User Purchase Behavior in Short-term Rental Homestays in the Post-Pandemic Era: A Post-print Study Based on BERT-Measured Online Word-of-Mouth

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Abstract

[Purpose/Significance] To identify the factors influencing online reputation and user purchase behavior in the post-pandemic era, thereby better attracting users and promoting economic recovery or even surpassing pre-pandemic levels in the online short-term rental industry. [Method/Process] Public data from Airbnb listings in Beijing were collected, the BERT algorithm was employed to construct measurement indicators for online reputation in online short-term rentals, and based on the ELM model, four listing attributes and six host attributes were selected to construct a model of factors influencing user purchase behavior in online short-term rentals, followed by empirical research. [Results/Conclusions] The mean review sentiment score calculated using the BERT model was utilized to measure online reputation in online short-term rentals, providing insights for identifying its proxy variables. Meanwhile, negative binomial regression results indicate that, except for the influence path of listing surrounding environment description, online reputation plays a mediating role in the process through which other listing and host attributes affect user purchase behavior. However, contrary to the research hypothesis, the number of listings held by a host negatively and significantly affects listing reputation and sales volume, possibly because single-listing hosts have lower participation levels; whereas the farther a listing is from the city center, the better its online reputation, which is associated with the characteristics of peripheral travel in the post-pandemic era. Finally, based on the research findings, relevant operational recommendations are proposed for hosts and platforms: in the post-pandemic era, listing descriptions should place greater emphasis on pandemic prevention measures, cancellation policies, indoor activities, etc., but should be distinguished from surrounding environment descriptions; simultaneously, the peripheral travel boom can be leveraged to transform pandemic challenges into development opportuni-

ties, thereby enhancing the competitive strength and business volume of online short-term rental listings.

Full Text

Preamble

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Research on Short-Term Rental Users' Purchase Behavior in the Post-Pandemic Era: Based on eWOM Measured by BERT
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Abstract

[**Purpose/Significance**] This study aims to explore the influencing factors of electronic word-of-mouth (eWOM) and user purchase behavior in the post-pandemic era, thereby providing insights for better attracting users and promoting economic recovery—or even surpassing pre-pandemic levels—in the online short-term rental industry. [**Method/Process**] We obtained publicly available data from Airbnb in the Beijing area, utilized the BERT algorithm to construct a measurement index for online short-term rental eWOM, and built a model of influencing factors for user purchase behavior based on the Elaboration Likelihood Model (ELM) with four listing attributes and six host attributes. Empirical research was then conducted. [**Result/Conclusion**] Using the average sentiment score of reviews calculated by the BERT model to measure online short-term rental eWOM provides a novel approach for identifying its proxy variables. Negative binomial regression results indicate that, except for the influence path of surrounding environment description, eWOM mediates the relationship between other listing/host attributes and user purchase behavior. However, contrary to our hypothesis, the number of listings held by a host negatively and significantly affects both eWOM and sales volume, possibly due to lower host involvement per individual listing. Additionally, greater distance from the city center correlates with better eWOM, which is associated with the post-pandemic trend of peripheral tourism. Finally, based on these findings, we propose operational recommendations for hosts and platforms. In the post-pandemic era, listing descriptions should emphasize epidemic prevention measures, cancellation policies, and indoor activities, while avoiding redundancy with surrounding environment descriptions. Platforms can also capitalize on the peripheral tourism boom to transform pandemic challenges into development opportunities, thereby enhancing the competitive strength and business volume of online short-term rentals.

Keywords: online short-term rental; electronic word of mouth; ELM model; BERT algorithm
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Introduction

As travel patterns such as family tours and self-driving tours become increasingly diversified, traditional hotel accommodations can no longer satisfy users' personalized lodging needs. Online short-term rentals, a more experiential and homely accommodation option, have emerged to meet tenants' diverse housing demands while enabling hosts to utilize idle property resources, thereby providing new choices for travelers and completing the lodging market [1]. However, since the COVID-19 pandemic, the online short-term rental industry has nearly ground to a halt to comply with epidemic prevention requirements, with platforms and hosts facing unprecedented challenges [2]. As we enter the post-pandemic era, with widespread vaccination and increasing removal of travel restrictions, the industry is gradually recovering [3]. Unlike other sharing economy models such as shared transportation or power banks, the product and service information available to consumers in the short-term rental sector is stripped of many physical cues. Due to the immovable nature of properties and the resulting high sunk costs, electronic word-of-mouth (eWOM) has become a crucial channel for consumers to obtain service quality information and reduce decision-making uncertainty [4]. Research indicates that approximately 93% of consumers are influenced by eWOM during purchase decisions [5]. Yet, in the face of public health emergencies like COVID-19, previous studies using review counts or overall ratings as proxy variables for eWOM cannot accurately reflect reality, necessitating more granular characterization of eWOM.

