Information Systems Review
Vol. 23, No. 3 August 2021 http://dx.doi.org/10.14329/isr.2021.23.3.127

온라인 리뷰 소비 및 생성에 대한 일시적 이상 현상의 차등 효과

The Differential Impacts of Temporary Aberration on Online Review Consumption and Generation

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요 약

많은 온라인 여행 대행사(OTA; online travel agencies)들은 고객 만족을 위해 호텔에 대하여 평균 평점과 함께 가장 최근에 게시된 리뷰 정보를 제공하고 있다. 이 두 가지 정보(평균 평점 및 최근 게시된 리뷰)가 행동 의사 결정 과정에 미치는 상대적 영향을 확인하기 위해, 본 논문에서는 두 가지 연구를 수행하였다. 첫째로, 실험 연구 설계를 사용하여 온라인 리뷰 소비에서 두 가지 정보의 상대적 영향을 조사하였고, 둘째로, 온라인 리뷰 생성에 대한 상대적 영향을 경험적 접근방식을 통해 확인하였다. 분석 결과, 리뷰 생성의 경우, 사람들은 평균 평점과 최근 리뷰의 불일치를 관찰할 때(일시적 이상 현상이 있을 때), 방향에 관계없이 최근 리뷰에서 벗어나려는 경향(반응 행동)을 보였다. 한편, 리뷰 소비자는 일시적 이상 현상에서 최근 게시된 리뷰의 의견에 순응하려는 경향(군집 행동)을 보였다. 그리고 두 경우 모두, 최근 게시된 리뷰가 부정적일 때 그 효과가 커짐을 확인하였다. 이 결과를 바탕으로, 본 연구는 평균 평점과 최근 게시된 리뷰라는 두 가지 정보 사이의 상대적 영향과 이들이 온라인 리뷰 소비와 생성에 미치는 다른 영향에 대한 이론적 및 실제적 시사점을 제공하였다.

키워드 : 온라인 리뷰, 평균 평점, 최근 게시된 리뷰, 일시적 이상 현상, 리뷰 생성, 리뷰 소비

Ⅰ. Introduction

Since humans are social creatures that are easily influenced by peers, online communication among customers plays a critical role in consumers' decision-making (Chevalier and Mayzlin, 2006; Li and Hitt, 2008; Xiang and Gretzel, 2010). It causes businesses to actively engage in their customer base via social media to understand their decision-making processes as a means of reputation management and sales improvement (BabićRosario *et al.*, 2016; Dijkmans *et al.*, 2015; Kaplan and Haenlein, 2010; Shen and Su, 2007). Harnessing this new social phenomenon, many go-to websites providing user-generated online customer reviews for hotels and restau-

† 이 논문은 2021년도 한국기술교육대학교 교수 교육연구진흥과제 지원에 의하여 연구되었음.

rants, such as TripAdvisor.com and Yelp.com, have achieved success in this fierce business field. With an increase in competition and development of information technology, these sites have tried to differentiate information delivery by providing diverse aspects of customer opinions such as the average star rating, which is also known as cumulative rating (Duan *et al.*, 2008), along with most recently posted reviews (Cheung *et al.*, 2008; Urban *et al.*, 2000). This is aimed at helping customers make decisions (Brynjolfsson and Smith, 2000) and, as a result, gaining a competitive edge over other sites (Clemons and Gao, 2008).

According to a local consumer review survey (BrightLocal, 2017), providing the overall opinion as well as recent information is beneficial for gaining an edge over competitor sites because the average rating (Chevalier and Mayzlin, 2006; Duan *et al.*, 2008) and recent reviews (timely information or recency effect, Cheung *et al.*, 2008; Sparks and Browning, 2011; Urban *et al.*, 2000) are important factors that customers pay close attention to when judging a product based on reviews. According to behavioral decision theory (Slovic and Lichtenstein, 1971; Tversky and Kahneman, 1974), with respect to the relationship between the average rating and the most recently posted reviews, customers are likely to regard average rating as the initial anchor while considering the information from recent reviews as the adjustment factor. This is because the average rating is clear for them to observe, while recent reviews require an extra click to view, or customers tend to read online reviews from top to bottom. This makes summary information, such as the average rating, especially critical (BrightLocal, 2017), while the information from recent reviews is ancillary. In addition, timely information is also helpful for users (Cheung *et al.*, 2008; Sparks and Browning, 2011; Urban *et al.*, 2000). As the huge number of reviews published on online travel agencies (OTAs) leads to an information overload that makes decision-making difficult (Lamest and Brady, 2019), this would improve the timeliness and credibility of reviews by making review readers perceive that the reviews reflect the current situation.

