overall rating	Superhost	Perceived trustworthiness	Deep learning	To reduce the effect of overvaluation, facial trust cues should be combined with more objective indicators of hosts' reputation on online platforms.
Barnes & Kirshner (2021)	Motivation theory	• Facial: perceived attractiveness; perceived trustworthiness • Non-facial: superhost; Host Verified; No. of listings	Listing price based on type of accommodatio n	Room type (e.g., entire apartment, shared room, shared apartment)	-	Machine learning and secondary data modelling	In Airbnb listings, the combination of trust and attractiveness can yield up to a 5% price increase. Trust is particularly crucial in smaller shared accommodations.
Zhang et al. (2021)	Trust theory	• Facial: facial features, specifically facial width to height ratio • Non-facial: number of people in the image	Listing price	-	-	Secondary data analysis	The lower a host's facial width-to-height ratio is, the higher the listing price.
Ert & Fleischer (2020)	-	• Facial: Face visibility; Smile • Non-facial: Age; gender; multi-person; photo-quality	Perceived attractiveness and Perceived trustworthiness	Perceived attractiveness	-	SEM analysis	Smiling young women are perceived as attractive, whereas older smiling women are deemed more trustworthy than others. Attractiveness and trustworthiness are positively linked.
Peng et al. (2020)	-	• Facial: Attractive–Unattractive	Product sales/ Purchase intention	Product relevance/ Cross-gender effect	Source credibility; Sociability/co mpetence	Machine learning and experimental design	Both attractive and unattractive hosts receive higher product sales than plain-looking hosts.

Zhang et al. (2020)	-	• Facial: Smile	Property demand	Gender	Perceptions of the host's warmth	Longitudinal dataset of Airbnb bookings and online experiment	A smile in the host's profile photo increases property demand by 1.9% on average
Jaeger et al. (2019)	-	• Facial: Perceived facial attractiveness and trustworthiness of Airbnb hosts • Non-facial: age, race, superhost, etc.	Listing price	-	-	Multiple regression analysis	Hosts with a higher facial attractiveness tend to set their rates 2.78% above those of comparable lodgings.
Fagerstrøm et al. (2017)	-	• Facial: facial image; facial expressions • Non-facial: price and customer ratings	Buying Behavior Likelihood To Rent	-	-	Secondary data analysis	The findings suggest that an image of a seller with a positive facial expression increases the likelihood to rent in a peer to peer property rental marketplace
Ert et al. (2016)	-	• Facial: visual-based trustworthiness and attractiveness • Non-facial: reputation, gender, review score, etc.	Listing price and probability of being chosen	-	-	Regression analysis and experimental design	Hosts perceived as trustworthy can command higher prices for similar accommodations, while mere attractiveness doesn't yield the same premium.
Our study	Dual system theory	• Facial: hosts' facial attractiveness; host visual self-disclosure: (1) The	Listing price and Willingness-to-pay	Price; host visual self-disclosure: (1) The percentage of facial area;	Perceived uncertainty	Econometric modeling & Experimental design	The impact of host's facial attractiveness differ by price segments; the visual self-disclosure attenuates the impact of beauty premium; the process is

	percentage of facial area; (2) The happiness degree	(2) The happiness degree		mediated by the perceived uncertainty.

