

The Impact of Heuristic Cues on User Purchase Decisions in Sharing-Based Short-Term Rental Platforms

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Abstract

Based on data from Airbnb, this study employs the Heuristic-Systematic Model as its theoretical framework. Utilizing facial recognition technology, we extract characteristic variables and construct a multiple linear regression model for empirical testing, aiming to explore the impact of heuristic cues on consumer purchase decisions in sharing-based short-term rental platforms. The main findings are as follows: the attractiveness score of the host's profile photo, stereotypical impressions, and word-of-mouth reputation all positively influence consumer purchase decisions, while the blurriness of the host's profile photo negatively affects them. These results provide valuable insights for sharing economy platforms and hosts to optimize information presentation and enhance transaction conversion rates.

Keywords

Heuristic Cues, Sharing-Based Short-Term Rentals, Consumer Purchase Decisions

1. Introduction

Against the backdrop of rapid advancements in internet technology and profound shifts in consumer attitudes, the sharing economy—aimed at enabling efficient and rapid matching of supply and demand—has demonstrated vigorous growth. The concept of the sharing economy was first introduced by American sociology professors Felson & Spaeth (1978) in a paper. In the context of the internet, the sharing economy refers to a model where internet platforms facilitate the more efficient allocation of idle resources from suppliers. Through specific transaction mechanisms, resource providers transfer the usage rights of these idle assets to

obtain expected economic benefits, while resource seekers gain access to desired services or products at a higher cost-performance ratio.

As a key component of the sharing economy ecosystem, the shared accommodation sector has reshaped the traditional lodging market through innovative service models, offering consumers diversified, convenient, and cost-effective accommodation solutions. Representative platform enterprises such as Airbnb have leveraged a disintermediated peer-to-peer (P2P) transaction model to integrate global accommodation resources. Their core technological infrastructure serves as a digital bridge enabling direct interactions between supply and demand, allowing users to complete full-process services—including property search, online booking, and electronic payment—seamlessly via smart devices.

The transaction process within the shared accommodation industry is also a process of information exchange between transacting parties. Information serves as one of the key bases for users to make purchase decisions after clarifying their needs (Deaton & Muellbauer, 1980). The Heuristic-Systematic Model (HSM), proposed by Chaiken (1980), is one of the important theoretical frameworks in the field of social cognition and is widely used to analyze the strategies individuals employ when receiving and processing persuasive information. This model categorizes two distinct modes of information processing during individual decision-making: “heuristic processing” and “systematic processing”. Among these, “heuristic processing” is particularly crucial for capturing consumer attention in online platform environments. Although some studies have explored how various information cues on shared short-term rental platforms influence consumer purchase decisions, there remains a lack of clear classification and quantitative characterization of these cues, making it difficult to gain a deeper understanding of the specific mechanisms through which information cues operate in the decision-making process.

Therefore, this study adopts the HSM as the theoretical framework to extract heuristic cues from the information presented on shared short-term rental platforms and systematically investigates their impact on consumer purchase decisions. It aims to address the following research questions: 1) How can heuristic cues on shared short-term rental platforms be categorized? 2) What features can be used to quantify these heuristic cues? 3) How do different heuristic cues vary in their influence on consumer purchase decisions in shared short-term rental platforms?

2. Theoretical Foundation and Research Hypotheses

Heuristic information processing relies on readily accessible informational cues and simple decision rules (Tam & Ho, 2005). In this mode of processing, individuals do not need to expend significant cognitive resources, relying instead on superficial characteristics of the information—such as the credibility of the source and the manner of presentation—and often make decisions based on intuition. In the context of shared short-term rentals, a property’s homepage generally contains

two main types of information: one is information self-presented by the host, and the other is evaluative information provided by other parties regarding the property or the host. Among these, visual elements such as images that offer an immediate impression to consumers, as well as processed secondary information such as word-of-mouth ratings and trust verifications, serve as heuristic cues that further influence consumers' booking behavior.

Current research exhibits the following limitations: First, most studies focus on a single type of cue—such as host photos or ratings—to explore their impact mechanisms, with few adopting the perspective of heuristic information cues to examine how effortlessly processed information characteristics influence purchase decisions. Second, existing studies on host photos in short-term rental platforms primarily use surveys or experiments to investigate the effect of a particular photo attribute on user behavior. To date, no study has conducted comprehensive facial analysis based on a large dataset of objective and authentic host photos from short-term rental platforms to examine how host photo characteristics and facial features affect user trust. Therefore, this study will focus on host profile photos, property word-of-mouth information, and host reputation data on sharing-based short-term rental platforms to investigate the impact of heuristic cues on consumer purchase decisions.

