

# The in-depth transmission and reception process of the factors influencing review helpfulness from the signaling timeline perspective

Mohan Wang<sup>1</sup>, Fei Wan<sup>1</sup> ✉, Jiaying Zhang<sup>1</sup>, and Songyun Xia<sup>2</sup>

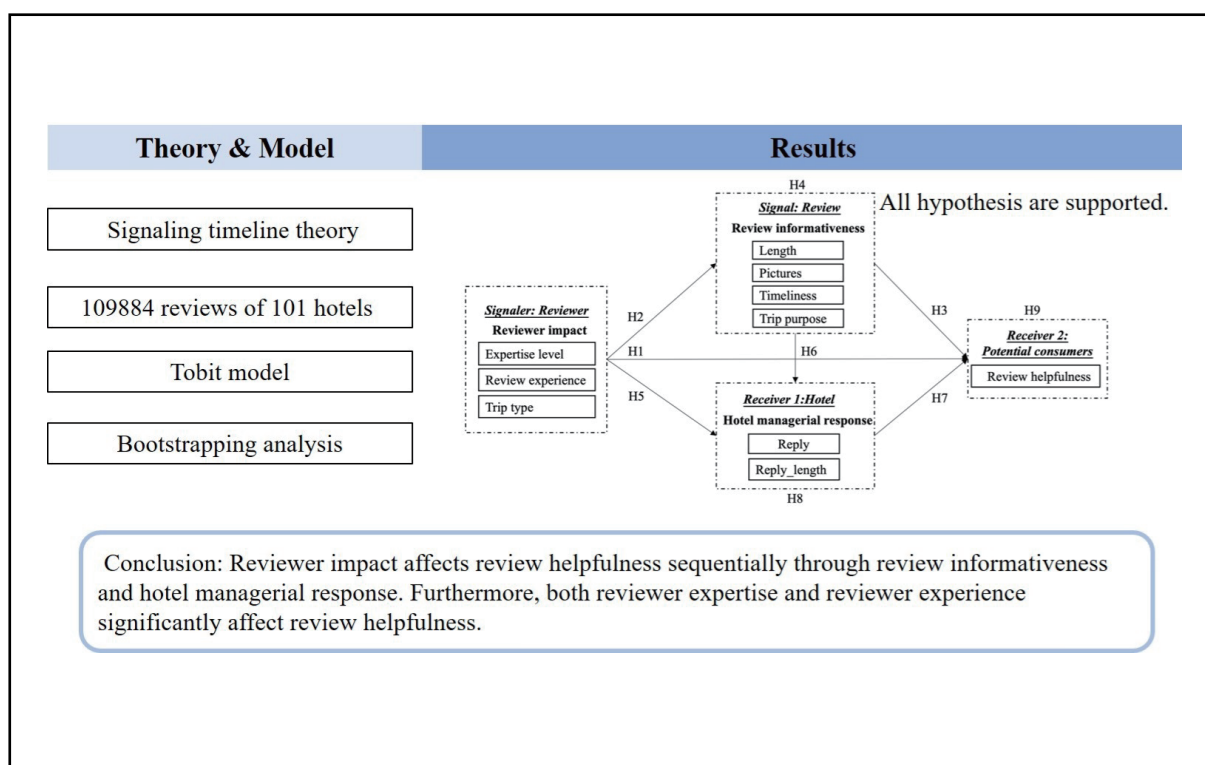
<sup>1</sup>Key Laboratory of Brain-Machine Intelligence for Information Behavior (Ministry of Education and Shanghai), School of Business and Management, Shanghai International Studies University, Shanghai 201620, China;

<sup>2</sup>McKelvey School of Engineering, Washington University in St. Louis, St. Louis, MO 63130, USA

✉Correspondence: Fei Wan, E-mail: [wanfei0304@shisu.edu.cn](mailto:wanfei0304@shisu.edu.cn)

© 2024 The Author(s). This is an open access article under the CC BY-NC-ND 4.0 license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

## Graphical abstract



Following the theoretical framework of the signaling timeline in signaling theory, this study examines how reviewer impact, review informativeness, and hotel managerial responses interact to influence review helpfulness.

## Public summary


- We followed the theoretical framework of the signaling timeline in signaling theory and employed a bootstrapping analysis to examine the transmission and reception process of the factors influencing review helpfulness.
- Reviewer impact may affect review helpfulness sequentially through review informativeness and hotel managerial responses.
- Both reviewer expertise and reviewer experience significantly affect review helpfulness.

# The in-depth transmission and reception process of the factors influencing review helpfulness from the signaling timeline perspective

Mohan Wang<sup>1</sup>, Fei Wan<sup>1</sup> , Jiaying Zhang<sup>1</sup>, and Songyun Xia<sup>2</sup>

<sup>1</sup>Key Laboratory of Brain-Machine Intelligence for Information Behavior (Ministry of Education and Shanghai), School of Business and Management, Shanghai International Studies University, Shanghai 201620, China;

<sup>2</sup>McKelvey School of Engineering, Washington University in St. Louis, St. Louis, MO 63130, USA

 Correspondence: Fei Wan, E-mail: [wanfei0304@shisu.edu.cn](mailto:wanfei0304@shisu.edu.cn)

© 2024 The Author(s). This is an open access article under the CC BY-NC-ND 4.0 license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).



Cite This: *JUSTC*, 2024, 54(10): 1004 (16pp)



Read Online

**Abstract:** Many existing studies have considered the factors influencing review helpfulness, mainly focusing on reviewer impact, review informativeness, and managerial response, based on signaling theory. However, previous studies have simply regarded these factors as independent signals, thus ignoring their in-depth transmission and reception processes. The conclusions about the impact of reviewers on review helpfulness are also inconsistent due to the inaccurate measurement of variables. To fill the above gaps, we followed the signaling timeline theoretical framework used in signaling theory and employed a bootstrapping analysis to examine how reviewer impact, review informativeness, and hotel managerial responses interact to influence review helpfulness. In this study, we used a unique dataset that included official labels from one leading online travel agency. The results show that reviewer impact may affect review helpfulness sequentially through review informativeness and hotel managerial response. Furthermore, by using official labels, both reviewer expertise and reviewer experience significantly affect review helpfulness. Finally, we discussed the theoretical and practical implications of these findings.

**Keywords:** signaling timeline; review helpfulness; reviewer impact; review informativeness; managerial response

**CLC number:** F274.6; F719.2

**Document code:** A

## 1 Introduction

The hospitality industry is strongly influenced by online reviews<sup>[1–4]</sup>. To address the issue of information overload caused by massive amounts of online reviews<sup>[5]</sup>, the majority of online travel agency platforms deploy helpfulness votes on webpages, which represent a review's value perceived by subsequent consumers<sup>[6]</sup>, to assist consumers' decision-making<sup>[7]</sup> and improve the customer conversion rate<sup>[8]</sup>. Therefore, identifying the factors that influence the perceived helpfulness of online reviews is crucial in online hospitality marketing. Many existing studies have considered factors that influence review helpfulness from three main perspectives: (a) reviewer impact, such as reviewer experience, expertise level<sup>[6, 9–11]</sup>, and reviewer historical performance<sup>[12, 13]</sup>; (b) review informativeness, such as review length<sup>[6, 12, 14, 15]</sup>, the number of user-generated photos (UGPs)<sup>[16–18]</sup>, valence, and rating<sup>[6, 14, 19, 20]</sup>; and (c) hotel managerial response (MR)<sup>[19, 21]</sup>.

However, some issues remain in prior studies. First, to better identify the factors influencing review helpfulness, some existing studies<sup>[11, 22]</sup> have introduced signaling theory as a theoretical foundation, conceptualizing reviewer impact, review informativeness, and hotel MRs as independent signals. However, these studies have ignored signals' holistic transmission and reception processes by distinguishing the three

important roles of signaler, signal, and receiver, which are emphasized in signaling theory<sup>[23]</sup>. For example, previous studies<sup>[19]</sup> have explored hotel MRs' direct impact on review helpfulness; the underlying assumption is that a hotel is a signaler sending a response signal to potential consumers, but this assumption ignores that the hotel is a receiver of both the reviewer and the review since the hotel lacks the reviewer's experience information. In this study, we will focus on the impacts of reviewer impact, review content, hotel MRs, and their relationships on review helpfulness based on a signal timeline.

Second, although abundant studies have examined the effect of reviewer experience or expertise on review helpfulness, few studies have investigated the impact of trip purpose on review helpfulness. However, reviewers with different trip purposes will focus on different aspects of hotels, which might be reflected in their review contents<sup>[22]</sup> and thus affect review helpfulness. Practically, many platforms have displayed information regarding reviewers' trip purposes on their review pages. For example, TripAdvisor provides five trip purposes: business, family, couple, solo, and friends. Therefore, understanding the effect of trip purpose on review helpfulness is an important issue in online hospitality marketing.

Third, inconsistent results exist concerning the effect of reviewer impact on review helpfulness since the literature often uses various proxy variables for reviewer impact because of the absence of official measures on platforms. For example, taken as a proxy of reviewer expertise, some scholars used the sum of historical reviews posted by a reviewer<sup>[6]</sup>, while others used the reviewer rank provided by the platform<sup>[12, 23]</sup>; thus, they made the results inconsistent. However, “reviewer expertise” refers to the level of knowledge, experience, and qualifications the reviewer possesses. The term indicates the reviewer’s depth of understanding and proficiency in the subject matter or domain of the review. A reviewer with high expertise is often considered more reliable and credible in providing insightful and informative evaluations or assessments. The sum of the historical review volume reflects only the reviewer’s experience. However, it could not reflect the reviewer’s professional ability, so it could not demonstrate their expertise. By utilizing official labels from a leading online travel agency in our unique dataset, we can provide a more accurate and reliable assessment of reviewer expertise to ensure robustness and validity.

To better identify the factors influencing review helpfulness and fill the above research gaps, we investigated in-depth the transmission and reception processes of the factors influencing review helpfulness in the signaling timeline theoretical framework by using official measures and revealing the roles of the reviewer, review, and hotel. In the signaling timeline, reviewers post reviews based on their experience, expertise, and trip purpose. The review content serves as a signal to hotels. They receive review content as receivers and respond to reviews. Potential consumers could observe reviewer impact, review content, and hotel MRs as signals. In this sense, reviewers and hotels are signalers, and potential consumers are receivers.