Appendix B. Variable definitions

Dimension	Variable name	Definition
Dependent variable	*Price*	Property listing price per night on Airbnb.com (in CNY)
Independent variable	*Beauty*	Facial attractiveness of the host's profile picture
Moderating variable: Host's self-disclosure	*Happiness*	Degree of host's facial expression of happiness in the profile picture
	Facial area	Facial area in the profile picture
Control variables		
Host's characteristics	*Superhost*	Superhost is defined by Airbnb. To become a Superhost, the host must meet the following four criteria: have (1) hosted at least 10 stays; (2) maintained a 90% response rate or higher within 24 hours; (3) received 4.8+ overall rating based on reviews; and (4) a cancellation rate of less than 1%. If the host is a Superhost, then the value of this variable is T; otherwise, the value is F.
	Identity	If the host has completed the "verified ID" procedure on Airbnb.com, the value is T; otherwise, the value is F.
	Listing	Number of host's property listings on Airbnb.com.
Host's textual self-description	*Emotion*	Degree of positivity in host's profile self-description, measured by the proportion of positive emotion-related words in the textual self-description.
	Length	Length of text in host's profile self-description, measured by the number of words.
	Topics	Number of topics in host's profile self-description.
Room-related features and services	*Accommodates*	Number of people that can be accommodated.
	Property	Property types are divided into five categories which include multiple styles of accommodation: Apartment and Condominium (Type 1); Bed and breakfast, Guest suite, and Serviced apartment (Type 2); Boutique hotel, Guesthouse, Hostel, Hotel and *Kezhan* (China) (Type 3); Bungalow, Cabin, Campsite, Castle, Cottage, Earth house, House, Hut, Loft, Nature lodge, Resort, Tiny house, Townhouse, and Villa (Type 4); and Other (Type 5). (Categorical variable)
	Room	Categorical variable (i.e., Entire home/apartment, Private room, or Shared room).
	Bed	If the property offers a real bed (vs. other types of beds such as airbeds), the value of this variable is T; otherwise, the value is F.
	Wifi	If the property offers wireless Internet access, the value of this variable is 1; otherwise, the value is 0.
	Breakfast	If the property offers breakfast, the value of this variable is 1; otherwise, the value is 0.
	Parking	Offers free parking/paid parking/other (categorical variable).
	Instantbook	If the property offers instant booking, the value of this variable is T; otherwise, the value is F.

	Cancellation	Flexible/moderate/strict 14-day cancellation policy with grace period. A flexible policy allows free cancellation up to 24 hours before check-in; a moderate policy limits free cancellation to 5 days before check-in; a strict 14-day policy limits cancellation to 14 days before check-in (categorical variable).
	Smoking	If the property allows smoking, the value of this variable is T; otherwise, the value is F.
	Location	Administrative region of listings (e.g., Chaoyang, Huairou, Haidian, Changping, Daxing, Fengtai, Shunyi, Xicheng, Tongzhou, Miyun, Dongcheng, Fangshan, Mentougou, Pinggu, Shijingshan, Yanqing) (categorical variable).

Appendix C. Details of control variables

To ascertain the degree of happiness expressed in the facial image, we utilized the API service provided by Face++. Upon inputting the host's profile picture, if a face is detected, the system delineates degrees of various emotions such as happiness, neutrality, surprise, sadness, disgust, anger, and fear, each ranging from 0 to 100. For the purposes of our study, we restricted our sample to listings that showcased a single face in the host's profile picture. Consequently, each happiness degree value derived from Face++ directly corresponded to the host's facial expression of happiness. Furthermore, the facial area of the host was computed by identifying the triangular region encompassing the nose and the left and right corners of the face within the profile image. This delineation was facilitated through the Face++ system when provided with the host's profile picture.

Control variables included hosts' characteristics, room-related features and services, and hosts' textual self-description, in line with the past literature (e.g., Wang & Nicolau, 2017). Specifically,

(a) According to Wang and Nicolau (2017), hosts' characteristics including the host's Superhost status (*Superhost_T*), whether their identity had been verified by Airbnb (*Identity_T*), and their number of listings (*Listing*) have been demonstrated to significantly influence property prices. In our study, these host-centric features were incorporated into the analysis as control variables. Information on hosts' Superhost status, identity verification, and number of listings was extracted from the Inside Airbnb dataset.

(b) Property characteristics, including amenities and services, have been empirically shown to positively correlate with property listing prices within the shared accommodation sector (Schamel, 2012; Salo et al., 2014). Building upon this, our analysis integrated these room-related attributes and services as control variables, including the number of guests a property could accommodate (*Accommodates*); the property type (*Property*) and room type (*Room_Private room; Room_Shared room*); location (*Location*); the presence of a real bed (*Bed_T*), Wifi availability (*Wifi*), breakfast (*Breakfast*), and parking (*Parking_others; Parking_paid*); whether the listing was instantly bookable (*Instantbook_T*); the host's cancellation policy (*Cancellation_moderate; Cancellation_strict*); and whether smoking was allowed (*Smoking_T*).