However, these two factors sometimes deliver contradictory information about the reviewed products in the dynamic flow of customer reviews. For instance, even when the average rating is low, the ratings of the most recently posted reviews can be considerably higher. Since consumers regard these two factors as important, they are likely to incorporate the difference in ratings into information processing before making a decision, especially when the two sources of information make different voices. In the dynamic flow of reviews (Moe and Trusov, 2011; Wu and Huberman, 2010), a certain number of recent positive reviews can be sequentially posted above the average rating of a product in some cases, and a certain number of recent negative reviews can be sequentially posted below the average rating in other cases. This positive or negative trend in recent reviews, also known as temporary aberration, can occur repeatedly over the product life cycle. If there is inconsistency between the voices of average rating and recent reviews, review readers and posters might reflect on this inconsistency during information processing depending on the relative impacts of the two factors. Martin-Fuentes *et al.* (2020) demonstrated that review scales and ways to display reviews can affect customers' hotel evaluations in OTAs. Therefore, quantifying the relative impacts of the average rating and the most recently posted reviews might help in examining the business values of providing diverse customer opinions in practice and thoroughly understanding the dynamic properties of online word-of-mouth (WOM). However, to the best of our knowledge, this inconsistency in the average rating and the most recently posted reviews has never been thoroughly explored with respect to both review generation and consumption in previous literature.

Previous studies have noted the impact of prior reviews on social influences from two behavioral perspectives: herding and reactance behavior. Herding refers to consumer behavior, that involves following the opinions of past consumers through information cascade and social influence (Banerjee, 1992; Bikhchandani *et al.*, 1992; Sridhar and Srinivasan, 2012). Consumers also exhibit a reactance behavior, for example, review posters want the benefit of differentiation from having left a review that deviated from the trend of recent reviews, since they want their reviews to receive attention from readers (Godes and Silva, 2012; Moe and Trusov, 2011; Wu and Huberman, 2010). Because previous studies have focused on the roles of prior reviews in leading to herding or reactance behavior, this study attempts to identify the relative impact of the average rating and recent reviews on such behavior. Moreover, customer attitudes can change after being exposed to negative (or positive) reviews (Lis and Fischer, 2020). People tend to consider the information from negative reviews as more influential than that from positive reviews; this is called a negativity bias (Basuroy *et al.*, 2003; Chevalier and Mayzlin, 2006; Mizerski, 1982). Thus, the impact of recently posted reviews could depend on the trend of recent reviews (positive or negative). We consider the trends separately to identify the adjustment mechanism related to the temporary aberration.

To thoroughly understand individual behaviors due to the inconsistency in the two sources of information in online reviews, two decision-making behaviors should be considered: online review consumption (i.e., referring to reviews for making purchase decisions) and online review generation (i.e., posting online reviews). It is important to consider the findings from both these behaviors in academia and put them into practice. While prior studies have typically conducted one of the two, Yang *et al.* (2012) noted the importance of simultaneously considering both WOM generation and consumption because they are synergistic and crucial for the success of WOM. Thus, we explore the relative relationship between representative rating and recent information in both online review generation and online review consumption processes. To this end, we use experimental and empirical approaches and explore the relative influence of these two different types of information on the processes.

Ⅱ. Literature Review

2.1 Average Rating and Recent Reviews

Behavioral decision theory suggests the concept of "anchoring and adjustment". Individuals often use this heuristic when making decisions (Slovic and Lichtenstein, 1971; Tversky and Kahneman, 1974). When individuals do not have specific knowledge, they rely on general information as an "anchor" which usually influences their decision-making process. When additional information is available, they make incremental "adjustments" to their judgments to reflect the additional information. However, they still depend on initial information as anchors (Venkatesh, 2000).

Previous studies have shown that in a sequential observation of two objects, the previously observed object serves as the reference point and the latter serves as the subject of comparison (Choi and Myer, 2012; de Bruin and Keren, 2003; Houston *et al.*, 1989; Mantel and Kardes, 1999; Sanbonmatsu *et al.*, 1991). When the two objects provide information about one subject (i.e., in a sequential observation of two types of information about a single subject), the relationship between the two can be explained by behavioral decision theory. According to this theory, the earliest observed information serves as the reference point (i.e., anchoring), and the latter information serves as the subject of comparison to adjust the initial anchor (i.e., adjustment). Applying this to the online review context, we expect that the average rating should prove to be the reference point, and the most recent review should act as an adjustment factor. People are likely to compare the average rating with the ratings of the recent reviews because consumers see the average rating first and recent reviews after clicking on the detail page of a hotel, or tend to read online reviews from top to bottom within the detail page. Depending on how the review rating is expressed and displayed, ratings of the same hotel tend to be perceived differently (Martin-Fuentes *et al.*, 2020; Mellinas and Martin-Fuentes, 2021).

