User Purchase Behavior on Information-Dominant Decision-Making Sharing Service Platforms: Configurational Effects of Multi-Agent Generated Signals Postprint

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Abstract

[Purpose/Significance] This study aims to explore the interactive influence of multi-agent generated information on resource demanders' purchasing behavior in shared service platforms, so as to facilitate the recovery and healthy sustainable development of the sharing economy in the post-pandemic era. [Method/Process] Grounded in signaling theory and incorporating the characteristics of multi-agent generated information on shared service platforms, we construct a configurational research model of consumer purchasing behavior in information-dominated decision-making shared service platforms. Using shared accommodation platforms as an example, we crawled shared housing data from Chengdu on the Airbnb platform using Python, and employed fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify the configurational effects of multi-agent generated information on user purchasing behavior. [Results/Conclusions] The findings reveal that there are three combinations of information features that facilitate purchasing behavior on shared platforms, with one necessary condition for generating such behavior; three combinations of information feature conditions lead to consumer non-purchase behavior, with one necessary condition for non-purchase behavior; and the paths leading to user purchasing behavior and non-purchase behavior are not opposite.

Full Text

Understanding Users' Purchase Behaviors on Information-Driven Decision-Making Sharing Service Platforms: The Configuration Effect of Multi-Agent Generated Signals

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Abstract: [Purpose/Significance] This study aims to explore the interactive influence of multi-agent generated information on resource demanders' purchasing behaviors on shared service platforms, thereby facilitating the recovery and sustainable development of the sharing economy in the post-pandemic era. [Method/Process] Based on signaling theory and incorporating the characteristics of multi-agent generated information on shared service platforms, this paper constructs a configuration research model of consumer purchasing behavior on information-driven decision-making sharing service platforms. Taking a shared accommodation platform as an example, we used Python to crawl shared housing data in Chengdu from the Airbnb platform and employed fuzzy-set qualitative comparative analysis (fsQCA) to identify the configuration effects of multi-agent generated information on users' purchasing behaviors. [Result/Conclusion] The findings reveal three combinations of information characteristics that encourage purchasing behavior on sharing platforms, with one necessary condition for generating purchases; three combinations of information characteristics that lead to non-purchasing behavior, with one necessary condition for non-purchase; and that the paths leading to purchasing behavior are not simply the opposite of those leading to non-purchasing behavior.

Keywords: signaling theory; purchasing decision behavior; sharing service platform; configuration perspective

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2. Related Research and Theoretical Foundation

2.1 Information's Influence on User Purchase Decisions Information generated by multiple agents on sharing service platforms serves as a crucial basis for resource demanders' purchase decisions and has attracted considerable scholarly attention. This section reviews existing literature from two perspectives: information dimensions affecting user purchase decisions and research methodologies.

Existing research identifies three main information dimensions influencing user purchase decisions: information source (generating agent), information format, and information content. Information sources on sharing service platforms primarily involve three agents: resource suppliers, resource demanders, and the platform itself. Supplier-generated information includes product information (e.g., product images and descriptions) and supplier profiles [4-6], demander-generated information comprises online reviews and ratings [3], while platform-generated information includes product certifications, supplier certifications, and platform recommendations [4,5]. Regarding information format, studies distinguish between textual information (such as online reviews [7,10]) and pictorial information (including image color, shape, and source [9]). Third, research on information content affecting resource demanders' purchase behavior has begun examining consumer repurchase behavior. For instance, K. Xie et al. found that hosts' acceptance rates, number of listings, and travelers' past booking frequency positively influence travelers' repurchase behavior from hosts, while hosts' confirmation efficiency, acceptance rate, and travelers' past booking frequency positively affect repurchase behavior for specific properties [8].