(c) Textual self-description variables, i.e., text length (*Length*), intensity of positive emotion (*Emotion*), and number of topics (*Topics*) were calculated based on the host's self-description in their profile. To achieve this, we utilized the Linguistic Inquiry and Word Count software (LIWC; Pennebaker et al., 2015), following conventions in marketing and management literature (e.g., Wang et al., 2022). The LIWC dissects the provided text into individual words, ascribes either a positive or negative emotion to each word based on an established lexicon, and then computes the percentage of words with a positive sentiment within a 0 to 100 range as the representation of positive emotion. The text length was calculated by the word count. In determining the number of topics in each self-description, we referred to the eight topics proposed by Ma et al., (2017). High-frequency keywords appearing more than 50 times in self-description text were manually classified into the following eight topics: Interests & Tastes, Life Motto & Values, Work & Education, Relationships, Personality, Place of Origin or Residence, Travel, and Hospitality. The number of topics was calculated based on the keywords for each topic using self-edited R programming. Descriptions of all continuous variables appear in Table E-1.

Table E-1. Descriptions of all continuous variables

Variable name	**Minimum**	**Maximum**	**Mean**	**SD**
Price	57.00	399.00	255.28	89.69
Beauty	24.27	90.48	64.72	11.58
Happiness	0.00	100.00	33.33	41.17
Facial area	0.14	31.66	8.15	5.16
Listing	1.00	216.00	10.68	17.59
Emotion	0.00	66.67	14.47	12.16
Length	1.00	1156.00	60.51	71.43
Topics	0.00	7.00	2.51	1.64
Accommodates	1.00	16.00	2.59	1.84

Appendix D. Secondary Airbnb data modeling robustness check results

Table D-1. Robustness check results for the low-priced market

	M-2-2 (Price<302)			**M-2-2 (Price<522)**		
	Coefficie		***p*-value**	**Coefficie**		***p*-value**
Intercept	110.793	***	0.000	191.194	***	0.000
Beauty	0.867	***	0.000	0.626	***	0.002
Happiness	0.365	***	0.001	0.309	**	0.036
Facial area	2.100	**	0.033	2.799	**	0.025
*Beauty*Happiness*	-0.005	***	0.004	-0.004	*	0.052
*Beauty*Facial area*	-0.033	**	0.029	-0.041	**	0.030
Superhost_T	-0.040		0.984	-0.312		0.901
Identity_T	-6.107	**	0.011	-4.887	*	0.099
Listing	0.266	***	0.000	0.429	***	0.000
Emotion	0.031		0.703	0.058		0.563
Length	0.018		0.273	0.038	**	0.031
Topics	2.316	***	0.001	3.379	***	0.000
Accommodates	-0.035		0.947	6.523	***	0.000
Room_Private room	-51.432	***	0.000	-114.477	***	0.000
Room_Shared room	-123.077	***	0.000	-220.727	***	0.000
Bed_T	20.625		0.180	39.249	*	0.052
Wifi	7.209	*	0.094	22.164	***	0.000
Breakfast	9.701	***	0.006	19.084	***	0.000
Parking_others	11.191	***	0.000	13.054	***	0.000
Parking_paid	9.896	***	0.000	13.794	***	0.000
Instantbook_T	5.551	***	0.006	4.666	*	0.050
Cancellation_moderate	3.795	*	0.083	5.483	**	0.039
Cancellation_strict	5.922	**	0.015	0.905		0.762
Smoking_T	5.862	***	0.003	-2.604		0.266
Property		Yes			Yes	
Location		Yes			Yes	
R-squared		0.3766			0.4051	
Adjusted R-squared		0.3693			0.4016	
Observations		3674			7191	

Table D-2. Robustness check results for the high-priced market and the whole market