2.1.1 Anchoring: Average Rating

Average rating can serve as a reference point in the context of online reviews. Over 80% of online shoppers refer to other customers' reviews while making their purchase decisions (BrightLocal, 2017). Online reviews are more frequently referred to and are more effective where the characteristics of the products or services make it difficult to evaluate their quality before consumption, such as hospitality (e.g., experience goods) (Mudambi and Schuff, 2010; Woodside and King, 2001). With several characteristics of online reviews, such as star ratings and review richness, consumers usually use the average rating as a heuristic information cue to condense information from previous reviews, thereby reducing the necessary amount of cognitive resources (Luca, 2016; Payne *et al.*, 1992).

Prior studies have examined the influence of previous ratings on subsequent review generation (Hu and Li, 2011; Ma *et al.*, 2013; Moe and Schweidel, 2012; Moe and Trusov, 2011; Sridhar and Srinivasan, 2012) and purchase decisions (i.e., review consumption) (Gavilan *et al.*, 2018; Vermeulen and Seegers, 2009; Xia and Bechwati, 2008). For example, Moe and Schweidel (2012) explained how prior ratings might affect subsequent review generation, in terms of incidence (the choice of individuals to contribute their own opinions) and evaluation (the decision of individuals to revise the evaluation by standing out from or being consistent with the previous rating). Prior studies have presented mixed empirical findings on the effect of previous ratings on online review generation (i.e., subsequent rating): a positive effect (Ma *et al.*, 2013) and a negative effect (Hu and Li, 2011). Regarding online review consumption for travel products (i.e., purchase decision), consumers search information to reduce uncertainty and risks when planning their trips (Bronner and De Hoog, 2011; Smith *et al.*, 2005; Sweeney *et al.*, 2008). While previous studies have shown the relationship between online ratings and product-level variables, including product sales (Chevalier and Mayzlin, 2006; Clemons *et al.*, 2006), there are few studies on the effect of the average rating on consumers' purchase decisions. For example, Vermeulen and Seegers (2009) showed the positive effect of review valence on consumers' awareness about hotels and attitudes toward them. Xia and Bechwati (2008) showed that high cognitive personalization when reading a positive review can enhance consumers' purchase intentions. Gavilan *et al.* (2018) showed that review ratings have a positive effect on hotel consideration, while they have a negative effect on trustworthiness.

2.1.2 Adjustment: Recent Reviews (temporary aberrations)

While consumers consider the average rating as a reference point when making their decision, there is another bit of information, such as timeliness of information, which can adjust the initial anchor. The role of the recency of reviews in consumer decision-making has been emphasized in both academia and practice, including online hotel bookings and online travel agencies in academia (Sparks and Browning, 2011; Zhao *et al.*, 2015) and popularity ranking in practice (TripAdvisor, 2018). Information timeliness in the case of online reviews influences review helpfulness, information adoption, and online satisfaction (Chang *et al.*, 2018; Filieri and McLeay, 2014; Fu *et al.*, 2017). Additionally, Chen *et al.* (2008) suggested that the impact of certain comments, which are labeled as "spotlight reviews" might be strong since these are seen before other reviews on the comments page. Jindal and Liu (2008) also revealed that the timeliness of reviews (more recent product reviews) would attract more attention from users in the e-commerce context. Similarly, Sparks and Browning (2011) also suggested the recency influences trust and booking intentions. Previous studies have also explored the timeliness of information as a dimension of information quality that can enhance perceived usefulness (Cheung *et al.*, 2008) or helpfulness (Liu *et al.*, 2008; Zhou and Guo, 2017), trust (Urban *et al.*, 2000), and popularity (Xie *et al.*, 2016) of the concerned product or service. In practice, since OTAs provide the most recently posted reviews, individuals can easily see and take note of them. Despite the impact of timely information provided by online reviews, it has been mostly overlooked in the literature (for example, in the hospitality literature, Zhao *et al.*, 2015).