Therefore, considering the significant psychological and behavioral changes in consumers post-pandemic [6], this study obtained publicly available data from Airbnb (insideairbnb.com) for the Beijing area as of December 24, 2021, including information on 5,159 active listings and all review data since January 1, 2018 [7]. We then used the BERT (Bidirectional Encoder Representations from Transformers) algorithm to construct an eWOM measurement index and built a model of influencing factors for online short-term rental user purchase behavior based on the Elaboration Likelihood Model (ELM). This approach aims to uncover post-pandemic consumer eWOM and purchase behavior factors, thereby informing more market-appropriate decision-making for platforms and hosts while assisting users in selecting better listings.

Theoretical Foundation and Literature Review

Online Short-Term Rental User Purchase Behavior

With the rapid development of the sharing economy, online short-term rentals have grown swiftly in major global cities, activating numerous idle housing resources and creating enormous economic value while providing personalized lodging services for billions of users. This phenomenon has attracted widespread scholarly attention. From the perspectives of cognitive trust and institutional trust, various online short-term rental information available on platforms—namely property, host, guest, and transaction data—has been studied. Factors such as listing location [8], property facilities [9], host reputation [10], and pricing [11] have been validated as trust metrics influencing user consumption. Building upon the understanding of trust-consumption relationships, a trust computation framework integrating image and text analysis has been proposed to effectively address host trust evaluation and provide a trustworthy environment for consumers [12]. However, existing research on user purchase behavior has primarily focused on user interaction and trust mechanisms, neglecting antecedent factors influencing the dissemination of listing reputation beliefs in the internet context—namely, the important role of eWOM. Moreover, most studies on the impact of COVID-19 on the industry remain at the qualitative level, analyzing declining consumer willingness and sales performance [13], with no empirical research on post-pandemic purchase behavior influencing factors.

Online Short-Term Rental eWOM

eWOM, first conceptualized by B. Gelb and M. Johnson, refers to information communication and exchange via the internet as a vital form of word-of-mouth propagation [41]. Manifested primarily through online reviews, eWOM represents a biased purchase attitude reflecting consumer recognition and dependence on products and services. As online short-term rental platforms strengthen their content community attributes, research has increasingly focused on how user-generated content (UGC) [15] and marketer-generated content (MGC) [16] influence user perception and booking intentions. Liang et al. explored how online merchant attributes related to service quality affect listing eWOM [4], while Z. Mao found that eWOM positively impacts user repurchase intention and indirectly influences repurchase through subjective norms [17]. Thus, eWOM plays a crucial role in how listing and host attributes affect booking behavior. However, current research often uses review counts or overall ratings as eWOM proxies, which is inaccurate [18]. Since eWOM embodies biased purchase attitudes and emotional tendencies, representing consumer recognition and trust, it can be quantified through sentiment in online reviews. Yet, using only sentiment orientation (positive, neutral, negative) is too coarse-grained. Therefore, this study employs BERT to calculate review sentiment scores, using the mean sentiment score of all reviews for a listing as its eWOM, providing a reference for constructing eWOM measurement indicators.

ELM Model

The ELM model, proposed by R. E. Petty and J. T. Cacioppo in 1986, is a dual-path information processing model suggesting that individuals process information through either central or peripheral routes based on motivation and ability [21]. The central path involves high motivation and ability, leading to careful analysis of information content to determine attitude and behavior change. The peripheral path involves less attention to information content itself, focusing instead on source characteristics and emotional factors to judge usefulness. The two key factors determining information processing path are motivation (desire to process received information) and ability (capacity to evaluate information effectively), which also determine the elaboration level [22]. Consumer product involvement reflects motivation magnitude [23], while professional background and information complexity relate to ability [22]. In internet contexts, platform quality and information quality represent central path variables, whereas spokespersons and emotional tendencies represent peripheral path variables [24]. Feng Jun found that descriptive product information affects purchase decisions through the central path, while knowledge provider reputation signals positively influence through the peripheral path [25]. Huang et al. validated that live streaming platform features and host characteristics positively promote user immersion and satisfaction through central and peripheral paths [24]. The ELM model is also considered important for eWOM research. I. Elvira et al. summarized findings and revalidated 19 factors on central (description length, consistency) and peripheral (source credibility, involvement) paths affecting eWOM and purchase intention [5]. Therefore, this study adopts the ELM model as the theoretical foundation, positing that listing attributes as direct objective descriptions of service quality affect eWOM and purchase behavior through the central path, while host attributes serve as important peripheral cues on the edge path.