	M-2-2 (Price≥302)			M-2-2 (Price≥400)			M-2-2 (Price≥522)			M-2-2 (Entire sample)		
	Coefficient		***p*-value**	**Coefficient**		***p*-value**	**Coefficient**		***p*-value**	**Coefficient**		***p*-value**
Intercept	387.27	***	0.000	468.742	***	0.000	599.585	***	0.000	306.215	***	0.000
Beauty	-0.015		0.938	-0.099		0.641	-0.331		0.189	-0.015		0.926
Superhost_T	10.466	**	0.031	9.584	*	0.083	6.116		0.346	7.427	*	0.077
Identity_T	21.516	***	0.000	22.068	***	0.000	6.312		0.368	13.220	***	0.004
Listing	-0.068		0.505	-0.131		0.255	0.044		0.741	0.351	***	0.000
Emotion	-0.344	*	0.077	-0.046		0.843	0.157		0.575	-0.124		0.447
Length	0.037		0.234	0.023		0.506	0.039		0.319	0.089	***	0.002
Topics	2.588		0.119	-0.406		0.832	-3.414		0.127	6.263	***	0.000
Accommodates	32.841	***	0.000	23.219	***	0.000	13.647	***	0.000	26.922	***	0.000
Room_Private room	5.317		0.411	25.710	***	0.001	31.505	***	0.001	-146.81	***	0.000
Room_Shared room	-34.169		0.244	-21.148		0.559	0.162		0.997	-285.24	***	0.000
Bed_T	70.774		0.449	76.267		0.492	146.809		0.294	51.047		0.234
Wifi	-15.165		0.259	-30.164	*	0.058	-22.515		0.217	18.343	*	0.074
Breakfast	56.388	***	0.000	31.087	***	0.001	17.894	*	0.089	58.982	***	0.000
Parking_others	-7.051		0.211	-2.874		0.661	-8.168		0.310	13.665	***	0.003
Parking_paid	0.815		0.893	7.965		0.259	-8.287		0.334	16.965	***	0.001
Instantbook_T	-5.756		0.210	-7.269		0.162	-5.169		0.402	-1.672		0.670
Cancellation_moderate	-24.760	***	0.000	-30.672	***	0.000	-19.712	***	0.004	-16.497	***	0.000
Cancellation_strict	-37.079	***	0.000	-25.359	***	0.000	1.109		0.891	-21.187	***	0.000
Smoking_T	-11.176	**	0.010	1.841		0.711	-3.019		0.610	-3.511		0.353
Property	Yes			Yes			Yes			Yes		
Location	Yes			Yes			Yes			Yes		
R-squared	0.2171			0.1608			0.1281			0.3498		
Adjusted R-squared	0.2122			0.1535			0.1148			0.3472		
Observations	6062			4426			2545			9736		

Table D-3. Results for the moderating effect of the price level (high vs. low) on beauty

	(Entire sample)		
	Coefficient		***p*-value**
Intercept	185.846	***	0.000
Beauty	0.485	***	0.000
High price_T	362.522	***	0.000
High price_T×Beauty	-1.021	***	0.000
Superhost_T	3.418		0.256
Identity_T	7.795	**	0.017
Listing	0.104		0.132
Emotion	0.161		0.147
Length	0.031		0.131
Topics	1.552		0.126
Accommodates	10.732	***	0.000
Room_Private room	-49.134	***	0.000
Room_Shared room	-139.220	***	0.000
Bed_T	30.354	*	0.082
Wifi	-3.248		0.647
Breakfast	25.081	***	0.000
Parking_others	7.317	**	0.019
Parking_paid	9.925	***	0.004
Instantbook_T	-0.484		0.860
Cancellation_moderate	-12.551	***	0.000
Cancellation_strict	-1.464		0.674
Smoking_T	9.008	***	0.001
Property	Yes		
Location	Yes		
R-squared	0.6863		
Adjusted R-squared	0.6850		
Observations	9736		

Appendix E. Experiment 1 stimuli and questionnaire

The face used in the experiment was selected from the SCUT-FBP5500 dataset, a facial beauty perception dataset constructed by Liang et al. (2018). The dataset contains numerous labels (e.g., beauty score and facial landmarks) and includes diverse properties (e.g., gender, age, and race). Therefore, this dataset was ideal for selecting a face with a high and low beauty score to suit our research setting. We chose two faces of the same race, gender, and similar age but with high and low beauty scores, respectively. The background color of the selected photos was made uniformly white using Adobe Photoshop 2020. Moreover, to avoid influences from additional factors on the experimental results, we kept all attributes except for facial attractiveness (e.g., the host's hairstyle, clothing, and facial expression) consistent (See Figure E-1).