2.1. Attractiveness Score

In the field of consumer behavior, physical appearance plays a pivotal role. For instance, the appearance of individuals in advertisements exerts a positive influence on consumers' attitudes toward both the advertisement and the product (Li et al., 2016). The physical attractiveness of service personnel can affect customers' perceptions of their credibility, professional image, and likability, thereby influencing perceived service quality (Li et al., 2016). Similarly, salespeople with higher levels of physical attractiveness are more likely to gain customer trust (Ahearne, Gruen, & Jarvis, 1999). Cyr et al. (2007) suggested that seller photos in online environments enhance consumer trust by increasing perceived credibility. Ying & Rao (2019) conducted research on how consumers' trust perception based on host photos influences their choice preferences, confirming the significant impact of attractiveness features. Therefore, this study proposes the following hypothesis:

H1: The attractiveness score of the host's photo significantly positively influences consumer purchase decisions on shared short-term rental platforms.

2.2. Smile Intensity

As a non-verbal form of communication, smiling can lead others to evaluate an individual more leniently and perceive them as trustworthy (LaFrance & Hecht, 1995) or kind and friendly (Hess et al., 2002). Scharlemann et al. (2001) found that individuals who smile are more likely to gain the trust of other participants. On shared short-term rental platforms, consumers typically cannot interact with hosts face-to-face. Therefore, the smile intensity in a host's profile photo becomes

an important cue for consumers to assess the host's attitude and warmth. In the context of online short-term rentals, Fagerstrom et al. (2017) employed an experimental simulation method and found that hosts who smile in their photos tend to receive more bookings. Accordingly, this study proposes the following hypothesis.

H2: The smile intensity in the host's profile photo has a significantly positive influence on consumer purchase decisions on shared short-term rental platforms.

2.3. Stereotypical Impression

Stereotype refers to a generalized and relatively stable perception or cognition that people hold toward a certain category of individuals or objects (Macrae, Stangor, & Hewstone, 1996; Fiske, Rosenblum, & Travis, 2009). The Stereotype Content Model (SCM) reveals that the content of stereotypes focuses on evaluations along two primary dimensions: competence and warmth, and many evaluations of individuals or groups are based on this framework. Fiske (2018) conducted cross-cultural studies on individuals and groups across different countries, and their results demonstrated the universal applicability of the SCM across cultural contexts.

On Airbnb, the personal photos provided by hosts often reveal information such as gender and age. Since people generally hold stereotypes toward unfamiliar individuals or groups, the information users infer from host photos—such as gender and age—can influence their perception of the host's trustworthiness, thereby affecting their booking decisions. According to the SCM: Older adults are stereotypically perceived as high in warmth but low in competence; University students (young people) are stereotypically perceived as high in both warmth and competence; Men are often stereotyped as low in warmth but high in competence; Women are often stereotyped as high in both warmth and competence. Therefore, this study proposes the following hypotheses:

H3: Stereotypes significantly influence consumer purchase decisions on shared short-term rental platforms.

H3a: Consumers are more inclined to book properties offered by female hosts.

H3b: Consumers are more inclined to book properties offered by younger hosts.

2.4. Blurriness

Within trust theory, trust is regarded as a form of dependency relationship, the establishment of which relies on the transparency and reliability of information. Multiple studies have indicated that image quality is an important factor affecting perceived trust. High-quality images provide richer and more authentic visual information, which helps enhance the sense of trust. Conversely, blurry or low-quality images may be perceived as indicative of missing or concealed information, thereby evoking distrust. Ambiguous risk information can influence decision-making behavior; factors such as information content, trust in the source, and aversion to ambiguity all play roles in the decision-making process (Melkonyan, 2011). Some scholars have experimentally quantified the relationship between the degree of photo blurriness and trust level (Hao, 2020). The results show that as

the level of blurriness in photos increases, consumer trust gradually decreases. Therefore, this study proposes the following hypothesis:

H4: The blurriness of the host's personal photo has a significantly negative influence on consumer purchase decisions.

2.5. Word-of-Mouth Reputation

Numerous studies have indicated that reputation systems on e-commerce platforms can effectively foster the formation of consumer trust. For example, Resnick et al. (2000) investigated e-commerce reputation on eBay and found that sellers with better reputations received more orders, as consumers tend to trust those with favorable reputations. Some studies have pointed out that the "Super host" badge can significantly enhance consumers' trust in hosts and subsequently influence their booking decisions (Li et al., 2023). This is because the "Super host badge" serves as an official endorsement by the platform of the host's service quality, providing consumers with a reliable reference. Ratings and acceptance rates are important indicators of host service quality. High ratings typically indicate that the host's service has been recognized by the majority of consumers, while a high acceptance rate reflects strong service efficiency and awareness. Together, these indicators form the host's word-of-mouth reputation system, profoundly influencing consumers' trust perceptions and purchase decisions. Therefore, this study proposes the following hypotheses:

H5: The host's word-of-mouth reputation has a significantly positive influence on consumer decisions on shared short-term rental platforms.

H5a: The host's attainment of a "Super host" badge has a significantly positive influence on consumer purchase decisions.

H5b: The host's booking acceptance rate has a significantly positive influence on consumer purchase decisions.

H5c: The property rating has a significantly positive influence on consumer purchase decisions.