Research Hypotheses and Model Construction

Influence of Listing Attributes

The listing is the direct purchase object in short-term rental transactions. Its attributes—including basic facilities, layout, surrounding environment, and location—are fundamental information consumers must analyze when making decisions. Listing overall feature descriptions summarize basic information and main advantages, forming the basis of first impressions. Impression management theory suggests individuals consciously manage impressions others form of them [26]. Hosts can strategically describe listing features to shape positive images, gain trust, and generate good eWOM. Research shows descriptive text length correlates with transaction success [27]. Therefore, more detailed overall feature descriptions deepen consumer understanding, build positive eWOM, and influence decision-making. We hypothesize:

H1a: Listing overall feature description positively affects short-term rental eWOM.
H1b: Listing overall feature description positively affects user purchase behavior.

According to business district theory [28] and core-periphery tourism structure theory [29], surrounding environment and location jointly reflect locational benefits. Administrative, market, and transportation factors divide tourism areas into central and non-central zones, with central areas offering richer resources and higher tourism efficiency [30]. Surrounding environment and location intuitively indicate whether a listing is in a central area. Chen et al. found different spatial distributions affect user trust and attention [8], while S. Jang et al. analyzed how destination location attributes caused consumer behavior heterogeneity during COVID-19 [31]. We hypothesize:

H2a: Listing surrounding environment description positively affects eWOM.
H2b: Listing surrounding environment description positively affects purchase behavior.
H3a: Distance from city center negatively affects eWOM.
H3b: Distance from city center negatively affects purchase behavior.

Internal facility conditions are indispensable for analyzing user behavior [28]. For tenants, the interior is a crucial activity and rest space. Well-equipped facilities eliminate concerns about inconvenience and safety risks, positively impacting eWOM and enabling confident purchase decisions. We hypothesize:

H4a: Number of amenities positively affects eWOM.
H4b: Number of amenities positively affects purchase behavior.

Influence of Host Attributes

Unlike other sharing economy models, short-term rentals involve more host-guest interaction, requiring hosts to provide detailed profiles to enhance source credibility and reduce information asymmetry risks [32]. The number of listings held reflects host experience and operational capability, significantly affecting pricing [33] and consumer trust [34]. "Superhost" status is an honorary title awarded by Airbnb based on annual rental performance across all listings, helping guests assess host capability and eWOM [32]. We hypothesize:

H5a: Number of listings held positively affects eWOM.
H5b: Number of listings held positively affects purchase behavior.
H6a: Superhost certification positively affects eWOM.
H6b: Superhost certification positively affects purchase behavior.

In e-commerce, buyers trust sellers who display authentic information [35]. Identity verification is one of two trust-building mechanisms [36]. Hosts with more comprehensive identity verification demonstrate willingness to share authentic information, gaining trust and eWOM. Longer platform tenure indicates more experience, understanding of consumer psychology, and service quality improvement, leading to higher booking rates [37]. We hypothesize:

H7a: Number of verification methods positively affects eWOM.
H7b: Number of verification methods positively affects purchase behavior.
H8a: Host platform tenure positively affects eWOM.
H8b: Host platform tenure positively affects purchase behavior.

Beyond descriptive information, consumers learn about listings through online chat tools. D. H. McKnight et al. argue trust builds through social interaction, with positive interaction demonstrating goodwill and enhancing trust [38]. Host responsiveness in creating a warm transaction atmosphere is crucial for positive eWOM [39]. Instant booking simplifies the reservation process, allowing immediate confirmation without host approval. This indicates hosts' willingness to take risks to facilitate guest convenience, significantly affecting pricing and bookings [40]. We hypothesize:

H9a: Host response rate positively affects eWOM.
H9b: Host response rate positively affects purchase behavior.
H10a: Instant booking availability positively affects eWOM.
H10b: Instant booking availability positively affects purchase behavior.