2.2 The Herding vs. Reactance Behavior: Differential Mechanisms of Aberration Impacts in Online Review Generation and Consumption

Prior literature on online reviews has shown two possible directions which individuals can take in terms of social influence by reading prior reviews: herding and reactance behavior. Herding indicates that consumers conform to the prior (established majority) opinion and thus converge in uniform social behavior (Banerjee, 1992; Bikhchandani *et al.*, 1992). On the other hand, according to a general overview of the psychological reactance theory (Brehm and Brehm, 2013; Wicklund, 1974), reactance refers to people's adoption or description of a behavior or position that is opposite to the norm (Worchel and Brehm, 1970).

Based on these two possible directions regarding the impact of social influence, this study attempts to identify the influence of the interplay of the two kinds of information, average rating and most recently posted reviews, on subsequent review generation and purchase decision (review consumption). The objectives of online review generation and consumption could be different: wanting to get attention from review readers by differentiating the review posted with self-selection (reviewer selection) and trying to avoid the worst-case scenario when booking hotels (Baek *et al.*, 2012; Moe and Schweidel, 2012). Based on the different objectives of these two consumer behaviors, we believe that the influence of a temporary aberration oneach behavior will be different.

2.3 Herding in Online Review Consumption

Typically, consumers believe that popular products are less of a purchase risk. This is exhibited in the findings of previous studies on herding behavior. Social cues draw consumers to popular products because of this perception of reduced risk (DeSarbo *et al.*, 2002). Since consumers who choose less popular items are more likely to be disappointed and regret their decision (Simonson, 1992), they tend to search for more information (e.g., WOM) to gain assurance (Chatterjee, 2001). Similarly, scholars of herding literature suggest that following the crowd is sometimes optimal for consumers (e.g., Banerjee, 1992; Bikhchandani *et al.*, 1992). Moreover, according to the concept of observational learning and information cascade theory (Bandura, 1977; Bikhchandani *et al.*, 1992), social interaction influences an individual's purchase decisions. People often use observations of other consumers' purchases to assist them in forming an opinion before their own purchase. These observations are more influential when faced with limited information. Thus, if an overwhelming number of consumers' voices express similar opinions, it will naturally be highly likely for many subsequent review consumers to echo the sentiment. Therefore, people engage in a kind of herd behavior by following the actions of prior consumers (Banerjee, 1992; Chen *et al.*, 2011). Although following the advice provided by prior reviews (i.e., herding behavior of prior reviews) is not necessarily optimal because buyers can have differing preferences, this herding behavior can lead to suboptimal choices (Li and Hitt, 2008; Simonsohn and Ariely, 2008). This tendency of herding behavior involving following of prior reviews can also be consistently shown with temporary aberrations (Sparks and Browning, 2011). This is because timely information plays a similar role as exhibited by the findings of previous studies on prior reviews, including risk reduction.

For our research question, individuals were asked to refer to the average rating and recent reviews while making a purchase decision for their hotel stay. For example, when the recently posted reviews are more positive than the average rating, consumers may interpret it to mean that the hotel has improved their services or facilities, and may therefore evaluate it more favorably. Conversely, recent negative reviews might imply that the recent performance of the hotel has been poor. Thus, we suggest:

H1: Individuals exhibit herding behavior for a temporary aberration while making a purchase decision regarding their hotel stay.

2.4 Social Influence on Online Review Generation

Similarly, in the context of review generation, prior-studies have reported broad conformity among review posters (Muchnik *et al.*, 2013; Schlosser, 2005). This means that review posters might consider opinions expressed by others when they provide their own product evaluations (Schlosser, 2005). This social influence may cause subsequent ratings to become more positive or negative. For example, individuals who observe a high rating from the crowd, are more likely to provide a higher rating (Marsh, 1985; McAllister and Studlar, 1991; Moe and Schweidel, 2012; Muchnik *et al.*, 2013). However, recent studies have revealed that the tendency to conform to their peers is influenced by the rating provided by their friends rather than the whole population (e.g., Lee *et al.*, 2015; Wang *et al.*, 2018).

Several studies have found that when people are aware that they have an unpopular opinion, they might exhibit either reactance or non-conformity (Pennebaker and Sanders, 1976), becoming even more set in their beliefs. For example, when people have fixed or firm views, they are less likely to conform to the view of the majority, and might even have reactance (Furth-Matzkin and Sunstein, 2017). Similarly, with respect to online reviews, numerous studies have revealed the desire to "stand out from the crowd" as a legitimate motivating factor for some people when they intentionally contradict the established popular opinion (Godes and Silva, 2012; Moe and Schweidel, 2012; Wu and Huberman, 2008). This is based on the expected effects of their reviews on the average rating and others' actions or preferences.