To test the above models, we collected a unique dataset including 109884 valid reviews from Ctrip.com. We used comprehensive bootstrapping analysis to explore the relationships among the factors influencing review helpfulness in signaling timeliness in-depth, including reviewer impact, review informativeness, and hotel MRs. Our empirical findings show that reviewer impact may affect review helpfulness sequentially through review informativeness and hotel MRs.

Furthermore, after distinguishing between reviewer expertise and reviewer experience with official labels, we found that both significantly affected review helpfulness. Moreover, the trip purpose, which reflects the reviewer’s real experience with the hotel, can significantly positively affect a review’s helpfulness. This study has both theoretical and practical implications.

## 2 Literature review

### 2.1 Review helpfulness and signaling theory

Review helpfulness refers to the extent to which an online review facilitates consumers’ purchase decisions<sup>[24]</sup> and can be measured by review helpfulness votes<sup>[6]</sup>. Several studies have applied signaling theory to explore the factors that affect review helpfulness<sup>[11, 25]</sup> because the introduction of signaling theory can better explain consumers’ behaviors when judging whether online reviews are helpful<sup>[26]</sup>. Signaling theory is fundamentally concerned with reducing information asymmetry between two parties<sup>[27]</sup>. The core ideas of signaling theory involve the proposal of three primary elements, as illustrated in Fig. 1, namely, the signaler, receiver, and signal<sup>[28]</sup>.

Signalers generate signals that include information about an individual<sup>[29]</sup>, product<sup>[30]</sup>, or organization<sup>[31]</sup>. Efficacious signals have two main characteristics: signal observability and signal cost<sup>[32]</sup>. Receivers receive signals, interpret signals, and send feedback, which might affect other receivers<sup>[28]</sup>.

In prior research<sup>[11]</sup>, the factors that affect review helpfulness can often be divided into three general categories: reviewer impact (i.e., reviewer expertise, reviewer experience), review informativeness (i.e., review length, the number of UGP reviews, timeliness, and trip purpose), and hotel MRs. Thus, we next review the literature on the factors influencing review helpfulness in the above three streams of literature.

### 2.2 Factors influencing review helpfulness

#### 2.2.1 The effect of reviewer impact on review helpfulness

The expertise level can be defined as the extent to which expert reviews are perceived as providing correct information<sup>[33]</sup>; this can be measured by evaluating the degree of

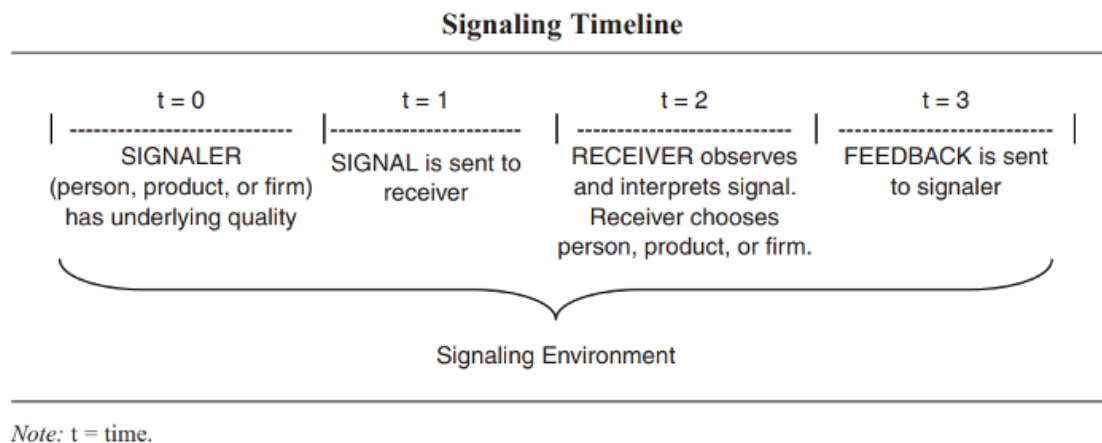


Fig. 1. Signaling timeline<sup>[28]</sup>.

competence and knowledge that a message contains<sup>[34]</sup>. However, because of the absence of formal and consistent measures, previous studies have often taken reviewers' past behaviors, such as their number of previous reviews<sup>[6, 20, 35]</sup> or the reviewer rank provided by the platform<sup>[11, 25]</sup>, as a proxy for the relationship between reviewers' expertise levels and review helpfulness. The variable measurement leads to inconsistent results in prior studies: Some research has reported that this relationship is positive<sup>[11, 25]</sup>, whereas other research has shown it to be negative<sup>[35]</sup> or even nonsignificant<sup>[6]</sup>.

Reviewer experience serves as an indicator of unobservable quality<sup>[36]</sup>. Because of the absence of a formal and consistent measure, reviewer experience has often been measured by the sum of historical reviews that reviewers have written<sup>[10, 12, 23]</sup> or through three dimensions: reviewer status, reviewer membership, and the average number of cities visited by reviewers<sup>[19]</sup>. This approach might lead to inconsistent findings on the relationship between reviewer experience and review helpfulness, with some indicating a positive relationship<sup>[19, 23]</sup> and others indicating an insignificant or negative relationship<sup>[12]</sup>. Additionally, prior studies have ignored reviewers' experience with posting pictures in reviews, which are more effective than review text to consumers.

Reviewer historical performance serves as an indicator of the unobservable quality signal that can be measured by the total votes on all reviews written by a reviewer<sup>[12]</sup>. There are inconsistent conclusions on whether the relationship between reviewer historical performance and review helpfulness is positive<sup>[13]</sup> or nonsignificant<sup>[12]</sup>.

Considerable attention has been given to the effect of reviewer impact on review helpfulness; however, previous studies have often used various methods to assess the same reviewer impact<sup>[6, 12, 23]</sup>, which has led to inconsistent results. Most importantly, in the context of the entire process of signal transmission and reception, the role of reviewer impact must be discussed in-depth.

## 2.2.2 Review informativeness

The review length refers to the number of words<sup>[10, 14, 15, 35]</sup> or characters<sup>[9]</sup> in a review. Review length may vary widely depending on reviewers' writing skills and expertise<sup>[10, 12]</sup>. Generally, reviews with more words may contain relatively more information to assist consumers in obtaining indirect consumption experiences<sup>[6, 24]</sup>. Prior research<sup>[6, 14]</sup> has paid attention to review length's positive and significant impact on review helpfulness. Furthermore, Huang et al.<sup>[12]</sup> argued that the likelihood of a review being valuable gradually decreases as the number of words surpasses a particular value.

According to previous research, UGPs have a significant and positive impact on review helpfulness<sup>[16–18]</sup> because reviewers often take advantage of visual information to increase credibility<sup>[37, 38]</sup>. The number of UGPs in a review has a positive relationship with the review's helpfulness<sup>[15]</sup>. Likewise, An et al.<sup>[18]</sup> asserted that UGPs are indicative of online hotel review helpfulness. Li et al.<sup>[17]</sup> revealed that reviews with UGPs obtained more helpfulness votes than reviews without UGPs.

Review timeliness has been measured using different methods; for example, measurements based on the number of

elapsed days since the review was posted revealed that reviews posted more recently tended to obtain more helpfulness notes than older reviews<sup>[13, 39]</sup>. In other words, review timeliness has a positive effect on review helpfulness<sup>[9, 40]</sup>. However, in the context of hospitality, long-term online reviews may be outdated because the hotel might be updated or redecorated. Thus, whether a review has been published recently seems important.

The purpose of a trip is an important personal characteristic of a traveler<sup>[41]</sup>. When sharing hotel reviews, consumers with various trip purposes tend to talk about different aspects that are important to them<sup>[22]</sup>. Various types of traveler groups demonstrate large differences in hotel attributes that they deem important<sup>[42]</sup>. However, little attention has been given to the impact of trip purpose on review helpfulness. Moreover, when studying trip purpose, some researchers have reclassified trip purpose into general categories, such as business and leisure<sup>[43, 44]</sup>, whereas others have used the labels provided by review platforms<sup>[22, 42]</sup>.

In brief, although some related research has focused on the effects of review informativeness on review helpfulness, several important dimensions related to reviews have not been thoroughly studied, such as the timeliness of reviews measured by the interval between reviewers' check-in times and their review times. In particular, most related research has ignored the mediating effect of review informativeness on the relationship between reviewer impact and review helpfulness.

## 2.2.3 Hotel managerial response

A MR refers to a company's effort to interact with and respond to its customers<sup>[45]</sup>, which can enhance customer satisfaction and trust<sup>[46]</sup>. For hotel managers, their MR strategy is highly important and effective in improving customer satisfaction<sup>[47]</sup>. Research has been conducted to explore the impact of MRs<sup>[21, 48]</sup>; for example, MR length moderates the effects of review sentiment and review length on review helpfulness<sup>[21]</sup>. However, most related research has ignored the mediating effect of hotel MRs on the relationships among reviewer impact, review informativeness, and review helpfulness.

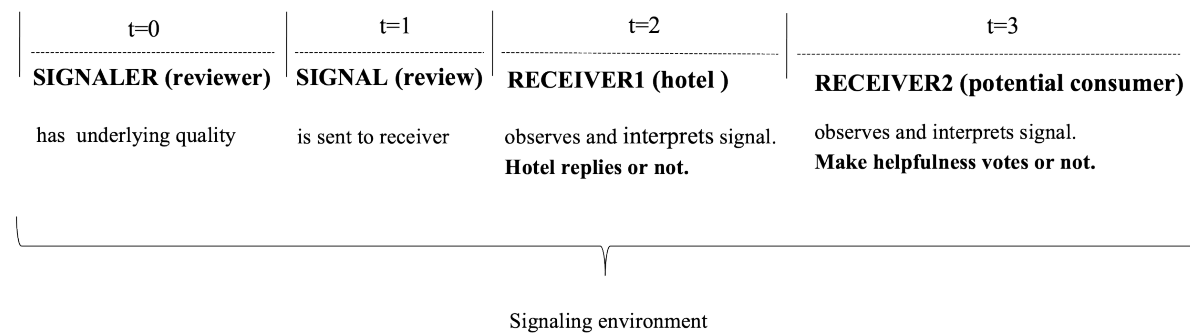
# 3 Hypothesis development

In our context, reviewers can be regarded as signalers who have specific and fresh experience with hotels and, therefore, who have knowledge that hotels and potential consumers have not yet gained. Hotels and potential consumers can be regarded as receivers who receive the signals sent by reviewers, interpret signals, and send feedback that might affect other receivers. Specifically, potential consumers can give helpfulness votes, and hotels can send MRs, which have an impact on potential consumers and thus affect review helpfulness<sup>[19]</sup>. We developed the signaling timeline model shown in Fig. 2.