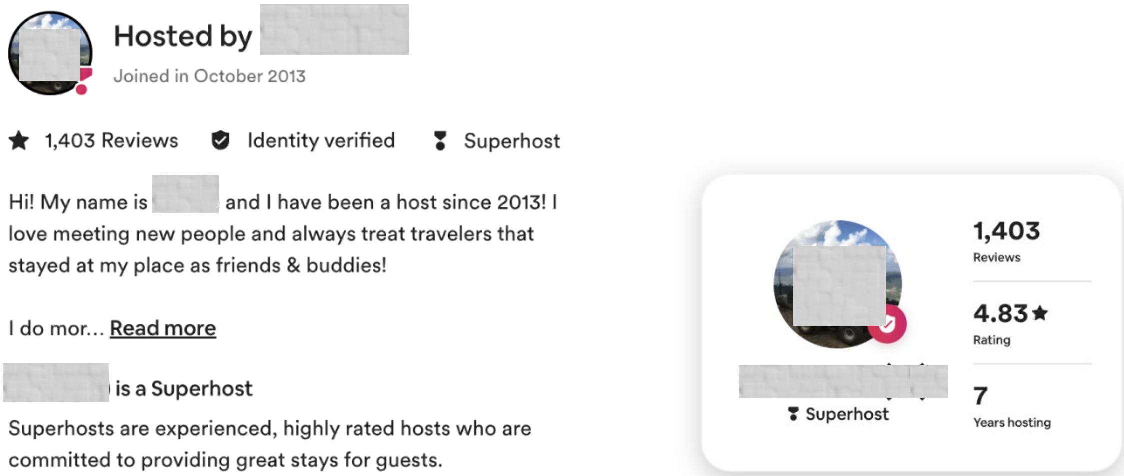


Figure E-1. Airbnb official website host information display sample

Reference

Liang, L., Lin, L., Jin, L., Xie, D., & Li, M. (2018, August). Scut-fbp5500: A diverse benchmark dataset for multi-paradigm facial beauty prediction. In *2018 24th International Conference on Pattern Recognition (ICPR)* (pp. 1598-1603). IEEE.