When only a few reviews have been posted or when their experiences deviate significantly from the average consumers' experiences, including recently posted reviews (Lee *et al.*, 2015), people are more likely to be contrarian. This is because differentiation contributes to self-expression that is universally adopted (Berger and Heath, 2008).

In this regard, previous scholars have been unable to come to an agreement on the influence of prior reviews on subsequent review generation. This study suggests that the impact of temporary aberration is associated with reactance behavior, since one of the major objectives of review posters is gaining attention from review readers. For our research questions, we assume that recent reviews also influence the decision making of review posters who adjust the initial anchor through comparison with the average rating. Individuals provide review ratings that deviate from recent reviews. Review posters tend to be anchored by the average rating and adjust the temporary aberration by deviating from it to get the attention of review readers. By doing so, the temporary aberration (i.e., positive or negative trend in recent reviews) becomes weaker and returns to the average rating. Thus, we suggest:

H2: Individuals exhibit reactance behavior againsttemporary aberrations when they post a review.

2.5 Negativity Bias

In addition, we also attempt to identify the differential impacts of temporary aberrations on online review generation and consumption when the trend of recent reviews is either positive or negative. Previous studies have shown that people perceive negative reviews as useful for product or service quality. This is referred to as the negativity bias (or negative bias). People subconsciously place more emphasis on negative than on positive information (Kanouse and Hanson Jr, 1972), because they believe that negative information ismore credible (Kanouse, 1984) and view it as a more important source with a more persuasive effect (Ito *et al.*, 1998). People might be more inclined to believe in negative feelings and expressions because of the normative pressure to speak only positive things (Jones and Davis, 1966). Negativity bias has been observed in a number of domains (Rozin and Royzman, 2001): many studies on online reviews have indicated that negative reviews are more influential than positive reviews (Baek *et al.*, 2012; Basuroy *et al.*, 2003; Chevalier and Mayzlin, 2006; Mizerski, 1982; Park and Lee, 2009). However, while temporary aberrations may cause conformity or reactance behavior in subsequent reviewers and their purchase decisions online, it is not clear whether the behavior varies with the direction of the aberration (whether positive or negative). Thus, we investigate these issues and hypothesize that both online review generation and consumption might be more influenced by temporary aberrations when the direction is negative. We suggest:

H3a: The impact of a temporary aberration on purchase decisions becomes stronger when the direction of the temporary aberration is negative.

H3b: The impact of a temporary aberration on subsequent review generations becomes stronger when the direction of the temporary aberration is negative.

Ⅲ. Study 1: Online Review Consumption

3.1 Research Design and Procedures

In Study 1, we answer the question of how two sources of information, the average rating and the most recently posted reviews, influence the true evaluation of a hotel when a potential consumer makesa purchase decision based on other customers' posted reviews. To answer this, we employ an experimental approach that allows for differences in the two reference points. Our experiments consisted of two sub-experiments: a between-subject (positive, negative, or normal trend) and within-subject (counterbalance). The effects of two sequential types of information on online review consumption were tested using analysis of variance (ANOVA).

At the start of the survey, the participants were asked a screening question through which we were able to filter out individuals who had no experience booking a hotel online they were excluded from the survey. After passing the screening, the participants were invited to read the scenarios. Our experiment comprised two parts: first, there were three settings to represent the recent trend of reviews: positive, negative, or normal, and second, a choice was provided between the average rating and the most recently posted review's rating when they have different voices (same treatment with counterbalance). To compare the effect of recently posted reviews with that of the average rating, we assumed our treatment to be an extreme case: the most recently posted reviews were all positive or all negative (positive or negative trend, respectively). Since our research questions are related to the effect of negativity bias, based on prior findings that the impacts of online reviews are different when the reviews are positive or negative (Basuroy *et al.*, 2003; Chevalier and Mayzlin, 2006; Mizerski, 1982), we designed our treatment to consider both directions. For the between-subject experiment, we created a difference in the number of reviews in the treatment group (three recent reviews: either positive or negative trend) and the control group (three recent reviews with normal trend). This is because, in practice, some OTAs such as TripAdvisor (a popular website allowing review generation without experience) provide new review posters with three recent reviews on their page. In addition, we used the reviews showing a normal trend, which indicates that the ratings of the most recently posted reviews were similar to the average rating. For the within-group experiment, we suggested two options: (1) a negative trend in recent reviews and an average rating higher than the trend or (2) a positive trend in recent reviews and an average rating lower than the trend. Since the former experiment was a between-group treatment and the latter experiment was a within-group treatment, we collected data separately via different links (between-group).