Based on the above hypotheses, this study treats host profile photos and word-of-mouth reputation cues as heuristic information cues on shared short-term rental platforms. These are operationalized through the following measures: for profile photo cues— attractiveness score, smile intensity, stereotypes (age and gender), and blurriness; for reputation cues—"Super host" status, booking acceptance rate, and property rating. The research aims to investigate the impact of these heuristic cues on consumer purchase decisions in shared short-term rental platforms.

Regarding control variables, drawing on relevant studies in the field of shared short-term rentals (Wang & Chen, 2021; Wang et al., 2024; Xu & Liang, 2022), variables that may influence the results are incorporated, including listing price, number of listings owned by the host, host response time, host response rate, and instant booking policy. Therefore, the research model of this chapter is illustrated in **Figure 1**.

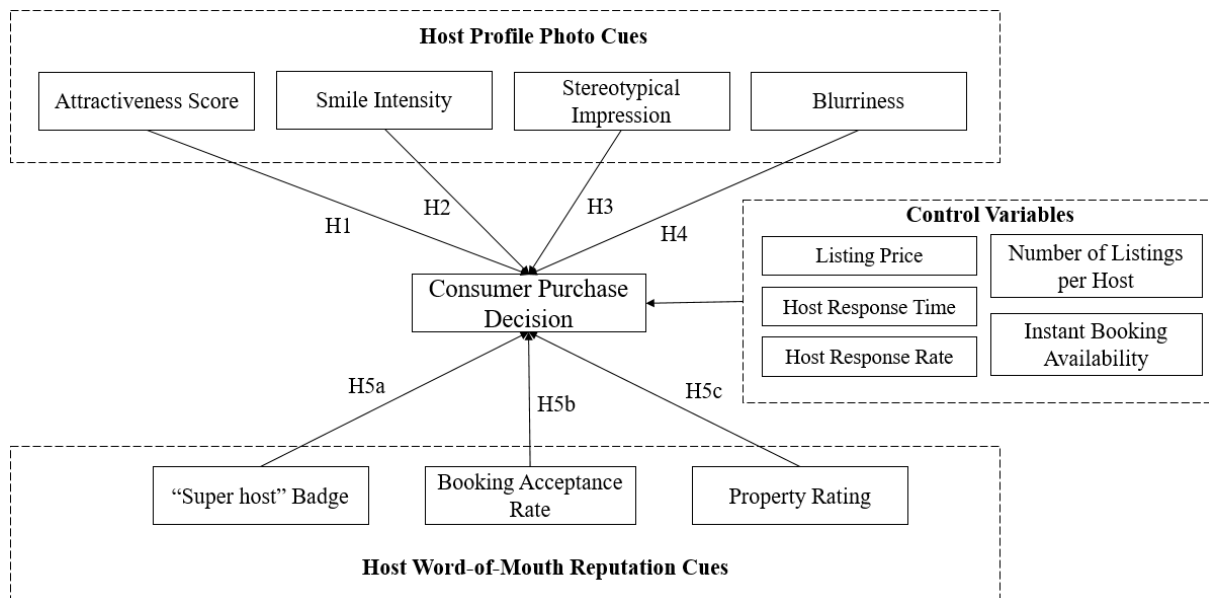


Figure 1. Heuristic information cues model.

3. Empirical Analysis

3.1. Data Collection and Preprocessing

This study uses the Airbnb short-term rental platform as a case study, with data sourced from <https://insideairbnb.com>. The dataset comprises 75,984 property listings from March 23, 2023, to March 24, 2024, covering nine countries including the United States, France, and Germany. The provided information includes property details such as listing descriptions, housing types, and review scores, as well as host information including profile photos, “Super host” status, and response rates. Records with incomplete or meaningless attributes (e.g., garbled text) were removed. Listings with missing or broken links to the host’s profile photo were excluded. Entries where the host’s profile photo did not meet the input requirements of the Face++ facial analysis API were also discarded. Finally, records that failed facial recognition by the Face++ API were eliminated. After preprocessing, a total of 8624 valid records were retained.

3.2. Variable Measurement

3.2.1. Facial Analysis Based on Face++

This study utilizes the Face++ platform to conduct in-depth facial analysis of host profile photos. As the output of the facial recognition process is a JSON file containing face_token, it is necessary to parse this JSON file to extract facial attributes such as the host’s age, gender, smile intensity, face blurriness, and attractiveness score. **Table 1** presents the results obtained from parsing four sample host photos (A, B, C, D) using a Python script, highlighting the key attributes under investigation: age, gender, smile intensity, face blurriness, and attractiveness score. In this encoding scheme, female hosts are labeled as 1, and male hosts are labeled as 0.

Table 1. Sample facial analysis results of host profile photos.