To better interpret the signal transmission process in online hospitality, as shown in Fig. 2, we developed our research hypotheses as follows.

According to prior studies<sup>[6, 10, 12]</sup>, review helpfulness can be affected by reviewer impact, including reviewer expertise level<sup>[6, 20]</sup>, reviewer experience<sup>[10, 12, 23]</sup>, and reviewer historical





Note: t = time

Fig. 2. Signaling timeline in this study.

performance<sup>[12, 13]</sup>. We selected the above variables as reviewers' impact because these characteristics exist before a reviewer posts a review. Different types of traveler groups may discuss different focuses when posting reviews<sup>[22]</sup>, which may affect their helpfulness. Thus, following prior research, we propose the following hypothesis.

**H1.** Reviewer impact significantly affects review helpfulness.

According to the theory of personality traits<sup>[49]</sup>, people's characteristics affect their behaviors. This theory provides a foundation for understanding how reviewers' characteristics can impact their review behaviors. For example, reviewers with expert-level badges tend to leave lower ratings and lengthier reviews than low-level reviewers<sup>[10, 50]</sup>. Reviewers with rich experience earning digest review badges tended to exert more effort than other reviewers when posting subsequent digest reviews<sup>[51]</sup>.

In addition, the reviewer's trip purpose might affect the focus of their review content; that is, reviewers with different trip purposes tend to discuss various aspects based on what is important to them<sup>[22]</sup>, which may affect review informativeness.

Thus, we propose the following hypothesis.

**H2.** Reviewer impact significantly affects review informativeness.

According to the extant studies, a review's length<sup>[6, 14]</sup> and number of UGPs<sup>[15, 17]</sup> are two important signals that readers use to judge whether the review is helpful. Longer reviews and a greater number of UGPs are often perceived as indicators of more detailed and informative reviews, thus increasing their perceived helpfulness. Moreover, according to forgetting theory<sup>[52]</sup>, it is reasonable to believe that after a longer interval between the review time and the hotel stay, a reviewer may forget more details. This implies that after a longer interval between the review time and the actual hotel stay, a reviewer may have a diminished recollection of specific experiences or incidents. The intervals between reviewers' check-in times and review times determine the reviews' timeliness, which can also be seen by potential consumers. Drawing from this understanding, we utilize the intervals between the reviewers' check-in times and the review times as a measure of review informativeness. A timelier review is likely to be more informative because it is based on recent experience, whereas a delayed review may be less detailed or accurate due to the

potential loss of specific memories.

Thus, we propose the following hypothesis.

**H3.** Review informativeness significantly affects review helpfulness.

In the signaling timeline, signalers with different qualities send signals at different costs<sup>[53]</sup>, which could affect the receivers' interpretations and, subsequently, their feedback<sup>[54]</sup>. This means that individuals who possess higher qualities or expertise are more likely to invest additional effort and resources in signaling their qualities. Likewise, individuals with lower qualities may send signals that require less investment or effort. In summary, signaling theory suggests that the impact of a signaler can influence the informativeness of their signals, which subsequently affects how helpful the signals are perceived by receivers.

In the context of online reviews, reviewer impact refers to the perceived influence or expertise of the reviewer. High-impact signalers are likely to provide more informative and detailed reviews, as they have the knowledge and experience to evaluate various aspects of the reviewed product or service. In contrast, signalers with low impact may provide less informative or less helpful reviews. When receivers (potential consumers) interpret these signals, they consider the impact of the signaler and make judgments about the review's informativeness and helpfulness. Higher-impact signalers are generally expected to provide more informative reviews due to their expertise; therefore, their signals are more likely to be perceived as helpful by receivers<sup>[54]</sup>.

That is, reviewer impact may affect review informativeness and, subsequently, review helpfulness. Thus, we propose the following hypothesis.

**H4.** Reviewer impact affects review helpfulness through review informativeness.

According to signaling theory, signal receivers, such as hotels, play a crucial role in the signaling process. When hotels receive reviews from signalers, they must decide whether to respond and, if so, how to provide feedback. The decision-making process of hotels in response to reviews is influenced by various factors, including the impact or status of the reviewer<sup>[49]</sup>.

Hotels tend to prioritize interactions with reviewers who have a higher status, such as senior reviewers, contributors, senior contributors, and top contributors. These reviewers are

seen as more influential, experienced, or knowledgeable, and their feedback carries more weight in the eyes of hotel management. Hotel managers may allocate more attention, resources, and effort to engaging with these high-impact reviewers, providing more detailed and personalized responses. Conversely, reviews from low-impact reviewers may receive relatively less attention or limited responses from the hotel. Therefore, it is reasonable to expect that reviewer impact, which captures the perceived influence or expertise of the reviewer, will affect the responses given by hotel managers. Thus, we propose:

**H5. Reviewer impact significantly affects hotel MRs.**

According to signaling theory, signal receivers, such as hotel managers, are motivated to respond to signals that provide valuable information or highlight areas of improvement. In the context of online reviews, hotel managers are inclined to address reviews with low ratings, as they indicate potential service failure or customer dissatisfaction<sup>[55]</sup>. By responding to these reviews, hotels can acknowledge and rectify any issues, ultimately aiming to increase customer satisfaction<sup>[56]</sup>.

This finding suggests that review informativeness plays a crucial role in influencing hotel MRs. Reviews that are informative, detailed, and provide specific feedback about the service experience are more likely to attract the attention of hotel managers. These reviews provide valuable insights into areas where improvements can be made, allowing hotel managers to respond accordingly. Conversely, hotel managers may receive relatively limited information from less informative reviews that lack specific details or fail to highlight any areas of concern. Informativeness serves as an important signal for hotel managers to identify issues and prioritize their responses. Thus, we propose the following hypothesis.

**H6. Review informativeness significantly affects hotel MRs.**

According to signaling theory, within the signaling environment, the presence of external referents, including other receivers, can influence the relationships between signalers and receivers<sup>[54]</sup>. In the context of online reviews, one such external referent is hotel MRs.

Research has consistently shown a significant relationship between hotel MRs and review helpfulness<sup>[21, 48]</sup>. Specifically, studies have shown that reviews that receive a response from a hotel are perceived as more helpful than reviews without a hotel MRs<sup>[19]</sup>. This finding suggests that the presence of a hotel's response in the review environment serves as a positive signal to potential consumers.

Hotel MRs not only address the concerns or issues raised by the reviewer but also reflects the hotel's attentiveness, commitment to customer satisfaction, and willingness to engage with guests. Consequently, reviews that involve hotel MRs are often perceived as more credible and reliable, which increases their perceived helpfulness.

Thus, we propose the following hypothesis.

**H7. Hotel MRs significantly affect review helpfulness.**

According to signaling theory, within the signaling environment, signaling agents can influence the feedback of receivers not only through the signals they issue directly but also by influencing feedback from other receivers<sup>[54]</sup>. In our context of online reviews, reviewers act as signalers who

possess unique experience information that is distinct from that of both the hotel and potential consumers.

Reviewers with greater impact, who are perceived as more influential or experienced, are likely to issue signals that carry greater weight in the eyes of both the hotel and potential consumers. As a result, hotels are more likely to pay closer attention to reviews from high-impact reviewers and to provide MRs. This response from the hotel acts as an additional signal that reinforces the reviewer's impact.

This interaction between the reviewer's impact, the hotel MRs, and potential consumers is a crucial aspect of the signaling environment. A hotel's response to reviews from high-impact reviewers may influence potential consumers' perceptions of the review's helpfulness. A hotel's acknowledgement and engagement with the reviewer's feedback through the response can contribute to the perceived credibility and usefulness of the review for potential consumers. Thus, we propose:

**H8. Reviewer impact affects review helpfulness through hotel MRs.**

In the context of online reviews, the impact characteristics of reviewers can influence the level of informativeness of their reviews. Previous research has shown that reviewers with higher impact tendencies tend to provide more detailed and informative reviews<sup>[10]</sup>. Because these reviewers possess greater expertise or experience, their reviews are likely to contain richer information that can help the hotel identify areas for improvement or address specific concerns. According to signaling theory, hotel feedback in response to reviews is influenced by various factors, including the informativeness of the reviews. Hotel managers tend to be more inclined to respond to reviews that provide informative and specific feedback<sup>[55]</sup>. This responsiveness is driven by the value they perceive in addressing and resolving any issues or concerns raised by the reviewer.

Considering these relationships, we propose a sequential causal path from reviewer impact to review helpfulness, mediated by review informativeness and hotel MRs. The reviewer impact, as an initial factor, influences the level of informativeness in the review itself. Higher-impact reviewers are more likely to provide informative reviews, which can then attract the attention of hotel managers. As a result, hotel managers are more likely to respond to reviews from high-impact reviewers, acknowledging and addressing the issues raised in the review. This MR from the hotel serves as an additional signal that contributes to the perception of review helpfulness among potential consumers.

Thus, we propose the following hypothesis.

**H9. Reviewer impact affects review helpfulness sequentially, first through review informativeness and then through hotel MRs.**

Fig. 3 shows our study's research framework.