Figure E-2. Samples of experimental stimuli

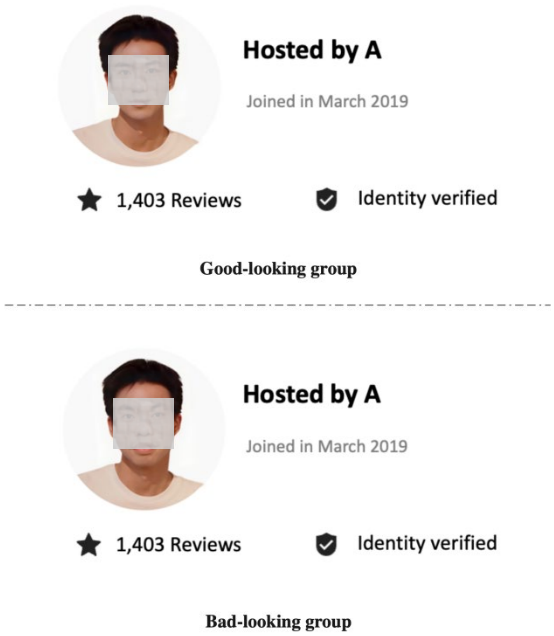
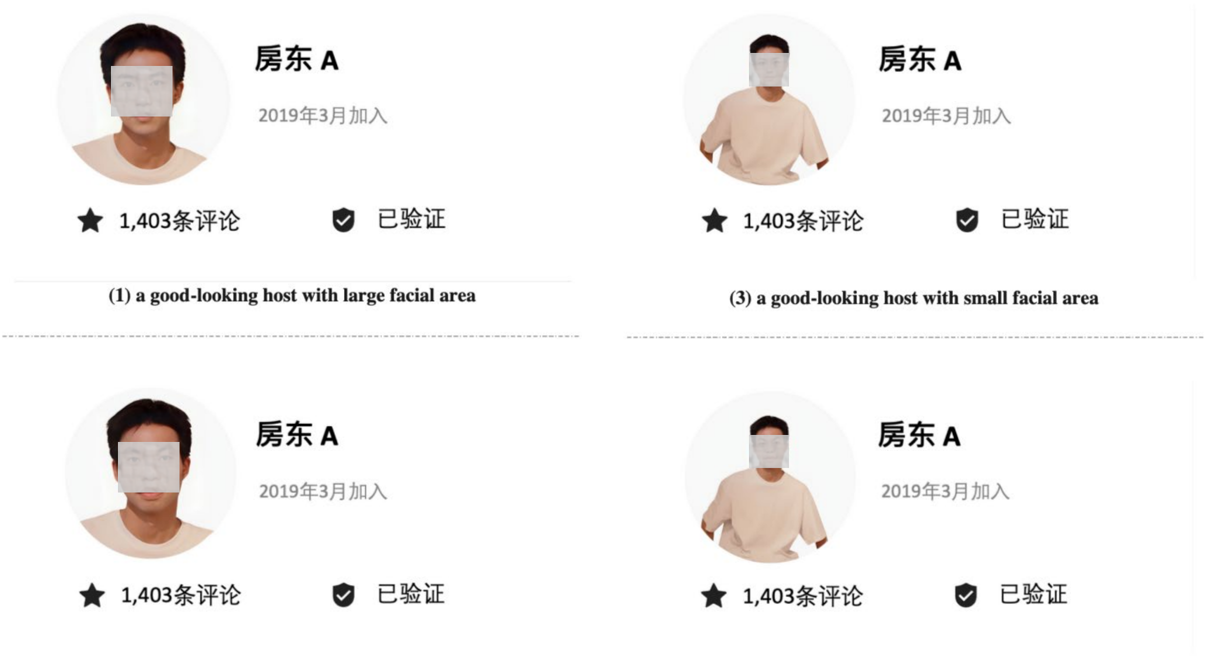


Figure E-3. Samples of english version experimental stimuli (Translate)

Appendix F. Experiment 2 supplements



(1) a good-looking host with large facial area

(3) a good-looking host with small facial area

(2) a bad-looking host with large facial area

(4) a bad-looking host with small facial area

Figure F. Samples of experimental stimuli

Among participants, 56% were between the ages of 26 and 40; 35.9% were younger than 26. The majority of subjects (90%) held a bachelor's degree or higher, and more than two thirds (66%) had experience booking P2P accommodations online and held a positive attitude towards such platforms (92.3%).

Perceived uncertainty [adapted from (Torkzadeh & Dhillon, 2002)]
7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*)
I feel that booking accommodation from this host involves a high degree of uncertainty
I feel the uncertainty associated with booking accommodation from this host is high
I am exposed to many transaction uncertainties if I book accommodation from this host is high
There is a high degree of accommodation uncertainty (i.e. the accommodation you book may not be exactly what you want) when booking accommodation from this host