Methodologically, most existing studies employ regression-based variance analysis to examine the net effects of individual factors on consumer purchasing behavior. For example, S. Liang et al. used a multilevel linear regression model based on rational decision theory and utility maximization theory to verify the impact of host-generated information on guests' purchase decisions [6]. Similarly, Chi Maomao et al. used a negative binomial regression model grounded in signaling theory to validate the effects of user-generated signals and platform certification signals on guests' sustainable consumption behavior [3]. However, variance-based statistical analyses assume symmetric distributions between independent and dependent variables [12], positing that high independent variable X (e.g., high property ratings in this study) is both sufficient and necessary for dependent variable Y (e.g., user purchase behavior). Yet asymmetric distributions are ubiquitous in reality. For example, scholars and practitioners widely believe positive reviews increase purchase behavior, yet L. Zhang et al. recently found that positive reviews can produce 逆反 effects and negative outcomes under certain conditions [13]. This asymmetry in how positive information influences user behavior challenges traditional variance-based conclusions. Configuration-based qualitative comparative analysis can compensate for this limitation in variance analysis, offering a new approach to exploring asymmetric relationships between variables. In recent years, configuration-based qualitative comparative analysis has been applied to study user information behaviors, such as social media user behavior [14] and online review behavior [15], and its empirical application in domestic library and information science is also emerging, as seen in Chi Maomao et al. [16].

2.2 Signaling Theory Signaling Theory was first proposed by M. Spence in 1973. The theory generally refers to how the better-informed party in a market transmits relevant information through signals to the less-informed party, thereby influencing or changing the latter's choice intentions and moving the market toward equilibrium [18]. In market transactions, buyers often possess less product information than sellers, creating information asymmetry. Sellers send signals about products to help buyers infer product quality and achieve potential transaction gains. Research demonstrates that signaling theory can explain consumer purchasing behavior. For example, K. Xie et al. found that "Superhost" status, experience, and response rate significantly positively influence property booking volumes [19].

In information-driven decision-making sharing service platforms, resource suppliers publish their idle resources on the platform, making it difficult for resource demanders to obtain physical information cues about products. To help demanders understand products and facilitate transactions, suppliers typically provide quality information, and platforms offer certification information. These signals provide reliability cues for consumers' purchase decisions. Therefore, signaling theory offers a theoretical framework for guiding and stimulating consumer purchasing behavior on sharing service platforms. Signal objects are generally categorized as product or supplier, with content including quality, emotional, and rational appeals. Quality appeals include supplier certification and reviews, emotional appeals include product and supplier descriptions, while rational appeals include price, images, star ratings, and sharing capacity [9]. C. Wang et al. applied signaling theory to categorize offline knowledge service quality signals into service attributes and supplier attributes [20], while Yao Bin combined signaling theory to classify Airbnb property attributes into functional attributes, signal attributes, and dual attributes to examine their impact on market demand [21].

3. Research Model

Based on signaling theory and incorporating information features on sharing service platforms, this study constructs a configuration model of consumer purchasing behavior on information-driven decision-making sharing service platforms. This section discusses the relationships between user-generated signals (from both supply-side and demand-side users), platform-generated signals, and demand-side users' purchase decision behaviors.

3.1 User-Generated Signals and Purchase Decision Behavior Users on sharing service platforms include resource suppliers and demanders. This study categorizes user-generated signals into supplier-generated signals and demander-generated signals. Supplier-generated signals primarily include product information and supplier information, while demander-generated signals mainly comprise online ratings.

On experiential sharing service platforms, products and services exhibit non-standardized characteristics, and consumers face high uncertainty and risk before making purchase decisions. Information provided by resource suppliers (S.Info) about products and suppliers becomes a critical basis for user purchase decisions. First, regarding the impact of shared resource information on user purchase decisions, existing research shows that shared property descriptions, image quantity, color, and source all influence consumer purchasing behavior. For instance, studies found that the number of property images on Airbnb positively affects consumer purchasing behavior [5], with image color having the greatest influence on consumer choice, followed by image shape and source [9]. The impact of product descriptions on consumer purchasing behavior 主要体现在 length and depth. Research on Airbnb found that property description length and depth positively correlate with consumer purchasing behavior [6], and lower product prices represent a competitive advantage for sharing service platforms and constitute an important factor influencing consumer purchasing behavior [3,6].

Second, resource supplier personal information influences user purchase decisions. Resource suppliers are owners and providers of services or goods. Supplier information helps consumers understand suppliers' personalities, thereby enhancing perceived trust and promoting purchase behavior. On Airbnb, host description length and depth positively influence consumer purchasing behavior [6]. Therefore, the length or detail of resource suppliers' self-descriptions may interact with other information dimensions to affect consumer purchasing behavior.

On shared accommodation platforms, review information provided by resource demanders also constitutes a primary information source for purchase decisions. Since short-term rental platforms offer experiential goods, consumers can increase their understanding of products through others' reviews to make purchase decisions. The impact of online ratings on consumer purchasing behavior 主要体现在 overall ratings and individual ratings. For example, research found that cleanliness ratings on short-term rental platforms positively influence guests' sustainable consumption behavior [3], and high overall ratings for shared resources positively affect consumer purchasing behavior [4-5].