## 4 Methodology

### 4.1 Data and variables

We obtained data from Ctrip.com, one of the world's leading online travel agencies. To collect adequate samples, we chose the Shanghai Jing'an Temple/Nanjing West Road area, which is a popular business district and tourist attraction. We

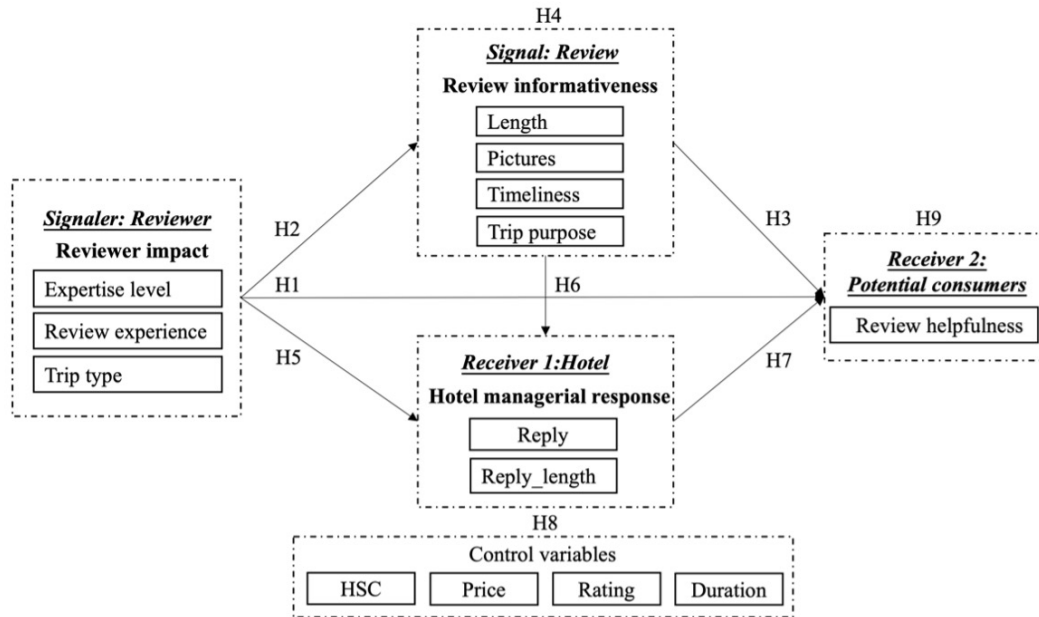


Fig. 3. Research framework.



Fig. 4. A snapshot of a review web page on Ctrip.com.

collected data from 109884 reviews of 101 hotels in this area on March 28, 2020<sup>①</sup>.

Notably, Ctrip.com authorizes official labels for reviewer characteristics, which are shown in Fig. 4. Reviewer expertise levels include newcomer, master, and expert. Reviewer experience includes the number of reviews and pictures in the reviews that the reviewer has posted. Following prior studies, reviewer impact is evaluated by the total number of helpfulness votes that the reviewer has gained<sup>[12]</sup>.

As shown in Fig. 5, Ctrip.com categorizes reviews based on seven kinds of trip purpose: business, family, solo, reserving for others, couples, friends, and others. In particular, the trip purpose label effect arises from subsequent consumers' ability to use the IT filter tool to search for reviews based on their trip purpose labels.

Hotels on Ctrip.com are classified as either star-hotels or diamond-hotels. The variable descriptions are shown in Table 1. The descriptive statistics of all the variables are displayed in Table 2.



Fig. 5. An IT filter tool based on the trip purpose to identify reviews on Ctrip.com.

① The data contains 164646 reviews for 160 hotels on March 28, 2020. However, Ctrip.com also featured 59 sharing houses, which are different from hotels in many aspects, such as scale, price, and experience. The data regarding those sharing houses was not acceptable for our research context, so we did not include them in our study.

**Table 1.** Variable descriptions.

Variable	Description
<i>Ln_helpfulness</i>	The logarithmic form of helpfulness votes received by the review <i>j</i> of hotel <i>i</i>
<i>Reviewer_impact</i>	<i>Expertise<sub>ijp</sub></i> The reviewer expertise <i>p</i> of review <i>j</i> of hotel <i>i</i> , including <i>Newcomer</i> , <i>Master</i> , <i>Expert</i>
	<i>Experience<sub>ijq</sub></i> The reviewer experience <i>q</i> of review <i>j</i> of hotel <i>i</i> , including <i>Sum_reviews</i> (the sum of reviews s/he posted), <i>Avg_pics</i> (the average number of pictures s/he posted per review)
	<i>Avg_helps<sub>ij</sub></i> The average number of helpfulness votes reviewer gained per review of hotel <i>i</i>
	<i>Trip_purpose<sub>ijm</sub></i> If the trip purpose of review <i>j</i> of hotel <i>i</i> is <i>m</i> , its value equals 1; otherwise 0. Specifically, <i>m</i> refers to <i>Family</i> , <i>Friends</i> , <i>Business</i> , <i>Couple</i> , <i>Solo</i> , <i>Other</i> , <i>ResforO</i> (reserving for other people)
<i>Review_informativeness</i>	<i>Length<sub>ij</sub></i> The number of words in the review <i>j</i> of hotel <i>i</i>
	<i>UGPs<sub>ij</sub></i> The number of use-generated photos in the review <i>j</i> of hotel <i>i</i>
	<i>Timeliness<sub>ij</sub></i> The interval between the review time of the review <i>j</i> of the hotel <i>i</i> and its check-in time
<i>Hotel_MRs</i>	<i>Reply<sub>ij</sub></i> If the review <i>j</i> of hotel <i>i</i> is replied to by the hotel manager, the value equals 1
	<i>Reply_length<sub>ij</sub></i> The number of reply words in the review <i>j</i> of hotel <i>i</i>
Control variables	<i>HSC<sub>i</sub></i> The star/diamond level of hotel <i>i</i>
	<i>Price<sub>ij</sub></i> The room price of review <i>j</i> of hotel <i>i</i> (take log)
	<i>Rating<sub>ij</sub></i> The rating of the review <i>j</i> of hotel <i>i</i>
	<i>Review_age<sub>ij</sub></i> The time elapsed (in days) since the date on which review <i>j</i> of hotel <i>i</i> was posted

∴ Hotels on Ctrip.com are classified as either star-hotels or diamond-hotels. If a hotel is rated by the Ministry of Culture and Tourism of the People's Republic of China, its star level is shown on its web page; otherwise, the diamond-level determined by Ctrip is shown on the web page.

#### 4.2 Econometric models

We employed a bootstrapping analysis<sup>[55]</sup> to test the complete review signaling transmission and reception process in our context. Unlike the traditional causal model for testing mediating effects<sup>[56]</sup> and the Sobel test<sup>[57]</sup>, the bootstrap method does not assume the distribution of coefficient products and can be extended to two or more mediating variables without prior analysis.

In the dataset, the distribution of review helpfulness appears to be left skewed; 99.12% of the data are between 0 and

5, with 142 as the maximum value, as shown in Table 3. Thus, we used the logarithmic form of review helpfulness as a dependent variable (i.e., *Ln\_helpfulness*). Because 91.67% of the review helpfulness scores were zero, which affected the estimation effect of the ordinary least squares model, we used a Tobit model rather than a linear model because of the sample's censored nature<sup>[24]</sup>. Additionally, when the dependent variable is *Reply*, which is a binary variable, a logistic regression is conducted.

To test our hypotheses, our model specifications are as follows:

$$Ln\_helpfulness_{ij} = \alpha_0 + \alpha_1 \sum_{p=1}^3 Expertise_{ijp} + \alpha_2 \sum_{q=1}^2 Experience_{ijq} + \alpha_3 Avg\_helps_{ijw} + \alpha_4 \sum_{m=1}^7 Trip\_purpose_{ijm} + \alpha_5 HSC_i + \alpha_6 Price_{ij} + \alpha_7 Rating_{ij} + \alpha_8 Review\_age_{ij} + \lambda_i + \epsilon, \quad (1)$$

$$Review\_informativeness_{ijr} = \beta_0 + \beta_1 \sum_{p=1}^3 Expertise_{ijp} + \beta_2 \sum_{q=1}^2 Experience_{ijq} + \beta_3 Avg\_helps_{ijw} + \beta_4 \sum_{m=1}^7 Trip\_purpose_{ijm} + \beta_5 HSC_i + \beta_6 Price_{ij} + \beta_7 Rating_{ij} + \beta_8 Review\_age_{ij} + \lambda_i + \epsilon, \quad (2)$$

$$Hotel\_MRs_{ijh} = \gamma_0 + \gamma_1 \sum_{p=1}^3 Expertise_{ijp} + \gamma_2 \sum_{q=1}^2 Experience_{ijq} + \gamma_3 Avg\_helps_{ijw} + \gamma_4 \sum_{m=1}^7 Trip\_purpose_{ijm} + \gamma_5 HSC_i + \gamma_6 Price_{ij} + \gamma_7 Rating_{ij} + \gamma_8 Review\_age_{ij} + \lambda_i + \mu, \quad (3)$$

$$Ln\_helpfulness_{ij} = \delta_0 + \delta_1 \sum_{p=1}^3 Expertise_{ijp} + \delta_2 \sum_{q=1}^2 Experience_{ijq} + \delta_3 Avg\_helps_{ij} + \delta_4 \sum_{m=1}^7 Trip\_purpose_{ijm} + \delta_5 \sum_{r=1}^3 Review\_informativeness_{ijr} + \delta_6 \sum_{h=1}^2 Hotel\_MRs_{ijh} + \delta_7 HSC_i + \delta_8 Price_{ij} + \delta_9 Rating_{ij} + \delta_{10} Review\_age_{ij} + \lambda_i + \omega. \quad (4)$$



**Table 2.** Descriptive statistics for the variables.

Variable		Min	Max	Mean	SD
Expertise	Newcomer	0	1	0.3585	0.4796
	Master	0	1	0.4506	0.4976
	Expert	0	1	0.1901	0.3930
Experience	Sum_reviews	0	4673	24.4775	90.1238
	Avg_pics	0	9	0.316	0.814
Reviewer historical performance	Avg_helps	0	150.091	0.241	1.6065
Trip purpose	Family	0	1	0.1519	0.3590
	Friends	0	1	0.1099	0.3127
	Business	0	1	0.4860	0.4998
	Couple	0	1	0.0849	0.2788
	Solo	0	1	0.0716	0.2578
	Other	0	1	0.0563	0.2305
	ResforO	0	1	0.0395	0.1948
Review_informativeness	Length	0	1439	30.9138	43.1085
	UGPs	0	9	0.2685	1.1100
	Timeliness	0	394	50.7795	68.5643
Hotel_MRs	Reply	0	1	0.5477	0.4977
	Reply_length	49	1161	129.33	68.9901
Control variables	HSC	2	5	3.908	0.94
	Price	4.3174	10.4625	6.101	0.7765
	Rating	1	5	4.6371	0.7301
	Review_age	0	1096	580.7437	312.3761
Dependent variables	Ln_helpfulness	0	4.9628	0.0874	0.3395

The sample size of *Reply\_length* is 60180, and the sample size of other variables is 109884.