Photo	Age	Gender	Smile Intensity	Blurriness	Attractiveness Score
A	49	Female	99.847	89.324	54.081
B	46	Male	0.891	3.256	52.484
C	50	Male	100	8.953	55.953
D	25	Female	15.049	0.117	50.405

3.2.2. Dependent Variable

Since Airbnb does not publicly disclose booking data but only provides review counts, and multiple studies have used and validated review volume as an effective proxy for booking volume (Ye, Law, & Gu, 2009; Lee et al., 2015), this study employs the average monthly number of reviews (total number of reviews divided by the number of months the listing has been active) as a smoothed measure of the dependent variable. This approach also accounts for variations due to the listing's exposure time and special booking periods such as holidays. The specific calculation is shown in Equation (1):

$$\left\{ \begin{array}{l} \text{Review permonth} = \text{Total review} , \text{Crawlerdate} - \text{firstdate} < 30 \\ \text{Review permonth} = \frac{\text{Total review}}{\frac{\text{Crawler date} - \text{first date} + 1}{\frac{365}{12}}} , \text{Crawler date} - \text{first date} \geq 30 \end{array} \right. \quad (1)$$

In Equation (1), Review permonth represents the average monthly number of reviews, Total review denotes the total number of reviews, Crawler date indicates the data crawling date, first date refers to the date of the first review.

3.2.3. Core Independent Variables

In the model of this study, the core independent variables include cues from the host's profile photo and cues from the host's platform-based word-of-mouth reputation. The host's profile photo cues are represented by the following attributes: attractiveness score, smile intensity, stereotypical impressions (operationalized using the host's age and gender obtained via facial analysis), blurriness. Each of these variables—attractiveness score, smile intensity, and blurriness—is represented as a numerical value in the range of 0 to 100.

The host's platform-based word-of-mouth reputation is measured using the following metrics from the dataset: "Super host" badge is a binary variable where 1 indicates that the host has obtained the "Super host" badge, and 0 indicates otherwise. The badge is awarded based on comprehensive criteria including total booking volume, cancellation rate, and host ratings. This study uses the overall property rating provided on Airbnb as a key variable, reflecting multi-dimensional evaluation aspects. Host booking acceptance rate represents the probability that a host accepts a booking request after it is submitted, reflecting the host's reliability and service quality.

3.2.4. Control Variables

Based on previous research designs and findings (Wang & Chen, 2021; Wang et al., 2024; Xu & Liang, 2022), this study incorporates the following control variables into the model: listing price, number of listings per host, host response time, host response rate, instant booking availability. Detailed descriptions and explanations of the dependent, independent, and control variables used in this study are provided in **Table 2**.

Table 2. Variable descriptions.

Variable Type	Variable	Variable Name	Description
Dependent Variable	Average Monthly Booking Volume	Review	The average monthly number of reviews is used as a proxy variable for booking volume.
Independent variable	Age	Age	Predicted age from host photo.
	Gender	Gender	Gender analyzed from host photo.
	Smile Intensity	Smile	Smile intensity in host photo.
	Attractiveness Score	Beauty	Facial attractiveness score (rated based on average aesthetic preferences of males and females).
	Blurriness	Blur	Degree of blurriness in host photo.
	“Super host” Badge	Superhost	“Super host” badge (1 if certified, 0 otherwise).
	Property Rating	Score	Overall property rating (on a 5-point scale).
	Host Booking Acceptance Rate	Acceptance	Booking acceptance rate.
Control Variable	Listing Price	Price	Listing price (in USD).
	Number of Listings per Host	Listnum	Number of listings per host.
	Host Response Time	Responsetime	Average host response time (categorized: 0 = within 1 hour, 1 = within a few hours, 2 = within one day, 3 = several days or more).
	Host Response Rate	Responserate	Host response rate.
	Instant Booking Availability	Instant	Instant booking enabled (1 = Yes, 0 = No).

3.3. Data Analysis and Results

3.3.1. Multicollinearity Test

The minimum, maximum, mean, standard deviation, tolerance, and variance inflation factor (VIF) values of the variables are presented in **Table 3**. Among these, tolerance and VIF are effective indicators for assessing the severity of multicollinearity. The results show that all variables have VIF values below 3 and tolerance values above 0.1, indicating that there are no significant multicollinearity issues among the variables in the model.

3.3.2. Multiple Linear Regression

As discussed above, the dependent variable is simultaneously influenced by multiple heuristic information cues. The multiple linear regression model can account

Table 3. Descriptive statistics and multicollinearity test of variables.

Variable	Min	Max	Mean	Std. Deviation	Tolerance	VIF
Review	0	59.240	1.431	1.862		
Beauty	17.707	92.155	56.820	10.763	0.745	1.341
Smile	0	100	76.004	37.158	0.919	1.088
Age	2	88	42.910	13.298	0.771	1.297
Gender	0	1	0.479	0.500	0.954	1.048
Blur	0.001	100	29.581	40.277	0.919	1.088
Superhost	0	1	0.356	0.479	0.775	1.291
Score	1	5	4.804	0.251	0.838	1.193
Acceptance	0	1	0.853	0.257	0.584	1.712
Price	10	999	136.974	116.058	0.948	1.055
Listnum	1	4432	22.241	168.286	0.915	1.093
Responsetime	0	3	0.387	0.752	0.541	1.850
Responserate	0	1	0.960	0.156	0.644	1.552
Instant	0	1	0.268	0.443	0.876	1.142

for the relationships between multiple independent variables and the dependent variable, quantify the extent of influence of the independent variables through regression coefficients, and provide explanatory and predictive power for the dependent variable. Therefore, this study employs a multiple linear regression model to examine the effects of independent and control variables on the dependent variable.