3.2 Platform Certification Signals and Purchase Decision Behavior Platform certification signals include platform certification labels for shared resources and certification information for resource suppliers. Product certification represents the platform's official quality certification for goods, such as Airbnb's "Clean & Safe" property certification tag launched during the pandemic, which certifies properties meeting "zero-contact" self-check-in, cleanliness ratings of 4.8 or above (out of 5), and other safety standards. Supplier certification provides platform certification signals for suppliers with specific qualifications, such as Airbnb's "Superhost" status representing experienced, highly-rated hosts. Compared to user-generated signals, platform certification signals represent official platform endorsements of product and supplier quality, helping consumers gain third-party evaluation perspectives. Additionally, as third-party signals independent of resource supply and demand parties, platform certification signals enable sustainable standardized management of products and suppliers, enhancing consumers' perceived trust in the platform and thereby promoting purchase decisions. Research found that platform property certification signals positively moderate the effect of user-generated signals on consumer purchasing behavior [3], and platform host certification signals significantly positively influence consumer purchasing behavior [4-5].

3.3 Multi-Agent Generated Information Configuration and User Decision Behavior Although existing research demonstrates that information generated by various agents on sharing service platforms affects user decision-making to varying degrees, current studies typically examine impacts from single-agent information using structural equation modeling or multiple regression to analyze net effects of different information dimensions on decision-making, while ignoring complexity in data and reality. On sharing service platforms, complex, asymmetric effects of different factors interacting on user purchasing behavior are widespread [22].

Complexity theory emphasizes a holistic view and "equifinality," providing a new perspective for analyzing nonlinear relationships between variables. When nonlinear interactions exist among factors, changes in individual elements may or may not significantly affect the entire system, requiring a holistic rather than net-effect perspective to understand variable relationships. "Equifinality" [23] refers to multiple different combinations of antecedent conditions (e.g., various combinations of information dimensions) equivalently leading to the same outcome (e.g., user purchasing behavior). The equifinality principle of complexity theory indicates that no single feature is necessary for achieving a specific result—for instance, high ratings may not be a necessary condition for user purchasing behavior [23]. Research found that when users face multiple inconsistent information cues, they tend to focus on negative cues, producing corresponding behaviors [24]. Therefore, on shared accommodation platforms, when signals generated by multiple agents appear simultaneously, complex interactions exist between signals, and multiple equivalent paths may lead to users' purchase or non-purchase decisions.

In summary, this study employs signaling theory, selecting three information dimensions as signals: platform-generated information (P.Info), resource supplier-generated information (S.Info), and resource demander-generated information (D.Info). From a complexity theory perspective, we analyze the configuration effects of signals generated by different agents on users' purchasing and non-purchasing decision behaviors. The configuration model of this study is shown in Figure 1 [Figure 1: see original paper].

4. Data Collection and Analysis

To explore the configuration effects of information generated by resource suppliers, demanders, and platforms on user purchasing behavior on sharing service platforms, this study selects the short-term rental platform Airbnb as a case, using Python to crawl publicly available multi-agent generated information as the data source. This section details the data collection, variable measurement, and data analysis processes.

4.1 Data Collection This study selects Airbnb for two main reasons: First, Airbnb is one of the world's largest short-term rental platforms, with over 7 million listings across more than 100,000 cities worldwide as of 2020 [25], and it holds a significant share of China's short-term rental market. Second, the platform generates certification signals for properties and hosts, such as launching tens of thousands of "Clean & Safe" properties during the pandemic. The "Clean & Safe" and "Superhost" series of platform-generated certification signals serve as important bases for users to evaluate property quality and make purchase decisions. Simultaneously, the platform allows resource suppliers and demanders to generate information, providing a scientific environment for this study.

City culture and economic development differences are important factors affecting local purchase decisions. To control for city differences' impact on user purchasing behavior, this study selects Chengdu property data as representative for two main reasons: First, the "China Shared Accommodation Development Report 2020" released by the State Information Center shows that in 2019, Chengdu ranked among the top three cities in property inventory alongside Beijing and Shanghai [26]. Second, Beijing and Shanghai were the first to introduce special policies for the shared accommodation sector during the pandemic [27-28], which would create policy effects on consumers' travel decisions. Therefore, this study only selects Chengdu's shared properties as the research sample. This study first crawled data at the end of September 2020 (time point T0) and conducted a second data crawl in November 2020 (time point T1), extracting data with review publication dates between October 1, 2020, and October 31, 2020. The entire dataset belongs to the "post-pandemic period" [29].