**Table 3.** Distribution of review helpfulness.

Review helpfulness	Frequency	Percent
0	100731	91.67%
1	5636	5.13%
2	1426	1.30%
3–10	1716	1.56%
>11	375	0.33%
Total	109884	100%

Following previous studies, we included control variables in all the models: *HSC*, i.e., hotel star level [26, 58–60]; *Price*, i.e., price [60, 61]; *Rating*, i.e., review rating [12, 24]; and *Review\_age*, i.e., time elapsed (in days) since the date on which the review was published until our data collection date [9, 39]. Furthermore, we also control for the effect of hotel heterogeneity  $\lambda_i$  in our model. To ensure that all the variables fit into the same model, we tested the multicollinearity of all the independent variables, and the mean VIF (variance inflation factor) was 2.23, which indicates that multicollinearity is not a problem in

our research.

## 5 Results

### 5.1 Main results

The results of the above-described models are shown in Table 4.

Model 1's results indicate that reviewer impact (including expertise, experience, and trip purpose) significantly affects review helpfulness; it's worth to note that we take "others" of trip purpose as the baseline. Thus, they support H1.

Model 2's results indicate that the reviewer impact significantly affects review informativeness; thus, they support H2.

Model 3's results indicate that both reviewer impact and review informativeness significantly affect hotel MRs; thus, they support H5 and H6.

Model 4's results clarify that both review informativeness and hotel MRs significantly affect review helpfulness; thus, they support H3 and H7. Moreover, *Reply\_length* has a significant and negative relationship with review helpfulness, whereas *Reply* has a positive relationship with review helpfulness. Thus, H6 is supported.

Considering the complete review signaling transmission and reception process, we employed a bootstrap analysis

**Table 4.** Estimation results.

		Model 1	Model 2			Model 3		Model4
		<i>Ln_helpfulness</i>	<i>Review_informativeness</i>			<i>Hotel_MRs</i>		<i>Ln_helpfulness</i>
			<i>Length</i>	<i>UGPs</i>	<i>Timeliness</i>	<i>Reply</i>	<i>Reply_length</i>	
<i>Expertise</i>	<i>Master</i>	−0.109*** (0.02)	−0.496* (0.29)	−0.035*** (0.01)	15.587*** (0.45)	0.073*** (0.01)	2.923*** (0.54)	−0.036* (0.02)
	<i>Expert</i>	−0.152*** (0.03)	6.821*** (0.40)	−0.003 (0.01)	13.430*** (0.66)	0.186*** (0.02)	7.505*** (0.73)	−0.140*** (0.03)
	<i>Sum_reviews</i>	0.025** (0.01)	3.497*** (0.20)	0.002** (0.00)	0.351 (0.28)	−0.026*** (0.01)	−1.161*** (0.24)	0.004 (0.01)
	<i>Avg_pics</i>	0.410*** (0.01)	12.998*** (0.31)	0.865*** (0.01)	−3.790*** (0.20)	0.014 (0.01)	1.007** (0.41)	0.011 (0.01)
<i>Experience</i>	<i>Avg_helps</i>	0.123*** (0.00)	1.064*** (0.17)	0.004** (0.00)	−0.681*** (0.13)	−0.071 *** (0.01)	−1.130*** (0.20)	0.106*** (0.00)
	<i>Family</i>	0.475*** (0.06)	10.418*** (0.59)	0.146*** (0.01)	−8.180*** (1.28)	0.161*** (0.04)	12.302*** (1.27)	0.194*** (0.06)
	<i>Friend</i>	0.337*** (0.06)	5.999*** (0.60)	0.104*** (0.01)	−4.937*** (1.31)	0.017 (0.04)	4.454*** (1.28)	0.152*** (0.06)
	<i>Business</i>	0.228*** (0.06)	1.080** (0.50)	0.102*** (0.01)	−5.459*** (1.19)	−0.041 (0.03)	2.112* (1.12)	0.097* (0.05)
<i>Trip_purpose</i>	<i>Couple</i>	0.393*** (0.06)	6.711*** (0.69)	0.125*** (0.01)	−6.918*** (1.33)	0.004 (0.04)	2.307* (1.33)	0.161*** (0.06)
	<i>Solo</i>	0.359*** (0.07)	6.309*** (0.71)	0.153*** (0.01)	−7.029*** (1.36)	−0.042 (0.04)	10.910*** (1.51)	0.132** (0.06)
	<i>Other</i>	0.508*** (0.07)	7.182*** (0.75)	0.120*** (0.01)	−11.141*** (1.41)	0.009 (0.04)	1.104 (1.47)	0.244*** (0.06)
<i>Length</i>						0.004*** (0.00)	0.192*** (0.01)	0.007*** (0.00)
<i>Review_infor-</i> <i>mativity</i>	<i>UGPs</i>					0.029*** (0.01)	1.070*** (0.30)	0.255*** (0.01)
	<i>Timeliness</i>					−0.001*** (0.00)	−0.024*** (0.00)	−0.009*** (0.00)
	<i>Reply</i>							0.073* (0.04)
<i>Hotel_MRs</i>	<i>Reply_length</i>							−0.001*** (0.00)
Control variables included & hotel heterogeneity effect included								
Constant		−1.111 (3.87)	103.179*** (14.33)	−0.467*** (0.07)	28.026*** (10.81)	45.861*** (10.30)	0.965 (4.02)	−1.229 (3.58)
<i>N</i>		109822	109822	109822	109822	109822	109822	109822
<i>R</i> <sup>2</sup>		0.161	0.148	0.451	0.052	0.602	0.231	

\*\*\*significance:  $p < 0.01$ , \*\*significance:  $p < 0.05$ , \*significance:  $p < 0.1$ .

according to the above regressions. Table 5 reports the results for the transmission and reception processes, which demonstrate that reviewer impact affects review helpfulness through review informativeness. Thus, these results support H4.

Table 6 reports the results for the transmission and

reception process, which show that reviewer impacts affect review helpfulness through hotel MRs. Thus, these results partially support H7.

Table 7 reports the results regarding the reviewer impact on review helpfulness through review informativeness and on

**Table 5.** Test results for the process: reviewer, review, and helpfulness.

<i>Reviewer_impact ⇒ Review_informativeness ⇒ Ln_helpfulness</i>	<i>Reviewer_impact and Trip_purpose</i>	Conf.	[95% conf. interval]	
<i>Reviewer_impact ⇒ Length ⇒ Ln_helpfulness</i>	<i>Master</i>	−0.0051**	−0.009546	−0.000708
	<i>Expert</i>	0.0274***	0.018674	0.036105
	<i>Sum_reviews</i>	0.0002***	0.000136	0.000213
	<i>Avg_pics</i>	0.0015***	0.001143	0.001872
	<i>Avg_helps</i>	0.0006***	0.000397	0.000779
	<i>Family</i>	0.1034***	0.091358	0.115434
	<i>Friends</i>	0.0568***	0.046540	0.067015
	<i>Business</i>	0.0097**	0.001926	0.017384
	<i>Couple</i>	0.0688***	0.057840	0.079743
	<i>Solo</i>	0.0688***	0.056906	0.080736
	<i>Others</i>	0.0600***	0.047100	0.072995
<i>Reviewer_impact ⇒ UGPs ⇒ Ln_helpfulness</i>	<i>Master</i>	−0.0171***	−0.022184	−0.012015
	<i>Expert</i>	−0.0714***	−0.083209	−0.059578
	<i>Sum_reviews</i>	−0.0001***	−0.000131	−0.000067
	<i>Avg_pics</i>	0.0037***	0.002931	0.004469
	<i>Avg_helps</i>	0.0003***	0.000128	0.000521
	<i>Family</i>	0.0875***	0.078875	0.096222
	<i>Friends</i>	0.0458***	0.037672	0.053977
	<i>Business</i>	0.0285***	0.022955	0.033958
	<i>Couple</i>	0.0732***	0.063645	0.082775
	<i>Solo</i>	0.0819***	0.071728	0.092111
	<i>Others</i>	0.0521***	0.042842	0.061439
<i>Reviewer_impact ⇒ Timeliness ⇒ Ln_helpfulness</i>	<i>Master</i>	−0.1832***	−0.200016	−0.166286
	<i>Expert</i>	−0.1836***	−0.203178	−0.203178
	<i>Sum_reviews</i>	−0.0002***	−0.000223	−0.000091
	<i>Avg_pics</i>	0.0013***	0.001018	0.001572
	<i>Avg_helps</i>	0.0009***	0.000578	0.001222
	<i>Family</i>	0.0979***	0.070445	0.125284
	<i>Friends</i>	0.0795***	0.051275	0.107758
	<i>Business</i>	0.0716***	0.046576	0.096557
	<i>Couple</i>	0.1053***	0.075979	0.134670
	<i>Solo</i>	0.1054***	0.076701	0.134099
	<i>Others</i>	0.1218***	0.090773	0.152859

\*\*\*significance:  $p < 0.01$ , \*\*significance:  $p < 0.05$ , \*significance:  $p < 0.1$ .

hotel MRs. These results partially support H9.

## 5.2 Robustness checks

To ensure the robustness of our main results, we conduct robustness checks in our study. Specifically, we conduct subsample analysis based on the hotel star level. The results are shown in Table 8. The results are mostly consistent with our main model, which indicates the robustness of our results.

## 6 Conclusions

From the signaling timeline perspective in signaling theory,

we employed a bootstrapping analysis to examine in-depth the transmission and reception processes among reviewer impact, review informativeness, hotel MRs, and review helpfulness. Using the data collected from Ctrip.com, our empirical results reveal the following findings.