Since the dependent variable, average monthly booking volume, exhibits a right-skewed distribution (skewness = 4.590) and contains zero values, a logarithmic transformation after adding one ($\log(y+1)$) is applied. Additionally, due to the large magnitude of the control variables “price” and “number of listings,” logarithmic transformations are also applied to these variables. The primary regression equation (Model 1) of this study is specified as follows:

$$\log(\text{Review}+1) = \beta_0 + \beta_1\text{Beauty} + \beta_2\text{Smile} + \beta_3\text{Age} + \beta_4\text{Gender} + \beta_5\text{Blur} + \beta_6\text{Superhost} + \beta_7\text{Score} + \beta_8\text{Acceptance} + \beta_9\text{Controls} + \varepsilon \quad (2)$$

In Equation (2), β_0 denotes the constant term (intercept), ε represents the random error term, Controls refers to the control variables.

In Model 1, the proposed core independent variables—including attractiveness score, smile intensity, age, gender, blurriness, “Super host” status, property rating, and host acceptance rate—were incorporated to investigate the influence of each core independent variable on users’ purchase decisions. On the basis of the core independent variables, control variables such as listing price, number of listings, response time, response rate, and instant booking policy were further included to

examine the impact of the core independent variables on consumer purchase decisions after removing potential confounding effects, as well as to observe changes in the model before and after adding the control variables.

Based on Model 1, this study employed a stepwise multiple regression method, incrementally adding variables in successive regression analyses. The regression results are presented in **Table 4**. Model M8 includes only the core independent variables, and its significance results indicate that each core independent variable has a significant relationship with consumer purchase decisions. Model M13 incorporates both the core independent variables and the control variables.

Table 4. Results of multiple stepwise regression.

Variables	M1 Review	M2 Review	M3 Review	M4 Review	M5 Review	M6 Review	M7 Review	M8 Review	M9 Review	M10 Review	M11 Review	M12 Review	M13 Review
Beauty	0.00 (-0.40)	0.00 (0.75)	0.003*** (4.19)	0.003*** (3.75)	0.001* (1.80)	0.001* (1.88)	0.001* (1.83)	0.001* (1.73)	0.001** (1.98)	0.002** (2.15)	0.00 (1.60)	0.00 (1.58)	0.001* (1.84)
Smile		0.001*** (7.61)	0.001*** (7.12)	0.001*** (8.28)	0.001*** (7.31)	0.001*** (4.37)	0.001*** (4.17)	0.000** (2.35)	0.001*** (3.51)	0.001*** (3.74)	0.000* (1.81)	0.000* (1.86)	0.00 (1.56)
Age			0.004*** (7.70)	0.004*** (7.88)	0.004*** (7.20)	0.00 (-0.26)	0.00 (-0.50)	-0.002*** (-4.67)	-0.004*** (-6.26)	-0.004*** (-6.37)	-0.004*** (-6.42)	-0.004*** (-6.06)	-0.003*** (-5.77)
Gender				0.098*** (7.53)	0.105*** (8.16)	0.069*** (6.23)	0.069*** (6.22)	0.059*** (4.68)	0.056*** (4.17)	0.056*** (4.12)	0.049*** (3.45)	0.050*** (3.52)	0.050*** (3.59)
Blur					-0.002*** (-9.75)	-0.001*** (-6.86)	-0.001*** (-6.82)	-0.001*** (-5.30)	-0.001*** (-4.67)	-0.001*** (-4.11)	-0.001*** (-3.18)	-0.001*** (-2.97)	-0.000*** (-2.71)
Superhost						0.642*** (57.23)	0.633*** (54.83)	0.394*** (28.63)	0.371*** (24.90)	0.367*** (24.69)	0.278*** (17.35)	0.277*** (17.35)	0.278*** (17.59)
Score							0.072*** (3.05)	0.093*** (3.18)	0.113*** (3.37)	0.093*** (2.73)	0.121*** (3.29)	0.140*** (3.80)	0.156*** (4.26)
Acceptance								0.641*** (23.39)	0.743*** (24.35)	0.763*** (24.76)	0.652*** (15.67)	0.710*** (16.83)	0.632*** (14.84)
Price									-0.074*** (-7.17)	-0.071*** (-6.94)	-0.062*** (-5.74)	-0.062*** (-5.77)	-0.066*** (-6.14)
Listnum										-0.004*** (-4.32)	-0.006*** (-6.22)	-0.006*** (-6.09)	-0.007*** (-7.19)
Re-sponsetime											-0.143*** (-12.06)	-0.180*** (-13.95)	-0.162*** (-12.51)
Re-sponserate												-0.464*** (-7.09)	-0.407*** (-6.24)
Instant													0.166*** (9.92)