The scenario in the former experiment read as follows:

> "Hotel A. 786 reviews. Average rating: 7/10. The most recent reviews were posted by verified customers. Customer 1: 9/10. Customer 2: 8/10. Customer 3: 10/10." (positive trend),
>
> "Hotel A. 786 reviews. Average rating: 7/10. The most recent reviews were posted by verified customers. Customer 1: 6/10. Customer 2: 4/10. Customer 3: 5/10." (negative trend), and
>
> "Hotel A. 786 reviews. Average rating: 7/10. The most recent reviews were posted by verified customers. Customer 1: 7/10. Customer 2: 8/10. Customer 3: 6/10." (normal trend)

One example of a scenario in the latter experiment read as follows:

> "Hotel ABC. 786 reviews. Average rating: 7/10. The most recent reviews were posted by verified customers. Customer 1: 9/10. Customer 2: 8/10. Customer 3: 10/10." and "Hotel XYZ. 785 reviews. Average rating: 8/10. The most recent reviews were

posted by verified customers. Customer 1: 7/10. Customer 2: 5/10. Customer 3: 6/10."

After reading the scenarios for at least 5 seconds, the participants were asked to complete the questionnaire about the constructs including perceived helpfulness, perceived credibility, perceived value of recent review, intention to book the hotel, and the variables for manipulation check of our research model. This procedure was repeated in both the experiments.

3.2 Measurements

The constructs were measured using items adapted from previous studies. The language of the questionnaire was modified to fit the research context. The items for intention to book the hotel wereadapted from Xie *et al.* (2011). Perceived helpfulness was measured using items adapted from Guilding (1999). Perceived credibility and value were assessed based on the items proposed by Sinkovics *et al.* (2012). All items were rated on a seven-point Likert scale. Additionally, we asked a six-point scale question to measure the true quality of hotel services between the two extreme ends: the cumulative rating and the ratings of the most recently posted reviews. During data collection, we used a counterbalance option to measure the true quality and the scale ranged from 1 (close to the cumulative rating) to 6 (close to the ratings of the most recently posted reviews) when analyzing data. To ensure the content validity of the constructs, the questionnaire was validated by researchers with experience in the relevant fields and further revised based on their comments. In addition, we conducted a pilot test with 10 experienced users of online hotel booking sites to confirm the validity of our questionnaire before distributing it to the participants. All the measurement items are described in <Appendix>.

3.3 Data Collection and Manipulation Check

The sample of this study consisted of South Korean participants who had experience in booking a hotel online. Data were collected through an online survey questionnaire over three weeks. The participants spent an average of 15 minutes completing the questionnaire. Since the between-subject experiment required three groups, we collected each group's data through a separate questionnaire. We collected 227 samples (91, 96, and 40), which included some incomplete and screened-out responses because respondents had no prior experience in booking a hotel online. After deleting these invalid responses, 144 valid surveys remained for further analysis (56, 57, and 31). <Table 1> summarizes the demographics of the respondents.

〈Table 1〉 Demographics of Respondents

Characteristics		Positive (N=56)	Negative (N=57)	Normal (N=31)
Gender	Male	21	34	18
	Female	35	23	13
Age	~19	1	0	0
	20s	46	48	15
	30s	9	9	16

To ensure that the respondents perceived the experimental conditions as we manipulated them, we conducted an ANOVA test for the positive, negative, and normal trends of recent reviews. <Table 2> shows the ANOVA test results of the three groups (positive, negative, and normal trends), with the independent sample t-test between the control group and the treatment group (positive or negative trends). With the same question of the manipulation check, respondents in the control group perceived higher ratings for the most recently posted reviews in the negative trend

〈Table 2〉 Manipulation Check Results

	Mean (Std. Dev)			Significance
Direction	Positive (N=56)	Negative (N=57)	Normal (N=31)	*F* (*sig.*)
	5.25 (1.13)	3.09 (1.48)	4.45 (1.12)	40.988($p<0.001$)
Direction	Positive (N=56)		Normal (N=31)	*t* (*sig.*)
	5.25 (1.13)		4.45 (1.12)	3.161 ($p = 0.002$)
Direction	Negative (N=57)		Normal (N=31)	
	3.09 (1.48)		4.45 (1.12)	-4.477 ($p < 0.001$)

as high, and lower ratings for the most recently posted reviews in the positive trend as low. Thus, our manipulation was well received.