First, considering the signaling timeline of reviews by distinguishing the three important roles of signaler, signal, and receiver, this study presents an important result: Reviewer impact may affect review helpfulness sequentially through review informativeness and hotel MRs. Specifically, the reviewer, as a signaler, sends signals that include both reviewer

**Table 6.** Test results for the process: reviewer, hotel MRs, and helpfulness.

<i>Reviewer_impact ⇒ Hotel MRs ⇒ Ln_helpfulness</i>	<i>Reviewer_impact</i>	Conf.	[95% conf. interval]	
<i>Reviewer_impact ⇒ Reply ⇒ Ln_helpfulness</i>	<i>Master</i>	−0.0265***	−0.037018	−0.016075
	<i>Expert</i>	−0.0644***	−0.083311	−0.045485
	<i>Sum_reviews</i>	−2.70E−05	−0.000099	0.000045
	<i>Avg_pics</i>	−0.0003**	−0.000562	−0.000024
	<i>Avg_helps</i>	0.0011***	0.000654	0.001472
	<i>Family</i>	−0.0415***	−0.065302	−0.177873
	<i>Friends</i>	0.0132	−0.010454	0.036936
	<i>Business</i>	0.0180*	−0.002742	0.038834
	<i>Couple</i>	0.0243*	−0.001051	0.049658
	<i>Solo</i>	0.0141	−0.011805	0.039930
<i>Reviewer_impact ⇒ Reply_length ⇒ Ln_helpfulness</i>	<i>Others</i>	−0.0041	−0.031120	0.022835
	<i>Master</i>	0.0012*	−0.000039	0.002510
	<i>Expert</i>	0.0032**	0.000130	0.006222
	<i>Sum_reviews</i>	−3.46E−06	−7.67E−06	7.51E−07
	<i>Avg_pics</i>	4.97E−06	−7.41E−06	0.000017
	<i>Avg_helps</i>	−1.31E−05	−0.000031	4.76E−06
	<i>Family</i>	0.0045**	0.000059	0.008988
	<i>Friends</i>	0.0001	−0.000566	0.002521
	<i>Business</i>	0.0008	−0.000531	0.002055
	<i>Couple</i>	−0.0005	−0.001830	0.000871
	<i>Solo</i>	0.0047*	−0.000035	0.009421
	<i>Others</i>	0.0006	−0.000900	0.002088

\*\*\*significance:  $p < 0.01$ , \*\*significance:  $p < 0.05$ , \*significance:  $p < 0.1$ .

impact characteristics and reviews. Hotels and potential consumers as two receivers receive and explain the signals since they lack hotel experience information. Then, the receivers provide feedback, i.e., hotel MRs and helpfulness votes, which will affect subsequent consumers. Rather than affecting review helpfulness directly according to the prior literature, these factors interact to affect review helpfulness.

Our results show that hotel managers tend to reply to reviews posted by reviewers with high expert levels and reviews containing several UGPs. Moreover, hotel MRs, as another receiver's feedback, may also significantly and negatively affect review helpfulness because it may resolve customer complaints and address service failures<sup>[62]</sup>. Additionally, our results show that if hotel managers respond to a review, a longer reply may slightly increase review helpfulness. This finding agrees with uncertainty reduction theory<sup>[63]</sup> because consumers perceive reviews with high amounts of information as more valuable than other reviews.

Second, there are several interesting results concerning the direct effect of reviewer impact on review helpfulness: (a) Reviewers with high expertise levels gained fewer helpfulness votes than did those with low expertise levels. One plausible explanation is that the role of the reviewer's expertise varies based on online information seekers' different goals<sup>[64]</sup>. Reviews written by expert reviewers may contain multiple perspectives, but consumers focus only on what they

most care about, so they may not resonate with those reviews. (b) A richer experience posting reviews was significantly and negatively related to review helpfulness, which contrasts with the findings of previous work<sup>[6]</sup>. One reasonable explanation may lie in the review-boosting mechanisms often used by on-line platforms, which encourage consumers to post reviews after consumption to obtain discounts or other benefits. If potential consumers view posting reviews as a habitual action motivated by the platform's review-boosting mechanism, the credibility of the reviews may decrease, which will negatively affect helpfulness votes. (c) Our findings indicating that consumers prefer reviews provided by reviewers with high impact who have gained many helpfulness votes over those from other reviewers align with findings from prior studies<sup>[13]</sup>.

Third, the results show that trip purpose plays an important role in obtaining review helpfulness votes. Compared to reviews written by reviewers reserving of other people, reviews posted by reviewers with other six trip purposes received more helpfulness votes. Reviewers who stay in hotels in person can provide more specific and authentic information than reviewers who book hotels for others, and this information may affect reviews' credibility and thus their helpfulness.

In addition, our results confirm previous conclusions that review informativeness depends on reviewer impact<sup>[10, 12]</sup>. For example, reviewers with high levels of expertise tend to post



**Table 7.** Test results for the process: reviewer, review, hotel MRs, and helpfulness.

<i>Reviewer_impact ⇒ Review_informativeness ⇒ Hotel MRs ⇒ Ln_helpfulness</i>	<i>Reviewer_impact</i>	<i>Conf.</i>	<i>[95% conf. interval]</i>	
<i>Reviewer_impact ⇒ Length ⇒ Reply ⇒ Ln_helpfulness</i>	<i>Master</i>	−0.0009*	−0.0000835	0.0016922
	<i>Expert</i>	−0.0047***	−0.0065716	−0.0029141
	<i>Sum_reviews</i>	−3.00E−05***	−0.0000396	−0.0000207
	<i>Avg_pics</i>	−0.0003***	−0.0003447	−0.0001774
	<i>Avg_helps</i>	−0.0001***	−0.000141	−0.0000626
	<i>Family</i>	−0.0179***	−0.0220992	−0.0137101
	<i>Friends</i>	−0.0098***	−0.0125559	−0.0071079
	<i>Business</i>	−0.0017**	−0.0030591	−0.0002848
	<i>Couple</i>	−0.0119***	−0.0151647	−0.0086599
	<i>Solo</i>	−0.0119***	−0.015248	−0.0085867
<i>Reviewer_impact ⇒ Pictures ⇒ Reply ⇒ Ln_helpfulness</i>	<i>Others</i>	−0.0104***	−0.0135974	−0.0071989
	<i>Master</i>	0.0004**	0.0000911	0.0006516
	<i>Expert</i>	−0.0016***	0.0004463	0.0026548
	<i>Sum_reviews</i>	2.15E−06**	5.01E−07	3.80E−06
	<i>Avg_pics</i>	−0.0001***	−0.0001368	−0.0000239
	<i>Avg_helps</i>	−7.05E−06**	−0.0000137	−3.78E−07
	<i>Family</i>	−0.0019***	−0.0032418	−0.000561
	<i>Friends</i>	−0.0010***	−0.0017027	−0.0002877
	<i>Business</i>	−0.0006***	−0.0010501	−0.000186
	<i>Couple</i>	−0.0016***	−0.002701	−0.0004789
<i>Reviewer_impact ⇒ Timeliness ⇒ Reply ⇒ Ln_helpfulness</i>	<i>Solo</i>	−0.0018***	−0.0030085	−0.0005498
	<i>Others</i>	−0.0011***	−0.0019574	−0.0003074
	<i>Master</i>	0.0018***	0.000731	0.00296
	<i>Expert</i>	0.0018***	0.000691	0.0030083
	<i>Sum_reviews</i>	1.58E−06**	3.64E−07	2.80E−06
	<i>Avg_pics</i>	−1.30E−05***	−0.0000212	−4.93E−06
	<i>Avg_helps</i>	−9.07E−06***	−0.0000157	−2.44E−06
	<i>Family</i>	−0.0010***	−0.0016363	−0.0003359
	<i>Friends</i>	−0.0008***	−0.0013923	−0.0002101
	<i>Business</i>	−0.0007***	−0.001226	−0.0002162
<i>Reviewer_impact ⇒ Length ⇒ Reply_length ⇒ Ln_helpfulness</i>	<i>Couple</i>	−0.0011***	−0.001758	−0.0003646
	<i>Solo</i>	−0.0012***	−0.001768	−0.0003561
	<i>Others</i>	−0.0012***	−0.002015	−0.0004399
	<i>Master</i>	−0.0001	−0.0001229	0.0000166
	<i>Expert</i>	0.0003**	5.54E−06	0.000562
	<i>Sum_reviews</i>	1.80E−06**	8.94E−09	3.60E−06
	<i>Avg_pics</i>	−1.17E−07**	2.85E−07	0.000031
	<i>Avg_helps</i>	6.09E−06**	2.40E−08	0.0000122
	<i>Family</i>	0.0011**	0.0000699	0.0020727
	<i>Friends</i>	0.0006**	1.31E−06	0.0011752
<i>Reviewer_impact ⇒ Length ⇒ Reply ⇒ Ln_helpfulness</i>	<i>Business</i>	0.0001	−0.0000308	0.0002308
	<i>Couple</i>	0.0007**	0.0000189	0.0014066
	<i>Solo</i>	0.0007**	0.0000366	0.0013896
	<i>Others</i>	0.0006**	0.0000115	0.001238

(To be continued on the next page)

(Continued)