The data collection process involved: (1) Original data source acquisition. The screening criteria set the city to "Chengdu," property type to "entire place," price range to 0-9999 RMB, and offset to 10. For each property link, we collected six fields: number of property images, overall rating, property description, price, host description, and number of reviews. We checked whether property descriptions contained "disinfection" or related terms and whether tags included "Clean & Safe" or "Superhost," coding these as 1 if present and 0 otherwise, while also calculating the string length of host descriptions. Properties with missing fields were removed, and properties with identical fields were treated as duplicates. After deduplication, 5,883 property records were obtained. (2) Data cleaning and screening. Since this study focuses on Chinese consumers' purchasing behavior, properties with foreign language reviews were removed. Additionally, due to significantly reduced travel accommodation demand during the pandemic, properties with ratings greater than 0 were selected to ensure subsequent data analysis. As consumer purchasing behavior is sensitive to price factors [30] and the price distribution of the 5,418 screened properties showed a peaked distribution between 68-9,999 RMB, this study limited the sample price to within 1,000 RMB, resulting in 5,316 samples. The 68-1,000 RMB range showed a positively skewed distribution (Median=280.00, SD=193.855, Mean=331.42, Mode=198). Since this study focuses on exploring the impact of multi-agent generated information on user purchase decisions, to control for price factors as much as possible, we selected properties within one standard deviation of the mean price (Mean-SD, Mean+SD) for properties under 1,000 RMB (accounting for 77% of total samples), i.e., properties priced between 138-525 RMB/night. The final valid dataset included 4,107 properties and 7,172 corresponding guest text reviews. (3) Variable measurement. The antecedent variables in this study include seven variables across three dimensions: resource supplier-generated signals, resource demander-generated signals, and platform certification signals. The outcome variable is user purchasing behavior. Supplier-generated signals include number of images, whether description contains "disinfection," property price, and host information length. Variable descriptions and measurement methods are shown in Table 1 . Demander-generated signals refer to the overall property rating at time T0. Platform certification signals include whether the property has the "Clean & Safe" tag and whether it has the "Superhost" tag.

Consumer purchasing behavior was measured using property sales volume. Due to platform data availability limitations, this study could not directly obtain sales information for corresponding time periods and thus adopted the widely used demand proxy approach [31]. Following existing research measurement methods [14,22-23,32], property sales volume has a high positive correlation with the number of online reviews received (i.e., ϕ represents booking quantity, where $0\,\% < \phi$). Therefore, the more reviews a property has, the more popular it is, representing more user purchasing behavior. Additionally, the sharing economy has collaborative consumption attributes, so users have high motivation to interact on sharing service platforms, and posting reviews is an important form of interaction that satisfies consumers' social needs and altruistic motives [34]. In summary, on shared accommodation platforms, since sales data cannot be directly obtained, using review numbers to represent sales is a universally applicable measurement method [32]. Thus, this study uses the number of reviews a property received between T1 and T0 to represent user purchasing behavior. Figure 2 [Figure 2: see original paper] shows the measurement model based on this study's configuration model, including measurements for each antecedent and outcome condition.

4.2 Descriptive Statistical Analysis First, this study used SPSS 24.0 to conduct descriptive statistical analysis on the collected data. Whether the description contains "disinfection," "Clean & Safe," and "Superhost" are categorical variables, for which frequency statistics were conducted. Among the 4,107 valid records, 698 properties (17%) had descriptions containing "disinfection," 1,011 properties (24.6%) had the "Clean & Safe" tag, and 2,534 properties (61.7%) had "Superhost" certified hosts. Number of images, price, host information length, overall rating, and number of reviews are numerical variables, for which means, standard deviations, minimums, maximums, medians, and percentiles were calculated. Specific results are shown in Tables 2 and 3 .

4.3 Fuzzy-Set Qualitative Comparative Analysis Results Qualitative Comparative Analysis (QCA) is used to explore how combinations of multiple variables influence a specific outcome and is currently one of the most widely used configuration analysis methods [35]. Since most variables measured in this study are continuous, fuzzy-set qualitative comparative analysis (fsQCA) was selected as the data analysis method.