Continued

Constant	0.715***	0.574***	0.267***	0.217***	0.362***	0.332***	(0.00)	-0.355**	(0.13)	(0.06)	0.05	0.365*	0.26
	(20.80)	(14.76)	(4.80)	(3.89)	(6.29)	(6.77)	(-0.03)	(-2.36)	(-0.78)	(-0.33)	(0.29)	(1.92)	(1.36)
F	0.163	29.060	39.260	43.830	54.470	608.700	523.600	302.000	245.000	223.000	178.500	169.400	166.900
R-squared	0.000	0.007	0.013	0.020	0.031	0.298	0.299	0.269	0.278	0.281	0.276	0.283	0.296
Adj R-squared	0.000	0.006	0.013	0.020	0.030	0.298	0.298	0.268	0.277	0.279	0.274	0.281	0.294
Observations	8624	8624	8624	8624	8624	8608	8608	6582	5731	5731	5174	5174	5174

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-statistics in parentheses.

According to the regression results, the attractiveness score ($\beta = 0.001$, $p < 0.1$) has a significant positive influence on consumers' purchase decisions. Profile photos of hosts with higher attractiveness scores are more likely to evoke consumers' trust, thereby increasing their inclination to make a booking. Therefore, Hypothesis 1 is supported.

However, the smile intensity in the host's profile photo ($\beta = 0.000$, $p > 0.1$) does not exert a significant impact on consumers' purchase decisions. Two possible explanations are proposed: Information cues on shared short-term rental platforms are highly diversified. A multitude of cues—such as informational tags assigned by the platform—can serve to convey the host's personal characteristics or emotional state, potentially diminishing the unique role of smile intensity. As shown in the study by Wang et al. (2017), in high-risk consumption contexts, a stronger smile may strengthen consumers' negative perceptions of the individual's competence, which in turn influences purchase intentions. Thus, Hypothesis 2 is not supported.

The age and gender of the hosts, as inferred from their profile photos, exert a significant influence on consumers' booking decisions. Younger hosts are more likely to gain user trust compared to older hosts ($\beta = -0.003$, $p < 0.01$), and female hosts are more trusted than male hosts ($\beta = 0.050$, $p < 0.01$). According to the Stereotype Content Model (SCM), males are typically perceived as high in competence but low in warmth, while females are stereotyped as high in both competence and warmth. Older adults are often categorized as low in competence but high in warmth, whereas younger individuals are viewed as high in both dimensions. Since shared short-term rentals belong to the service industry and involve social interactions between users and hosts, a host's high level of professionalism and reliability can lead to a better accommodation experience. Therefore, users tend to prefer female and younger hosts, providing support for Hypothesis 3a and Hypothesis 3b.

Blurriness of the host's profile photo exerts a significantly negative influence on consumers' booking decisions ($\beta = -0.000$, $p < 0.01$). In the shared short-term rental market, information asymmetry often exists between consumers and hosts. When choosing accommodations, consumers not only consider factors such as

the quality, price, and location of the property but also pay particular attention to the host's credibility and reliability. The profile photo serves as a key representation of the host's image, and its clarity directly affects consumers' perceived trustworthiness. When a host's photo is blurry, consumers may become suspicious, inferring that the host is intentionally concealing their true appearance or lacks sincerity in presenting the property. Such perceptions can diminish trust in the host and negatively influence the booking decision. Therefore, Hypothesis 4 is supported.

The "Super host" badge exerts a significantly positive influence on consumers' booking decisions ($\beta = 0.278, p < 0.01$). In the shared short-term rental market, the "Super host" badge typically represents outstanding performance and high-quality service by the host on the platform. This certification is generally awarded based on multiple dimensions, including the host's historical ratings, property quality, and service attitude. When making booking decisions, consumers often face information overload and uncertainty. The "Super host" badge serves as a credibility signal, indicating that the host's trustworthiness and service level have been officially endorsed by the platform, which can effectively reduce consumers' perceived risk and enhance their trust and purchase intention. Furthermore, hosts who have obtained the "Super host" status often provide more high-quality listings and possess better service experience, further strengthening consumers' preference and choice tendency. Therefore, Hypothesis 5a is supported.

The property rating has a significantly positive impact on consumers' booking decisions ($\beta = 0.156, p < 0.01$). The property rating reflects direct feedback and evaluation from consumers regarding the quality of the host's services on the platform. A high rating generally indicates that the accommodation service provided by the host has been recognized by consumers in multiple aspects. In the context of information asymmetry in the shared short-term rental market, consumers often rely on property ratings to assess the quality and reliability of the host. Hosts with high ratings are more likely to gain consumers' trust and preference, thereby increasing the probability of bookings. Moreover, property ratings also carry social influence and a demonstration effect, attracting more potential consumers to consider and choose the accommodations offered by highly-rated hosts. Therefore, Hypothesis 5b is supported.