<i>Reviewer_impact</i> ⇒ <i>Review_informativeness</i> ⇒ <i>Hotel_MRs</i> ⇒ <i>Ln_helpfulness</i>	<i>Reviewer_impact</i>	Conf.	[95% conf. interval]	
<i>Reviewer_impact</i> ⇒ <i>UGPs</i> ⇒ <i>Reply_length</i> ⇒ <i>Ln_helpfulness</i>	<i>Master</i>	−2.02E−05	−0.000045	4.19E−06
	<i>Expert</i>	−0.0001*	−0.000184	0.000016
	<i>Sum_reviews</i>	−1.17E−07	−2.62E−07	−2.82E−07
	<i>Avg_pics</i>	4.37E−06	−9.32E−07	9.66E−06
	<i>Avg_helps</i>	3.83E−07	−1.51E−07	9.17E−07
	<i>Family</i>	0.0001	−0.000023	0.000230
	<i>Friends</i>	0.0001	−0.000013	0.000122
	<i>Business</i>	3.36E−05	−8.14E−06	0.000075
	<i>Couple</i>	0.0001	−0.000017	0.000190
	<i>Solo</i>	0.0001*	−0.000015	0.000208
<i>Reviewer_impact</i> ⇒ <i>Timeliness</i> ⇒ <i>Reply_length</i> ⇒ <i>Ln_helpfulness</i>	<i>Others</i>	0.0001	−0.000014	0.000137
	<i>Master</i>	−0.0001*	−0.000279	5.93E−06
	<i>Expert</i>	−0.0001*	−0.000278	4.26E−06
	<i>Sum_reviews</i>	−1.17E−07*	−2.56E−07	2.18E−08
	<i>Avg_pics</i>	9.66E−07*	−4.04E−08	1.97E−06
	<i>Avg_helps</i>	6.71E−07*	−7.20E−08	1.41E−06
	<i>Family</i>	0.0001*	−5.26E−06	0.000151
	<i>Friends</i>	0.0001*	−9.76E−06	0.000128
	<i>Business</i>	0.0001*	−7.05E−06	0.000114
	<i>Couple</i>	0.0001*	−7.01E−06	0.000164
	<i>Solo</i>	0.0001*	−4.42E−06	0.000162
	<i>Others</i>	0.0001*	−6.93E−06	0.000189

\*\*\*significance:  $p < 0.01$ , \*\*significance:  $p < 0.05$ , \*significance:  $p < 0.1$ .

fewer photos later than newcomer reviewers. One possible reason is that image-related utility is a realistic motivation for people to contribute content on social media<sup>[63]</sup>. When reviewers reach the expert level, their motivation to improve their self-image may decrease, leading them to post fewer photos. Additionally, reviewers who book hotels for family trips may post reviews with more words and photos than other reviewers. Finally, the empirical results are consistent with prior research revealing that online reviews are perceived as more helpful if they contain more UGPs<sup>[4]</sup> and words<sup>[24]</sup>, and they confirm the expectation that timeliness will positively affect review helpfulness.

## 6.1 Theoretical implications

First, to our knowledge, this paper represents the first study to focus on the in-depth transmission and reception processes among reviewer impact, review informativeness, hotel MRs, and review helpfulness from the perspective of the signaling timeline. In contrast to most of those previous studies, which investigated only the direct effects of review informativeness and hotel MRs on review helpfulness, considering them two mediators enabled us to comprehensively explore their in-depth relationships in this study.

Second, unlike previous research, which used inconsistent proxy variables to measure reviewer expertise or experience, we used official labels provided by one leading platform to

study the influence of these variables on review helpfulness. We are able to provide a more accurate and reliable assessment of reviewer expertise. The findings of this paper highlight that reviewer expertise is not equal to reviewer experience. The official measurement of reviewer expertise contributes to the robustness and validity of our findings, which we believe is an important methodological improvement.

Third, this research sheds light on the important influence of trip purpose on review helpfulness to provide a novel direction for related research. This approach involves discussing how different trip purposes can influence the expectations, preferences, and evaluation criteria of travelers when reading and writing reviews, which has rarely been explored in prior studies.

## 6.2 Practical implications

This study represents an important step toward developing a more generalized model of online reviews to help platform operators and hotel managers better manage online reviews. First, our results demonstrate that reviewer impact significantly affects review helpfulness via review informativeness and hotel MRs. Online travel agencies can consider providing training or guidelines to reviewers to improve the expertise and quality of their reviews. Recognizing experienced reviewers and involving them in collaborations or special programs may also enhance the helpfulness of reviews.

**Table 8.** Subsample analysis for hotel star level.

	(1)	(2)	(3)	(4)
	<i>HSC</i> = 2	<i>HSC</i> = 3	<i>HSC</i> = 4	<i>HSC</i> = 5
<i>Reply_length</i>	0.001 (0.00)	0.000 (0.00)	−0.000 (0.00)	−0.004*** (0.00)
<i>Reply</i>	−0.256** (0.12)	−0.391*** (0.10)	0.320*** (0.05)	−0.005 (0.08)
<i>Length</i>	0.007*** (0.00)	0.009*** (0.00)	0.006*** (0.00)	0.007*** (0.00)
<i>UGPs</i>	0.138*** (0.03)	0.212*** (0.02)	0.292*** (0.01)	0.236*** (0.01)
<i>Timeliness</i>	−0.006*** (0.00)	−0.008*** (0.00)	−0.008*** (0.00)	−0.010*** (0.00)
<i>Master</i>	−0.103* (0.06)	0.031 (0.05)	0.013 (0.03)	−0.022 (0.04)
<i>Expert</i>	−0.155 (0.10)	−0.043 (0.09)	−0.158*** (0.05)	−0.088** (0.04)
<i>Sum_reviews</i>	0.005 (0.02)	−0.020 (0.05)	−0.029 (0.04)	0.007 (0.01)
<i>Avg_pics</i>	0.072** (0.03)	−0.009 (0.03)	0.021 (0.02)	−0.039** (0.02)
<i>Avg_helps</i>	0.073*** (0.01)	0.046*** (0.01)	0.109*** (0.01)	0.115*** (0.00)
<i>Family</i>	0.572*** (0.22)	−0.032 (0.16)	0.195** (0.09)	0.097 (0.08)
<i>Friend</i>	0.563** (0.22)	−0.147 (0.16)	0.099 (0.10)	0.181** (0.09)
<i>Business</i>	0.509** (0.21)	−0.123 (0.15)	0.051 (0.09)	0.065 (0.08)
<i>Couple</i>	0.532** (0.23)	0.023 (0.16)	0.142 (0.10)	0.084 (0.09)
<i>Solo</i>	0.537** (0.22)	−0.080 (0.17)	0.157 (0.10)	0.106 (0.09)
<i>Others</i>	0.578*** (0.22)	0.052 (0.17)	0.205** (0.10)	0.232** (0.09)
<i>Ln_price</i>	0.005 (0.11)	−0.116 (0.16)	−0.421*** (0.05)	−0.077 (0.08)
<i>Rating</i>	−0.255*** (0.03)	−0.383*** (0.03)	−0.431*** (0.02)	−0.203*** (0.02)
<i>Duration</i>	0.001*** (0.00)	0.001*** (0.00)	0.001*** (0.00)	−0.002*** (0.00)
<hr/>				
Hotel effect included				
_cons	−3.197*** (0.66)	−0.394 (0.87)	1.671*** (0.40)	−0.546 (0.50)
<hr/>				
<i>N</i>	12065	17901	47978	31878
<i>R</i> <sup>2</sup>	0.247	0.237	0.254	0.247

\*\*\*significance:  $p < 0.01$ , \*\*significance:  $p < 0.05$ , \*significance:  $p < 0.1$ .

Additionally, we suggest that platform operators rearrange the display order of reviewer impact labels to highlight factors positively associated with review helpfulness (e.g., review time or specific trip purpose). Second, we suggest that hotel managers carefully implement MR strategies. Our study highlights the significance and mediating effect of hotel MRs on shaping review helpfulness. Hotel managers should recognize the impact of their responses on the perceived usefulness of reviews. They should develop effective strategies for engaging with reviewers, addressing concerns, and providing relevant information to enhance the overall helpfulness of online reviews. For example, they should strategically pay attention to reviews with certain trip purposes, such as couple trips. The hotel should encourage newcomer reviewers to post reviews with as many photos as possible. Third, we suggest that consumers pay attention to trip purpose and review timeliness when browsing booking platforms. Doing so can help consumers optimize the time spent viewing reviews and gain more helpful information.

### 6.3 Limitations

This study has several limitations that could be addressed in the future. First, we obtained reviews for only one location, which is a popular business district and tourist attraction. Using a broader range of places would be better for obtaining a more generalized understanding of how hotels' online reviews gain helpfulness votes. Second, although we developed a more comprehensive model, we used only a cross-section of data, and the effects related to hotel attributes were partially controlled. It may be ideal for future research to apply a fixed-effects model using panel data.

### Acknowledgements

This work was supported by the Philosophy and Social Science Planning Program of Shanghai (2021BGL018).

### Conflict of interest

The authors declare that they have no conflict of interest.

### Biographies

**Mohan Wang** is an Assistant Professor at the School of Business and Management, Shanghai International Studies University. She received her Ph.D. degree in Information Systems from the Harbin Institute of Technology in 2015. Her research mainly focuses on electronic word of mouth, consumer behavior, and online marketing strategy.

**Fei Wan** is an Associate Professor at the School of Business and Management, Shanghai International Studies University. She received her Ph.D. degree in Management Science and Engineering from Peking University in 2017. Her research mainly focuses on the impact of information technology on firm performance, social media marketing, and online consumer behavior.

### References

- [1] Yacouel N, Fleischer A. The role of cybermediaries in reputation building and price premiums in the online hotel market. *Journal of Travel Research*, **2011**, 51 (2): 219–226.
- [2] Torres E N, Adler H, Behnke C. Stars, diamonds, and other shiny

things: The use of expert and consumer feedback in the hotel industry. *Journal of Hospitality and Tourism Management*, **2014**, 21: 34–43.