4.3.1 Calibration This study used the direct calibration method to calibrate raw data. First, based on each variable's distribution characteristics, three critical values were set: full membership, crossover point, and full non-membership.

The data were then calibrated into set membership scores between 0-1 [36]. Binary variables were directly calibrated as 0 or 1. For continuous variables, distribution characteristics were examined and calibration criteria were referenced [37]. Since none of the continuous variables in this study followed a normal distribution, the 80th percentile, median, and 20th percentile were calculated and calibrated as full membership, crossover point, and full non-membership values, respectively. Overall rating values were measured on a 5-point Likert scale, with full membership anchor set at 4, crossover point at 3, and full non-membership at 2. Additionally, fsQCA requires avoiding membership scores equal to 0.5; if a condition's fuzzy-set membership is less than 1, 0.001 is added to the original membership [35]. Specific calibration points are shown in Table 4 .

4.3.2 Necessary Condition Analysis for Platform Information's Impact on Purchasing Behavior Necessary condition analysis tests whether a single condition is necessary for an outcome. Based on necessary condition analysis results, sufficient condition analysis is conducted for conditions that cannot individually serve as necessary conditions. If the consistency of necessary condition analysis is greater than or equal to 0.9, the condition is considered necessary [38].

As shown in Table 5 , high overall rating is simultaneously a necessary condition for both user purchasing behavior and non-purchasing behavior, meaning properties with high ratings are a superset of both high-sales and low-sales property sets. This occurs because of the widespread phenomenon of positive ratings on shared accommodation platforms. Existing research found that on short-term rental platforms, due to extensive online and offline interactions between demanders and hosts, demanders often deliberately avoid negative reviews based on empathy and social intimacy [32]. Additionally, Airbnb's reciprocal review mechanism creates a tacit understanding of mutual positive reviews between guests and hosts [34]. These factors collectively contribute to rating bias. The rating data distribution in this study confirms the existence of this universal positive rating phenomenon, with an average overall rating of 4.85 (Min=1, Max=5, SD=0.3059), and ratings of 3 and above accounting for 99.63% of total samples (4,092/4,107).

4.3.3 Sufficient Condition Analysis for Platform Information's Impact on Purchasing Behavior After necessary condition analysis, this section constructs a truth table for sufficient condition analysis. To identify core and peripheral elements, the frequency threshold was set to retain at least 75% of samples, the raw consistency threshold was set at 0.8 [17,39], and PRI consistency was set at 0.65 to obtain complex, parsimonious, and intermediate solutions. Since the intermediate solution does not eliminate necessary conditions [40], it was used as the sufficient condition analysis result. If an antecedent condition appears in both the parsimonious and intermediate solutions, it is a core condition; if it appears only in the intermediate solution, it is a peripheral condition [36].

The sufficient condition analysis results are shown in Tables 6 and 7 . Each column represents a configuration. Solid circles ( ) indicate condition presence, crosses ( ) indicate condition absence, and blanks indicate the condition may be present or absent. Large circles represent core conditions, while small circles represent peripheral conditions [41]. Consistency reflects the degree to which a configuration consistently exhibits the outcome, while coverage reflects the proportion of outcome cases explained by configurations passing consistency tests. Raw coverage includes overlapping explanations among configurations for individual configuration coverage, unique coverage excludes overlapping explanations, and overall coverage reflects the proportion of outcome cases covered by all configurations [36]. In this study, the overall coverage for high user purchasing behavior solutions is 0.242, covering 24.2% of outcome cases; the overall coverage for low user purchasing behavior solutions is 0.386, covering 38.6% of outcome cases.

The data analysis results show three conditional configurations leading to consumer purchasing behavior. Configuration 1 reveals that for lower-priced shared properties (below 268 RMB/night), if the property description does not contain "disinfection," but the property has high overall ratings (above 3.0), "Superhost" certification, and "Clean & Safe" certification, consumers are highly likely to purchase. Thus, when product prices are not high, product and supplier certifications can compensate for the absence of "disinfection" in descriptions, as consumers' quality requirements decrease with price and they can rely on platform certifications to confirm cleanliness.