Appendix G. Experiment 3 supplements

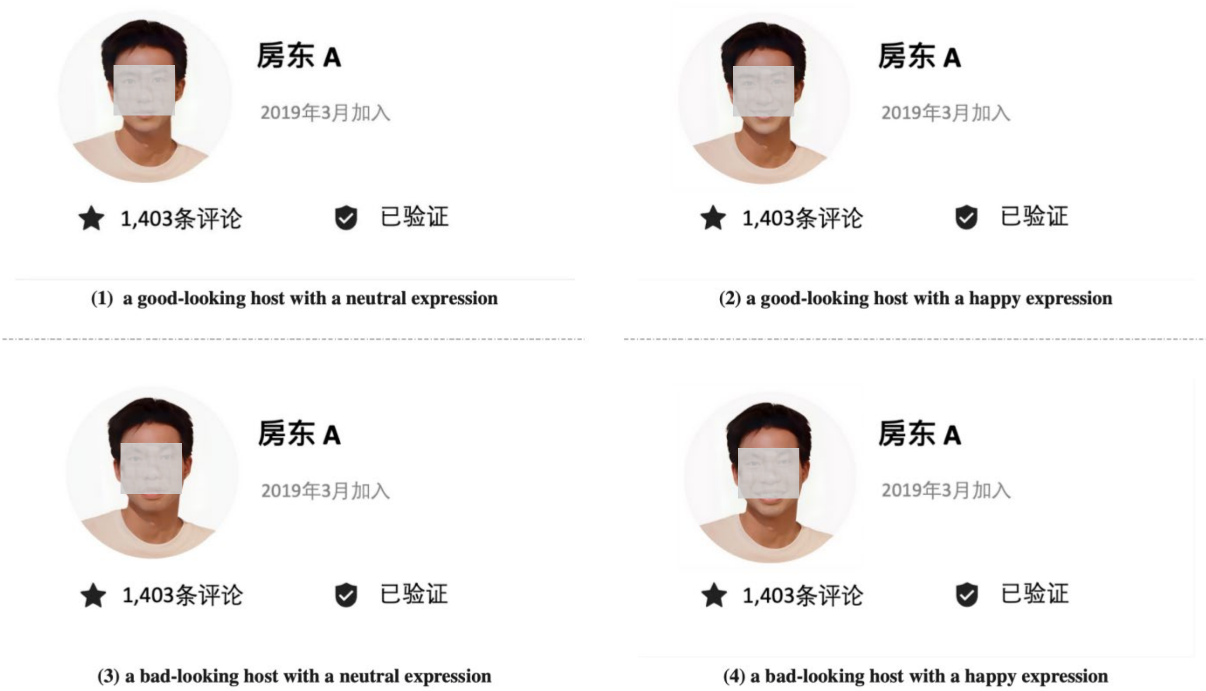


Figure G. Samples of experimental stimuli

Subjects were required to be over 18 years old, Chinese, and to have used P2P accommodation at least once in the past year. Out of the 260 subjects who met screening criteria, 125 (48%) were men. Most subjects were between 18 and 40 years old (89.7%), with many (73.1%) having a bachelor's degree. More than half (54.4%) earned between 5,001 and 12,000 CNY (about 720–1740 USD) per month.

Appendix H. Demographic information

	Study2 Experiment 1 N = 254	Study 3 Experiment 2 N = 259	Study 4 Experiment 3 N = 260
Gender %			
Male	49.6	48.3	48.1
Female	50.4	51.7	51.9
Age %			
18-25	21.3	35.9	26.2
26-30	36.2	24.3	28.8
31-40	25.2	31.7	34.6
41-50	7.9	4.6	3.8
51-60	9.4	3.5	6.5
Over 60	/	/	/
Using Experience %			
No	22	34	19.6
Yes	78	66	80.4
Attitude %			
Completely Unwilling to Use	/	/	/
Very Unwilling to Use	/	/	/
Somewhat Unwilling to Use	3.9	3.5	/
Neutral	8.7	4.2	4.6
Somewhat Willing to Use	22.8	35.1	26.2
Very Willing to Use	45.7	34.4	48.5
Extremely Willing to Use	18.9	22.8	20.8
Education %			
Vocational School or Below	0.8	/	3.1
High School	/	2.3	1.5
Associate Degree/Higher Vocational School	17.3	7.7	8.8
Bachelor Degree	66.1	71.4	73.1
Master Degree	15.7	17.8	11.5
Doctoral Degree or Above	/	0.8	1.9
Monthly income (in CNY) %			
Below 2,000	3.9	8.5	7
2,001 – 5,000	14.2	21.6	18.3
5,001 – 8,000	33.9	25.5	27.6
8,001 – 12,000	28.3	23.6	26.8
Above 12,000	19.7	20.8	20.2