The host's booking acceptance rate has a significantly positive influence on consumers' booking decisions ($\beta = 0.632, p < 0.01$). The booking acceptance rate reflects the popularity and bookability of the host's listings. A high acceptance rate usually indicates that the host's property is highly competitive and attractive in the market and can promptly meet consumers' accommodation needs. For consumers, choosing a host with a high booking acceptance rate can significantly reduce the inconvenience and disappointment caused by limited availability or unsuccessful booking attempts. Furthermore, a high acceptance rate also indirectly reflects the host's service capability and responsiveness, making consumers feel more confident in selecting the accommodations provided by such hosts. Hence,

the host's booking acceptance rate becomes one of the key factors influencing consumers' purchase decisions. Therefore, Hypothesis 5c is supported.

Models M9 to M12 gradually incorporated the control variables. The results indicate that price, number of listings, response time, response rate, and instant booking availability all significantly influenced consumers' booking decisions, underscoring the importance of including these control variables in the study. Furthermore, the gradual inclusion of the control variables did not alter the significance or the direction (positive/negative) of the core independent variables, demonstrating the robustness of the model.

3.4. Heterogeneity Analysis

The supply types of listings on shared short-term rental platforms are highly diverse, including private rooms, entire homes/apartments, shared rooms, and hotel rooms, with the majority being the first two types. Different types of listings attract different target consumer groups, and consumers' booking purposes and needs also vary. Therefore, heuristic information cues may play differentiated roles on shared short-term rental platforms. Generally speaking, private rooms offer less privacy but higher cost-effectiveness, while entire homes or apartments provide greater privacy and well-equipped facilities, attracting target consumers with higher expectations and requirements. It can be speculated that, compared to private rooms, heuristic information cues may play a more substantial role in the decision-making process of users booking entire homes/apartments.

This study categorizes the sample based on listing type into a private room group (Roomtype = Private Room) and an entire home/apartment group (Roomtype = Entire Home/Apartment) to conduct subgroup regression analyses. The aim is to explore the differential impact of heuristic information cues on user booking decisions across different listing types. Since listing type can be considered an ordinal variable from the perspectives of privacy level and consumption level, it can be distinguished by assigning different encoding values to the same variable. Based on Model 1, multiple linear regression was conducted, and the results are presented in **Table 5**.

Table 5. Heterogeneity analysis results based on room type.

Variables	M1	M2
	Review Private Room	Review Entire Home/Apartment
Beauty	-0.001 (-0.71)	0.002** (2.41)
Smile	-0.000 (-0.90)	0.001** (2.38)
Age	-0.003** (-2.06)	-0.003*** (-4.58)

Continued

Gender	0.033 (0.97)	0.051*** (3.32)
Blur	-0.001*** (-2.86)	-0.000 (-1.60)
Superhost	0.256*** (6.68)	0.272*** (15.68)
Score	0.126 (1.26)	0.180*** (4.56)
Acceptance	0.427*** (4.72)	0.671*** (13.95)
Price	-0.157*** (-4.41)	-0.098*** (-7.58)
Listnum	-0.009** (-2.08)	-0.007*** (-7.26)
Responsetime	-0.107*** (-3.58)	-0.175*** (-12.26)
Responserate	-0.199 (-1.20)	-0.439*** (-6.24)
Instant	0.073 (1.61)	0.183*** (10.19)
Constant	0.861* (1.70)	0.241 (1.18)
F-value	16.35	158.4
R-squared	0.189	0.328
Adj R-squared	0.178	0.326
Observations	924	4,230

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-statistics in parentheses.

The results indicate, in the private room subgroup, among the core independent variables, only age ($\beta = -0.003$, $p < 0.05$), blurriness ($\beta = -0.001$, $p < 0.01$), “Super host” badge ($\beta = 0.256$, $p < 0.01$), and booking acceptance rate ($\beta = 0.427$, $p < 0.01$) showed a significant impact on booking decisions. This can be attributed to the fact that consumers choosing private rooms often prioritize cost-effectiveness and may compromise on certain services or amenities. However, the blurriness of the host’s photo shapes consumers’ first impression and may trigger perceived risk due to information uncertainty. The “Super host” badge serves as an official credibility endorsement from the platform, appearing more professional

and visually prominent in listings. The booking acceptance rate directly influences the efficiency and experience of completing a transaction. Thus, these variables play crucial roles in users' purchase decisions for private rooms.

In the entire home/apartment group, all core independent variables except blurriness showed a significant positive influence on booking decisions. A possible explanation is that entire homes or apartments inherently offer greater privacy and involve relatively less social interaction with hosts, leading to lower perceived risk among users and consequently less sensitivity to photo blurriness. Furthermore, in terms of significance levels, compared to the private room group, the host's age and the number of listings per host had a relatively stronger influence on consumers' booking decisions in the entire home/apartment group. This is because the target audience for entire homes/apartments generally consists of consumers with higher expectations for accommodation experience and property quality. The host's age is associated with perceived competence and warmth, while the number of listings managed by the host is often linked to their service capability. As a result, these service-related cues play a more prominent role in the booking decisions of consumers seeking entire homes/apartments.

Therefore, for hosts offering entire homes or apartments, providing high-quality photos, completing official platform certifications, and improving service levels are crucial for building trust. These measures not only enhance the attractiveness and competitiveness of their listings but may also reduce users' sensitivity to price fluctuations, thereby facilitating transactions. For hosts of private rooms, it is particularly important to focus on improving service quality and striving to meet the platform's "Super host" certification standards.