Mediating Role of eWOM

First proposed by B. Gelb and M. Johnson, eWOM represents internet-based information exchange [41]. As a biased purchase attitude reflecting consumer recognition and dependence, positive eWOM stimulates consumption [42]. Sentiment polarity divides eWOM into positive, neutral, and negative categories. Positive eWOM triggers impulse buying, while negative eWOM inhibits it [43-44]. Studies have validated how perceived value affects eWOM and how eWOM influences booking volume [45-46]. Recent scholarship has achieved finer-grained characterization by calculating review sentiment indices to explore their impact on sales [47-48]. Therefore, we hypothesize:

H11: eWOM affects user purchase behavior.

Based on this literature review and the ELM model, we constructed a research framework for online short-term rental purchase behavior with eWOM as mediator, shown in Figure 1 [Figure 1: see original paper]. Price, private bathroom availability, and bedroom count—common user filter criteria—are included as control variables.

Data Acquisition and Variable Construction

Founded in 2008, Airbnb has become the world's leading short-term rental platform, accumulating vast amounts of consumption and feedback data. This study collected publicly available Beijing area data from Inside Airbnb as of December 24, 2021 (Table 1).

Table 1 Beijing Area Airbnb Public Dataset

Dataset Name	Fields	Data Volume
listing.csv	Listing ID, reviews in last 30 days, price, type, host join date, 24-hour response rate, listings count, etc.	5,159
Reviews.csv	Listing ID, review ID, date, reviewer ID, nickname, review content	232,224

Since Airbnb does not display transaction order volumes, we use review volume to reflect transaction activity [18]. Based on the research model and collected data, referencing previous Airbnb studies [54-55], we defined variables as shown in Table 4 .

Table 4 Variable Description

Category	Variable	Description
Dependent Variable	User Purchase Behavior (number_{{{of}}_{{orders}}})	Cumulative review count for the listing
Listing Attributes	Overall Feature Description (len_{description})	Text length describing listing features
	Surrounding Environment Description (len_{neighborhood})	Text length describing neighborhood
	Distance from City Center (distance)	Distance from Beijing center (39.91667, 116.41667) in km
	Number of Amenities (amenities_{count})	Count of amenities provided
Host Attributes	Listings Held (host_{{{listings}}_{{count}}})	Total listings owned by the host
	Superhost Certification (host_{{{is}}_{{superhost}}})	1 if superhost, 0 otherwise

Category	Variable	Description
	Verification Methods (host_{{{verifications}}_{{{count}}})	Number of identity verification methods completed
	Platform Tenure (host_{since})	Years since host joined platform (as of Dec 24, 2021)
	Response Rate (host_{{{response}}_{{{rate}}})	Percentage of inquiries responded to
	Instant Booking (instant_{bookable})	1 if enabled, 0 otherwise
Mediator	eWOM (avg_{sentiment})	Mean sentiment score of all reviews (BERT-calculated)
Control Variables	Price, Private Bathroom, Bedroom Count	Current price, bathroom availability, bedroom count

Analysis Results

Correlation Analysis

Correlation and collinearity analysis (Table 5) shows all correlation coefficients below 0.8, with variance inflation factors (VIF) well below 5 (average VIF = 1.370), indicating no serious multicollinearity.

Table 5 Correlation Analysis

[Correlation matrix data preserved with VIF values]

Negative Binomial Regression Analysis

We used Stata for negative binomial regression to test hypotheses. Listing and host attribute results are shown in Tables 6 and 7 . Model (1) shows control variable effects. Models (2)-(5) and (1)-(6) examine direct effects on purchase behavior. Models (11)-(14) and (13)-(18) examine effects on eWOM. Models (6)-(10) and (7)-(12) examine eWOM mediation.

Influence of Listing Attributes Listing overall feature description significantly and positively affects both eWOM (β=0.0004, p<0.001) and purchase behavior (β=0.0017, p<0.001). Surrounding environment description significantly affects purchase behavior (β=0.0006, p<0.05) but not eWOM (β=-0.0001). Distance from city center significantly negatively affects purchase behavior (β=-0.0096, p<0.001) but positively affects eWOM (β=0.0025, p<0.001). Number of amenities significantly positively affects eWOM (β=0.0195, p<0.001) and purchase behavior (β=0.0535, p<0.001). Results are summarized in Table 8 .

Influence of Host Attributes Number of listings held significantly negatively affects eWOM (β=-0.0048, p<0.001) and purchase behavior (β=-0.0065, p<0.05). Superhost certification significantly positively affects eWOM (β=0.4730, p<0.001) and purchase behavior (β=1.1268, p<0.001). Number of verification methods significantly positively affects eWOM (β=0.0438, p<0.001) and purchase behavior (β=0.1434, p<0.001). Platform tenure significantly positively affects eWOM (β=0.0881, p<0.001) and purchase behavior (β=0.3141, p<0.001). Response rate significantly positively affects eWOM (β=0.4141, p<0.001) and purchase behavior (β=0.8976, p<0.001). Instant booking significantly positively affects eWOM (β=0.1246, p<0.001) and purchase behavior (β=0.2773, p<0.001). Results are summarized in Table 9 .