Configuration 2 shows that for lower-priced shared properties (below 268 RMB/night), when properties have many images (more than 26), descriptions containing "disinfection," detailed host self-descriptions (more than 29 characters), high overall ratings (above 3.0), and "Superhost" certification, consumers are highly likely to purchase. This configuration has the highest consistency, indicating it is the most likely combination to generate substantial consumer purchasing behavior.

Configuration 3 shows that when properties have many images (more than 26), descriptions containing "disinfection," detailed host self-descriptions (more than 29 characters), high overall ratings (above 3.0), and both "Superhost" and "Clean & Safe" certifications, consumers are highly likely to purchase.

The results also indicate three conditional configurations leading to consumer non-purchasing behavior. Configurations 4 and 6 both describe scenarios leading to non-purchase of higher-priced properties (above 268 RMB/night). Configuration 4 reveals that for higher-priced properties without "disinfection" in descriptions and without "Superhost" or "Clean & Safe" certifications, even with high overall ratings (above 3.0), consumers are unlikely to purchase.

Configuration 5 shows that without "disinfection" in descriptions and without "Superhost" or "Clean & Safe" certifications, when properties have few images (fewer than 26), brief host self-descriptions (fewer than 29 characters), but high overall ratings (above 3.0), consumers are unlikely to purchase.

Configuration 6 shows that for higher-priced properties without "disinfection" in descriptions and without "Clean & Safe" certification, when properties have few images (fewer than 26), detailed host self-descriptions (more than 29 characters), and high overall ratings (above 3.0), consumers are unlikely to purchase.

5. Research Implications

The study found three equivalent paths encouraging consumer purchasing behavior and three paths discouraging it, with the paths leading to purchasing and non-purchasing behaviors not being complete opposites. The theoretical and practical contributions are mainly reflected in the following aspects:

5.1 Theoretical Implications

(1) In terms of research perspective, this paper employs complexity theory to holistically examine the complex effects of multi-agent generated information on user purchase decision-making in experiential resource sharing platforms. From the perspective of resource supplier-generated signals, price is a primary consideration in consumer purchase decisions, and both high-priced and low-priced properties have configurations leading to high purchase likelihood (Configurations 1, 2, 3). The study reveals that when multiple information cues affecting user decisions coexist, multiple equivalent paths exist for generating consumer purchasing behavior (Configurations 1, 2, and 3). Moreover, the three equivalent paths leading to consumer non-purchasing behavior (Configurations 4, 5, and 6) are not simply the opposite of those leading to purchasing behavior.

(2) Methodologically, this paper combines platform big data with qualitative comparative analysis, verifying the causal asymmetry of consumer purchasing behavior generation. This approach compensates for measurement bias in existing research that collects subjective self-reported data through questionnaires, while also addressing limitations of regression-based analyses in adequately explaining asymmetric relationships between variables. Using QCA methods, this study identifies factors influencing high consumer purchasing behavior and those leading to non-purchasing behavior, finding that the factor combinations causing high purchasing behavior are not opposite to those causing non-purchasing behavior. That is, the reasons for non-purchasing cannot be directly inferred from the opposite of purchasing behavior reasons.

5.2 Practical Implications The findings on how information influences user behavior on experiential resource sharing platforms can guide platforms in promoting consumer purchasing behavior: (1) The study reveals the existence of concurrent synergistic effects between user-generated signals and platform certification signals, demonstrating the complexity of consumer purchasing behavior.

Sharing service platforms can further standardize and improve user-generated signal mechanisms and platform certification signal mechanisms. After major public health emergencies closely related to resource usage, platforms should provide risk-reduction-related information certifications to decrease uncertainty in user decision-making. (2) High consumer purchasing behavior exhibits asymmetry. Therefore, sharing platforms and service providers should not infer reasons for high purchasing behavior from traditional experience summarizing non-purchasing behavior reasons. They must identify key core factors when promoting consumer purchasing behavior.

6. Research Limitations and Future Directions

This study has several limitations for future research to address: (1) As sharing service models further develop and social integration increases, future research could compare information's influence mechanisms on user purchasing behavior across multiple different sharing resource platforms to derive mechanisms specific to sharing resource characteristics. (2) This study obtained cross-sectional data for a one-month period in the post-pandemic era. Future research could incorporate time-series factors and subsequent social emergency events affecting sharing economy activities, such as sporadic outbreaks in multiple Chinese provinces, to further explore dynamic patterns of information's influence on user behavior in information-driven decision-making sharing service platforms, aiding post-pandemic recovery of sharing service models and enhancing their resilience to emergencies.