3.5. Robustness Test

To assess the robustness of the findings, this study replaced the original dependent variable (the average monthly number of bookings during the listing's active period) with the number of bookings in the past year (using the number of reviews in the past year as a proxy variable). Multiple linear regression was then performed based on Model 1.

As shown in **Table 6**, which presents the regression coefficients and significance levels after the dependent variable substitution, the results demonstrate that stereotypical impressions (age and gender), smile intensity, attractiveness score, blurriness, Superhost status, property rating, and booking acceptance rate all exert a significant influence on users' booking decisions. These findings are consistent with those of the main model, confirming that the model passes the robustness test.

4. Conclusions and Prospects

4.1. Summary of Findings

Regarding the independent variables, a multiple linear regression model was constructed and empirically tested. The results indicate that, with the exception

Table 6. Robustness test results.

Variables	M1 Average Monthly Review Volume (During Listing's Active Period)	M2 Number of Reviews in the Past Year
Beauty	0.001* (1.84)	0.004** (2.46)
Smile	0.000 (1.56)	0.000 (0.95)
Age	-0.003*** (-5.77)	-0.007*** (-5.87)
Gender	0.050*** (3.59)	0.055* (1.94)
Blur	-0.000*** (-2.71)	0.000 (0.73)
Superhost	0.278*** (17.59)	0.726*** (22.80)
Score	0.156*** (4.26)	0.107 (1.46)
Acceptance	0.632*** (14.84)	1.889*** (22.03)
Price	-0.066*** (-6.14)	-0.160*** (-7.44)
Listnum	-0.007*** (-7.19)	-0.018*** (-9.90)
Responsetime	-0.162*** (-12.51)	-0.222*** (-8.51)
Responserate	-0.407*** (-6.24)	-0.617*** (-4.70)
Instant	0.166*** (9.92)	0.163*** (4.83)
Constant	0.257 (1.36)	1.381*** (3.63)
F-value	166.9	208.6
R-squared	0.296	0.345
Adj R-squared	0.294	0.343
Observations	5174	5174

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-statistics in parentheses.

of smile intensity in the host's profile photo, variables such as attractiveness score, stereotypical impressions, blurriness, and the host's word-of-mouth reputation all exert a significant influence on users' booking decisions. Thus, H1, H3, H4, and H5 are supported.

Among the control variables, listing price, number of listings, response time, response rate, and instant booking availability all significantly affect consumers' booking decisions.

Building on the main effect analysis, a heterogeneity test was conducted to examine the impact of room type on user decision-making in shared short-term rental platforms. In the private room subgroup, only age, blurriness, "Super host" badge, and booking acceptance rate significantly influenced booking decisions. In the entire home/apartment subgroup, all core independent variables had a significant impact on booking decisions. Moreover, compared to the private room subgroup, variables such as age, "Super host" badge, and booking acceptance rate demonstrated higher levels of significance and exerted a more substantial influence on consumers' decisions in the entire home/apartment subgroup.

4.2. Managerial Implications

This study offers substantial practical guidance for shared short-term rental platforms, hosts, and the overall development of the sharing accommodation industry.

Firstly, the research highlights the importance of host profile photos and word-of-mouth reputation information in consumers' booking decisions. Platforms can leverage these insights to optimize information presentation strategies—such as improving the readability of reputation information—and design more intuitive user interfaces to help consumers access and evaluate heuristic cues more efficiently.

Secondly, hosts can utilize the findings to better understand consumer preferences and the weight placed on different heuristic cues, thereby adjusting their marketing strategies accordingly. For example, hosts can actively maintain a positive reputation record to enhance the appeal and competitiveness of their listings, attracting more potential consumers.

Lastly, this study contributes to the healthy development of the shared short-term rental industry. By revealing the mechanisms through which heuristic cues influence consumer decision-making, it provides a scientific and rational basis for industry standards and management recommendations. For instance, platforms can establish stricter host verification and reputation management systems to ensure the authenticity and reliability of information.

4.3. Research Limitations and Future Prospects

This study focuses on the impact of heuristic information cues on user purchase decisions in shared short-term rental platforms, thereby broadening the research perspective in this field. However, several limitations remain, and future studies could expand on the following aspects:

1) Improving Sample Generalizability: The data in this study cover listings from nine countries, including the United States, France, Germany, Italy, Belgium, Spain, Australia, Greece, and the Netherlands. Due to Airbnb's exit from the Chinese market, data from within China were not available. Future research could extend the study to domestic short-term rental platforms such as Xiaozhu Short-Term Rental to enhance the generalizability of the findings and facilitate cross-country or regional comparisons.

2) Diversifying Research Methods: This study primarily employs econometric modeling to examine the relationship between information cues and purchase decisions through data observation and testing. Future research could introduce experimental methods, such as conducting grouped experiments on different information cues, to explore the underlying mechanisms of these influences.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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