Ⅳ Study 1: Experiment Results

Since our experiment involves a treatment (either positive or negative trends of recent reviews) with the three groups, we used the ANOVA test. The results are summarized in <Table 3> For consumers without experience, recent reviews were found to exert a significant influence on the intention to book the hotel. In other words, people rely on the most recently posted reviews when making booking decisions. Moreover, the trend had a significant influence on the perceive true quality of hotel services without experience. However, regarding perceived helpfulness, credibility, and value, we found no significant differences among the three groups.

To understand the different effects of the type of trends on intention and true quality (identified significant dependent variables), we conducted an independent sample t-test between the control and treatment groups (positive or negative groups). <Table 4>, which presents the results of the t-test, shows that both intention and true quality are significantly affected by the negative trend, while the results are insignificant with respect to the positive trend (the effect on intention is marginally significant). This means that people who observe a negative trend tend to check the most recent reviews when evaluating the true quality of hotel services and thus are less likely to book a hotel at that stage of review consumption. However, when they observe a positive trend, they are slightly more likely to book a hotel, although the evaluation of the hotel's true quality is not statistically different in case of positive and normal trends.

To broaden our understanding of the relative impacts

〈Table 3〉 The Results of the ANOVA Test on Dependent Variables for the Former Experiment

Dependent Variables	Mean (Std.Dev)			*t* (*sig.*)
	Positive (N=56)	Negative (N=57)	Control (N=31)	
Intention	4.80 (1.18)	3.02 (1.52)	4.35 (1.05)	28.057 ($p<0.001$)
Helpfulness	5.48 (1.11)	5.60 (1.12)	5.42 (1.09)	0.294 ($p=0.746$)
Credibility	4.92 (1.02)	5.22 (0.95)	4.88 (0.94)	1.800 ($p=0.169$)
Value	5.15 (0.97)	5.51 (0.90)	5.22 (1.02)	2.190 ($p=0.116$)
True quality	3.43 (1.51)	3.95 (1.42)	3.16 (1.53)	3.290 ($p=0.040$)

Note: True quality ranged from 1 (cumulative rating) to 6 (rating of the most recently posted reviews).

〈Table 4〉 The Results of the Independent Sample t-test on Intention and True Quality for the between-subject Experiment

Variables	Mean (Std.Dev)		t (*sig.*)
	Positive (N=56)	Control (N=31)	
Intention	4.80 (1.18)	4.35 (1.05)	1.763 (p=0.082)
True quality	3.43 (1.51)	3.16 (1.53)	0.786 (p=0.434)
	Negative (N=57)	Control (N=31)	
Intention	3.02 (1.52)	4.35 (1.05)	-4.365 (p<0.001)
True quality	3.95 (1.42)	3.16 (1.53)	2.414 (p=0.018)

Note: True quality ranged from 1 (cumulative rating) to 6 (ratings of the most recently posted reviews).

of the two types of information, the cumulative rating and the ratings of the most recently posted reviews, we analyzed the results of the second experiment. Using the manipulation question, “Which of the two ratings provided forthe chosen hotel was higher?”, we checked whether the respondents remembered the scenario when they responded to our questionnaire. Based on the results, 91 out of 144 responses were used for further analysis.

Before conducting the analysis, we defined the independent and dependent variables. We coded Hotel ABC (low cumulative rating and positive trend of recent reviews) as 1, and Hotel XYZ (high cumulative rating and negative trend of recent reviews) as 0 for the dependent variable. We then used true quality, value, gender, and age as independent variables to predict the decision. Helpfulness and credibility were excluded due to high correlations with value thus, the variance inflation factors (VIF) of using variables did not exceed three, indicating that multicollinearity was not a serious concern (Diamantopoulos, 2006). We also included a dummy variable to control for the effect of post-ordering. If Hotel ABC is displayed earlier, it is 1; otherwise, it is 0. The descriptive statistics and correlation matrix of the variables are presented in <Table 5>.