References

[1] State Information Center. China Sharing Economy Development Report (2021) [EB/OL]. [2021-04-12]. http://www.sic.gov.cn/News/557/10779.

[2] Engel JF, Kollat DT, Blackwell RD. Consumer behaviour[M]. New York: Holt, Rinehart and Winston, 1968: 345-.

[3] Chi Maomao, Pan Meiyu, Yan Wanxuan. Research on the formation mechanism of guests' sustainable consumption behavior in shared accommodation: The interactive effect of user-generated signals and platform certification signals[J]. Tourism Tribune, 2020, 35(07): 36-48.

[4] Xu X, Zeng S, He Y. The impact of information disclosure on consumer purchase behavior on sharing economy platform Airbnb[J]. International journal of production economics, 2021, 231: 1-23.

[5] Han H, Shin S, Chung N, et al. Which appeals (ethos, pathos, logos) are the most important for Airbnb users to booking?[J]. International journal of contemporary hospitality management, 2019, 31(3): 1205-1223.

[6] Liang S, Schuckert M, Law R, et al. The importance of marketer-generated content to peer-to-peer property rental platforms: Evidence from Airbnb[J]. International journal of hospitality management, 2020, 84: 1-11.

[7] Xu X. How do consumers in the sharing economy value sharing? Evidence from online reviews[J]. Decision support systems, 2020, 128: 1-13.

[8] Xie KL, Kwok L, Wu J. Are consumers loyal to home-sharing services?: impacts of host attributes and frequency of past stays[J]. International journal of contemporary hospitality management, 2019, 31(3): 1066-1085.

[9] Liu X, Guo S. The influence of picture information on consumers' purchase decision[J]. IOP Conference series: earth and environmental science, 2019, 252(4): 1-10.

[10] Chang W, Wang J. Mine is yours? using sentiment analysis to explore the degree of risk in the sharing economy[J]. Electronic commerce research and applications, 2018, 28: 141-158.

[11] Li Quanxi, Xu Jiahui, Wei Junwei, et al. Research on resource information quality evaluation of sharing service platforms based on BP neural network: Taking short-term rental sharing service platforms as an example[J]. Library and Information Service, 2019, 63(10): 125-133.

[12] Woodside AG. Moving beyond multiple regression analysis to algorithms: calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory[J]. Journal of business research, 2013, 66(4): 463-472.

[13] Zhang L, Wei W, Line ND, et al. When positive reviews backfire: the effect of review dispersion and expectation disconfirmation on Airbnb guests' experiences[EB/OL]. [2021-05-20]. https://www.sciencedirect.com/science/article/pii/S0278431921001225.

[14] Xie X, Tsai N. The effects of negative information-related incidents on social media discontinuance intention: evidence from SEM and fsQCA[EB/OL]. [2021-05-20]. https://www.sciencedirect.com/science/article/pii/S0736585320301623.

[15] Wang P, Li H, Liu Y. Disentangling the factors driving electronic word-of-mouth use through a configurational approach[J]. Internet research, 2020, 30(3): 925-943.

[16] Chi Maomao, Du Yunzhou, Wang Weijun. Configuration perspective and qualitative comparative analysis (QCA): A new path for empirical research in library and information science[J]. Journal of the China Society for Scientific and Technical Information, 2021, 40(04): 424-434.

[17] Fiss PC. A set-theoretic approach to organizational configurations[J]. Academy of management review, 2007, 32(4): 1180-1198.

[18] Spence M. Job market signaling[J]. The quarterly journal of economics, 1973, 87(3): 355-374.

[19] Xie K, Mao Z. The impacts of quality and quantity attributes of Airbnb hosts on listing performance[J]. International journal of contemporary hospitality management, 2017, 29(9SI): 2240-2260.

[20] Wang C, Mei J, Feng J. Exploring influencing factors of offline knowledge service transactions on an online-to-offline knowledge-sharing economy platform[J]. Journal of knowledge management, 2020, 24(8): 1777-1795.

[21] Yao Bin. Signaling theory and sharing economy[D]. Dalian: Liaoning University, 2019.

[22] Pappas N. The complexity of purchasing intention in peer-to-peer accommodation[J]. International journal of contemporary hospitality management, 2019, 31(3): 1066-1085.