- [3] Akhtar N, Ahmad W, Siddiqi U I, et al. Predictors and outcomes of consumer deception in hotel reviews: The roles of reviewer type and attribution of service failure. *Journal of Hospitality and Tourism Management*, **2019**, 39: 65–75.
- [4] Ma Y, Xiang Z, Du Q, et al. Effects of user-provided photos on hotel review helpfulness: An analytical approach with deep learning. *International Journal of Hospitality Management*, **2018**, 71: 120–131.
- [5] Hu H F, Krishen A S. When is enough, enough? Investigating product reviews and information overload from a consumer empowerment perspective. *Journal of Business Research*, **2019**, 100: 27–37.
- [6] Liu Z W, Park S. What makes a useful online review? Implication for travel product websites. *Tourism Management*, **2015**, 47: 140–151.
- [7] Gupta P, Harris J. How e-WOM recommendations influence product consideration and quality of choice: A motivation to process information perspective. *Journal of Business Research*, **2010**, 63: 1041–1049.
- [8] Kumar N, Benbasat I. Research note: The influence of recommendations and consumer reviews on evaluations of websites. *Information Systems Research*, **2006**, 17 (4): 425–439.
- [9] Pan Y, Zhang J Q. Born unequal: A study of the helpfulness of user-generated product reviews. *Journal of Retailing*, **2011**, 87 (4): 598–612.
- [10] Hlee S. How reviewer level affects review helpfulness and reviewing behavior across hotel classifications: the case of Seoul in Korea. *Industrial Management & Data Systems*, **2021**, 121 (6): 1191–1215.
- [11] Siering M, Muntermann J, Rajagopalan B. Explaining and predicting online review helpfulness: The role of content and reviewer-related signals. *Decision Support Systems*, **2018**, 108: 1–12.
- [12] Huang A H, Chen K, Yen D C, et al. A study of factors that contribute to online review helpfulness. *Computers in Human Behavior*, **2015**, 48: 17–27.
- [13] Otterbacher J. 'Helpfulness' in online communities: A measure of message quality. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. New York: ACM, **2009**: 955–964.
- [14] Fang B, Ye Q, Kucukusta D, et al. Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. *Tourism Management*, **2016**, 52: 498–506.
- [15] Yang S B, Hlee S, Lee J, et al. An empirical examination of online restaurant reviews on Yelp.com. *International Journal of Contemporary Hospitality Management*, **2017**, 29 (2): 817–839.
- [16] Lee I. Usefulness, funniness, and coolness votes of viewers. *Industrial Management & Data Systems*, **2018**, 118 (4): 700–713.
- [17] Li C, Kwok L, Xie K L, et al. Let photos speak: The effect of user-generated visual content on hotel review helpfulness. *Journal of Hospitality & Tourism Research*, **2023**, 47 (4): 665–690.
- [18] An Q, Ma Y, Du Q, et al. Role of user-generated photos in online hotel reviews: An analytical approach. *Journal of Hospitality and Tourism Management*, **2020**, 45: 633–640.
- [19] Kwok L, Xie K L. Factors contributing to the helpfulness of online hotel reviews. *International Journal of Contemporary Hospitality Management*, **2016**, 28 (10): 2156–2177.
- [20] Zhou S, Guo B. The order effect on online review helpfulness: A social influence perspective. *Decision Support Systems*, **2017**, 93: 77–87.
- [21] Chen Y, Jin W, Hu Y, et al. Does managerial response moderate the relationship between online review characteristics and review helpfulness? *Current Issues in Tourism*, **2021**, 25: 2679–2694.
- [22] Yadav M L, Roychoudhury B. Effect of trip mode on opinion about hotel aspects: A social media analysis approach. *International*



- Journal of Hospitality Management*, **2019**, *80*: 155–165.
- [23] Agnihotri A, Bhattacharya S. Online review helpfulness: Role of qualitative factors. *Psychology Marketing*, **2016**, *33*: 1006–1017.
  - [24] Mudambi S M, Schuff D. What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly*, **2010**, *34* (1): 185–200.
  - [25] Yang S, Zhou Y, Yao J, et al. Understanding online review helpfulness in omnichannel retailing. *Industrial Management & Data Systems*, **2019**, *119* (8): 1565–1580.
  - [26] Wang M, Lu Q, Chi R T, et al. How word-of-mouth moderates room price and hotel stars for online hotel booking an empirical investigation with expedia data. *Journal of Electronic Commerce Research*, **2015**, *16* (1): 72–80.
  - [27] Spence M. Signaling in retrospect and the informational structure of markets. *American Economic Review*, **2002**, *92* (3): 434–459.
  - [28] Connelly B L, Certo S T, Ireland R D, et al. Signaling theory: A review and assessment. *Journal of Management*, **2011**, *37*: 39–67.
  - [29] Spence M. Job market signaling. In: *Uncertainty in Economics*. New York: Academic Press, **1978**: 281–306.
  - [30] Kirmani A, Rao A R. No pain, no gain: A critical review of the literature on signaling unobservable product quality. *Journal of Marketing*, **2000**, *64* (2): 66–79.
  - [31] Ross S A. The determination of financial structure: the incentive-signalling approach. *The Bell Journal of Economics*, **1977**, *8*: 23–40.
  - [32] Moss T W, Neubaum D O, Meyskens M. The effect of virtuous and entrepreneurial orientations on microfinance lending and repayment: A signaling theory perspective. *Entrepreneurship Theory and Practice*, **2015**, *39* (1): 27–52.
  - [33] Bristor J. Enhanced explanations of word of mouth communications: The power of relations. *Research in Consumer Behavior*, **1990**, *4*: 51–83.
  - [34] Gotlieb J B, Sarel D. Comparative advertising effectiveness: The role of involvement and source credibility. *Journal of Advertising*, **1991**, *20* (1): 38–45.
  - [35] Racherla P, Friske W. Perceived ‘usefulness’ of online consumer reviews: An exploratory investigation across three services categories. *Electronic Commerce Research and Applications*, **2012**, *11*: 548–559.
  - [36] Hoenig D, Henkel J. Quality signals? The role of patents, alliances, and team experience in venture capital financing. *Research Policy*, **2015**, *44* (5): 1049–1064.
  - [37] Filieri R. What makes an online consumer review trustworthy. *Annals of Tourism Research*, **2016**, *58*: 46–64.
  - [38] Park C W, Sutherland I, Lee S K. Effects of online reviews, trust, and picture-superiority on intention to purchase restaurant services. *Journal of Hospitality and Tourism Management*, **2021**, *47*: 228–236.
  - [39] Lee S, Choeh J Y. Predicting the helpfulness of online reviews using multilayer perceptron neural networks. *Expert Systems with Applications*, **2014**, *41* (6): 3041–3046.
  - [40] Hu X, Yang Y. What makes online reviews helpful in tourism and hospitality? A bare-bones meta-analysis. *Journal of Hospitality Marketing & Management*, **2021**, *30* (2): 139–158.
  - [41] Radojevic T, Stanic N, Stanic N, et al. The effects of traveling for business on customer satisfaction with hotel services. *Tourism Management*, **2018**, *67*: 326–341.
  - [42] Rhee H T, Yang S B. How does hotel attribute importance vary among different travelers? An exploratory case study based on a conjoint analysis. *Electronic Markets*, **2015**, *25* (3): 211–226.
  - [43] Liu S, Law R, Rong J, et al. Analyzing changes in hotel customers’ expectations by trip mode. *International Journal of Hospitality Management*, **2013**, *34*: 359–371.
  - [44] Sung H H, Morrison A M, Hong G S, et al. The effects of household and trip characteristics on trip types: A consumer behavioral approach for segmenting the U.S. domestic leisure travel market. *Journal of Hospitality & Tourism Research*, **2001**, *25* (1): 46–68.
  - [45] Gu B, Ye Q. First step in social media: Measuring the influence of online management responses on customer satisfaction. *Production and Operations Management*, **2014**, *23* (4): 570–582.
  - [46] Min H, Lim Y, Magnini V P. Factors affecting customer satisfaction in responses to negative online hotel reviews: The impact of empathy, paraphrasing, and speed. *Cornell Hospitality Quarterly*, **2014**, *56* (2): 223–231.
  - [47] Schuckert M, Liang S, Law R, et al. How do domestic and international high-end hotel brands receive and manage customer feedback. *International Journal of Hospitality Management*, **2019**, *77*: 528–537.
  - [48] Moro S, Esmerado J. An integrated model to explain online review helpfulness in hospitality. *Journal of Hospitality and Tourism Technology*, **2021**, *12* (2): 239–253.
  - [49] Fleenon W, Jayawickreme E. Whole trait theory. *Journal of Research in Personality*, **2015**, *56*: 82–92.
  - [50] Liu X, Schuckert M, Law R. Utilitarianism and knowledge growth during status seeking: Evidence from text mining of online reviews. *Tourism Management*, **2018**, *66*: 38–46.
  - [51] Liu X, Zhang Z, Law R, et al. Posting reviews on OTAs: Motives, rewards and effort. *Tourism Management*, **2019**, *70*: 230–237.
  - [52] Ebbinghaus H. Memory: A contribution to experimental psychology. *Annals of Neurosciences*, **2013**, *20* (4): 155–156.
  - [53] Ndofo H A, Levitas E. Signaling the strategic value of knowledge. *Journal of Management*, **2004**, *30* (5): 685–702.
  - [54] Branzei O, Ursacki-Bryant T J, Vertinsky I, et al. The formation of green strategies in Chinese firms: Matching corporate environmental responses and individual principles. *Strategic Management Journal*, **2004**, *25* (11): 1075–1095.
  - [55] Preacher K J, Hayes A F. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, **2008**, *40* (3): 879–891.
  - [56] Baron R M, Kenny D A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality Social Psychology*, **1986**, *51* (6): 1173–1182.
  - [57] Sobel M E. Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology*, **1982**, *13*: 290–312.
  - [58] Hu Y H, Chen K C. Predicting hotel review helpfulness: The impact of review visibility, and interaction between hotel stars and review ratings. *International Journal of Information Management*, **2016**, *36* (6): 929–944.
  - [59] O’Mahony M P, Smyth B. A classification-based review recommender. In: *Research and Development in Intelligent Systems XXVI: Incorporating Applications and Innovations in Intelligent Systems XVII*. London: Springer, **2009**: 49–62.
  - [60] Zhu L, Yin G, He W. Is this opinion leader’s review useful? Peripheral cues for online review helpfulness. *Journal of Electronic Commerce Research*, **2014**, *15* (4): 267–280.
  - [61] Ye Q A, Law R, Gu B, et al. The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior*, **2011**, *27* (2): 634–639.
  - [62] Xie K L, Zhang Z, Zhang Z. The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, **2014**, *43*: 1–12.
  - [63] Daft R L, Lengel R H. Organizational information requirements, media richness, and structural design. *Management Science*, **1986**, *32* (5): 554–571.
  - [64] Weiss A M, Lurie N H, Macinnis D J. Listening to strangers: Whose responses are valuable, how valuable are they, and why. *Journal of Marketing Research*, **2008**, *45* (4): 425–436.
  - [65] Toubia O, Stephen A T. Intrinsic vs. image-related utility in social media: Why do people contribute content to Twitter. *Marketing Science*, **2013**, *32* (3): 368–392.