Mediating Role of eWOM Using stepwise testing [56], we found eWOM significantly mediates the relationship between all listing/host attributes (except surrounding environment description) and purchase behavior (Table 10). eWOM serves as a crucial driver of listing sales by transmitting authentic experiences and building trust.

Robustness Check

Following A. Lawani et al. [58] and Yang et al. [54], we used the sum of Airbnb's six review sub-scores as an alternative eWOM measure. Regression results (Tables 11 and 12) are consistent with original findings, confirming model robustness.

Discussion

Influence of Listing Attributes

As shown in Table 8 , listing overall feature description significantly positively affects both eWOM and purchase behavior. As Figure 3 [Figure 3: see original paper] illustrates, these descriptions provide accurate psychological expectations. According to impression management theory, hosts can strategically shape listing images to build trust and eWOM [24,27]. However, surrounding environment descriptions, while reflecting natural, transportation, and economic resources (Figure 4 [Figure 4: see original paper]), become redundant when overlapping with overall descriptions, creating unnecessary cognitive burden that fails to improve eWOM.

Distance from city center significantly negatively affects purchase behavior but positively affects eWOM. Beijing's city center (Dongcheng and Xicheng districts) remains a listing concentration area with high average sales (Figure 5 [Figure 5: see original paper]), consistent with business district theory [28] and core-periphery theory [29]. However, as "suburban tourism" gains popularity post-pandemic, peripheral listings with natural scenery generate more positive sentiment and higher eWOM (Figures 6 [Figure 6: see original paper] and 7 [Figure 7: see original paper]) [59].

Finally, number of amenities significantly positively affects both eWOM and purchase behavior. Comprehensive facilities enhance the "homey" experience and "sense of experience," meeting expectations for "family atmosphere" and differentiating short-term rentals from hotels [28].

Influence of Host Attributes

As Table 9 shows, Superhost certification, verification methods, platform tenure, response rate, and instant booking all significantly positively affect eWOM and purchase behavior. Superhost status, as an authoritative platform certification based on comprehensive annual evaluations, signals quality and facilitates positive eWOM and purchase decisions [32]. More verification methods increase perceived authenticity and reliability [60]. Longer-tenured hosts have optimized their offerings through market adaptation, earning tenant recognition.

Response rate and instant booking also significantly positively affect eWOM and purchase behavior. Pre-transaction communication is vital for information acquisition; timely, detailed responses demonstrate professionalism and build trust, guiding user choices [61]. Instant booking simplifies the reservation process, avoids booking conflicts, and improves communication efficiency, making such listings more attractive [62].

Conversely, number of listings held significantly negatively affects eWOM and purchase behavior. While more listings suggest professional hosts with stronger operational capabilities, research shows professional hosts often charge higher prices [63] and exhibit lower involvement per listing [28], reducing eWOM and purchase intention.

Mediating Role of eWOM

As Table 10 demonstrates, eWOM mediates the relationship between all attributes (except surrounding environment description) and purchase behavior. Addressing trust issues between consumers and service providers is key to sustainable sharing economy operation [64]. As short-term rental platforms strengthen their content community attributes, eWOM transmits authentic experiences to potential users, playing a vital role in building trust and host reputation, and driving listing sales.

Limitations and Future Research Directions

This study explores how specific listing and host attributes affect eWOM and purchase behavior, providing insights for eWOM proxy variable identification and extending ELM model applications. However, limitations remain. First, review sentiment scores may be biased due to platform review control behaviors. Second, using Beijing data limits generalizability to other cities. Future research could integrate text and image analysis, collect multi-city data for comparative analysis, and examine regional differences. Additionally, following Airbnb's exit from China, future studies could apply this model to domestic platforms like Xiaozhu and Tujia to identify operational issues and sustainable development paths for Chinese short-term rental platforms.

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Author Contributions

Huang Qian: Designed research framework, analyzed data, and wrote the paper.
He Chaocheng: Proposed research topic and ideas, conducted data analysis.
Li Xinru: Collected and processed data.
Wu Jiang: Proposed research direction and finalized topic selection.

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