[23] Woodside AG. Embrace perform model: complexity theory, contrarian case analysis, and multiple realities[J]. Journal of business research, 2014, 67(12): 2495-2503.

[24] Anderson NH. Foundations of information integration theory[M]. New York: Academic Press, 1981.

[25] Airbnb. Airbnb newsroom[EB/OL]. [2020-11-08]. https://news.airbnb.com/zh/about-us/.

[26] State Information Center. China Shared Accommodation Development Report 2020[EB/OL]. [2020-11-20]. http://www.sic.gov.cn/News/557/10549.htm.

[27] Beijing Municipal Bureau of Culture and Tourism. Notice on printing and distributing "Several Measures to Respond to the Impact of COVID-19 and Promote the Healthy Development of the Tourism Industry"[EB/OL]. [2021-05-13]. http://whlyj.beijing.gov.cn/zwgk/zcfg/zcwj/202003/t20200325_{1735371}.html.

[28] Shanghai Municipal Development and Reform Commission. Several policy measures on Shanghai's all-out efforts to prevent and control the epidemic and support the stable and healthy development of service tourism enterprises[EB/OL]. [2021-05-13]. http://fgw.sh.gov.cn/qswglqyjqfd/20200219/0025-39270.html.

[29] People's Daily. Life attitudes in the post-pandemic era[EB/OL]. [2021-01-31]. https://baijiahao.baidu.com/s?id=1662365923608467219&wfr=spider&for=pc.

[30] Liang LJ, Choi HC, Joppe M. Understanding repurchase intention of Airbnb consumers: perceived authenticity, electronic word-of-mouth, and price sensitivity[J]. Journal of travel & tourism marketing, 2018, 35(1): 73-89.

[31] Chevalier JA, Mayzlin D. The effect of word of mouth on sales: online book reviews[J]. Journal of marketing research, 2006, 43(3): 345-354.

[32] Pera R, Viglia G, Grazzini L, et al. When empathy prevents negative reviewing behavior[J]. Annals of tourism research, 2019, 75: 265-278.

[33] Ye Q, Law R, Gu B, et al. The influence of user-generated content on traveler behavior: an empirical investigation of the effects of e-word-of-mouth to hotel online bookings[J]. Computers in human behavior, 2011, 27(2): 634-639.

[34] Cheng M, Jin X. What do Airbnb users care about? an analysis of online review comments[J]. International journal of hospitality management, 2019, 76: 58-70.

[35] Fiss PC. Building better causal theories: a fuzzy set approach to typologies in organization research[J]. Academy of management journal, 2011, 54(2): 393-420.

[36] Du Yunzhou, Jia Liangding. Configuration perspective and qualitative comparative analysis (QCA): A new road for management research[J]. Management World, 2017(6): 155-167.

[37] Pappas IO, Woodside AG. Fuzzy-set qualitative comparative analysis (fsQCA): guidelines for research practice in information systems and marketing[J]. International journal of information management, 2021, 58: 1-23.

[38] Ragin CC. Fuzzy-set social science[M]. Chicago: University of Chicago Press, 2000: 55-64.

[39] Sun Yongqiang. Information behavior research from a configurational perspective: research themes, theory building, and analytical methods[J]. Journal of Information Resources Management, 2019, 9(3): 4-17.

[40] Ragin CC. Redesigning social inquiry: fuzzy sets and beyond[M]. Chicago: University of Chicago Press, 2008.

[41] Ragin CC, Fiss PC. Net effects analysis versus configurational analysis: an empirical demonstration[M]//Redesigning social inquiry: fuzzy sets and beyond. Chicago: University of Chicago Press, 2008: 190-212.

[42] Xie K, Mao Z, Wu J. Learning from peers: the effect of sales history disclosure on peer-to-peer short-term rental purchases[J]. International journal of hospitality management, 2019, 76: 173-.

[43] Kwok L, Xie KL. Buyer-seller similarity: does it lead to a successful peer-to-peer transaction of room-sharing services?[J]. International journal of contemporary hospitality management, 2018, 30(9): 2925-2944.

[44] Zhang X, Wang T. Understanding purchase intention in O2O e-commerce: the effects of trust transfer and online contents[J]. Journal of theoretical and applied electronic commerce research, 2021, 16(2): 101-115.

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Note: Figure translations are in progress. See original paper for figures.