We conducted binary logistic regression to find the relative effects of the cumulative rating and recent reviews when consumers make a booking decision. The logistic regression results are presented in <Table 6>. The results show that the effects of perceived value, true quality, and post ordering (marginally) are significant, while those of age and gender are insignificant. The post-ordering results show that people tended to prefer the earlier listed hotels. Interestingly, the coefficient of true quality indicates that people who perceived the true quality of hotel services to be similar to the most recent reviews, tended to choose Hotel ABC with a positive trend, even though the hotel has a lower cumulative rating than Hotel XYZ. The results of perceived value are consistent. When people perceived the recent reviews to be valuable, they tended to choose the hotel with a positive trend in recent reviews. Additionally, since an increase in the Wald statistics typically indicates an increase in the effect of the corresponding independent variable on the dependent variable (Peng *et al.*, 2002), the effects of value and true quality are higher than the effect of post-ordering. This shows the active adjustment of an individual’s decision-making process with timely information. Therefore, consumers are more likely to book a hotel with a low average rating and a positive trend in recent reviews than those with a high average rating and a negative trend. In other words, it indicates

〈Table 5〉 Descriptive Statistics and Correlation Matrix for the Latter Experiment (N=91)

Variables	Mean	SD	(1)	(2)	(3)	(4)	(5)
(1) Hotel choice	.81	.39					
(2) Post ordering	.64	.48	.17				
(3) Age	28.33	2.66	.02	.09			
(4) Gender	1.47	.60	.06	.03	-.21*		
(5) Value	5.45	.97	.30**	.05	.01	.12	
(6) True quality	3.88	1.44	.45**	-.05	-.08	.11	.27*

** $p < 0.01$, * $p < 0.05$.

〈Table 6〉 The Results of the Logistic Regression Analysis for the Latter Experiment (N=91)

Variables	B	S.E.	Wald	*p-value*(*sig.*)
Post ordering	1.267	.695	3.328	.068
Age	.063	.133	.273	.637
Gender	-.128	.695	.034	.854
Value	.714	.338	4.469	.035
True quality	1.018	.284	12.829	.000
Constant	-7.924	4.557	3.024	.082

Note: For the dependent variable, Hotel ABC (low cumulative rating and positive trend) was chosen as 1, and Hotel XYZ (high cumulative rating and negative trend) as 0. Post ordering 1 (0) is Hotel ABC (XYZ), located at the top.True quality ranged from 1 (the cumulative rating) to 6 (the rating of the most recently posted reviews).

that people tend to consider recent review trends when choosing a hotel.

Our analysis of the two experiments shows that when people make a decision based on online reviews, they integrate two types of information: the average rating and the recent reviews. They rely more on the most recently posted reviews to evaluate hotel services, which can lead to making a purchase decision. In other words, according to the theory, review consumers adjust their opinions more actively using additional information acquired when they observe a different trend in recent reviews compared to the average rating. This tendency is stronger when people observe a negative trend than a positive trend in recent reviews. Thus, H1 is partially supported and H3a is fully supported.

Ⅴ. Study 2: Online Review Generations

5.1 Research Design

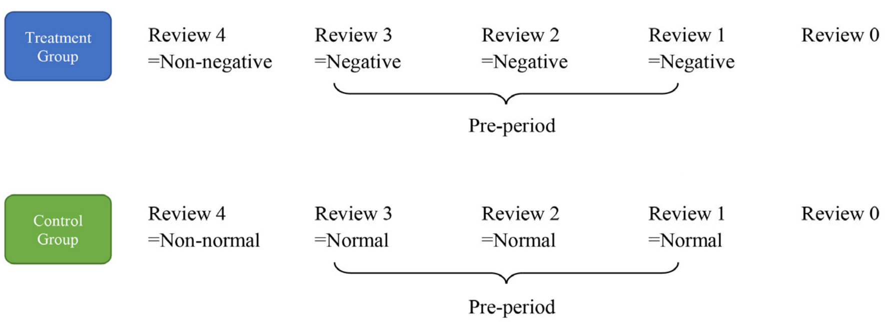
In Study 2, we developed empirical settings similar to those from the experiments in the previous section (Study 1) to focus on the influence of the trends of recent reviews (temporary aberration) on new reviews. Review posters are expected to be influenced when the ratings of recently posted reviews temporarily deviate from the average rating. To explore this, we closely observed the differences between the average rating of customer reviews and the ratings of recent reviews that deviated from the average rating. By comparing the influence of the temporal aberration with a normal trend, we demonstrate the influence of recent review aberrations on new review posts.

To empirically investigate the influence on review generation, in Study 2, we leveraged a series of empirical research designs that incorporate the differences in the average rating in the ratings of temporary aberration. To do this, we intentionally selected sets of reviews corresponding to the experimental research designs and tested the influence on the review generation process, using online customer review data for hotels listed on Ctrip.com, one of the most popular online travel websites. Similar to the experiment setting for online review consumption, we specifically chose three consecutively posted reviews, because real business models, such as TripAdvisor.com, provide prospective review posters with three most recently posted reviews.

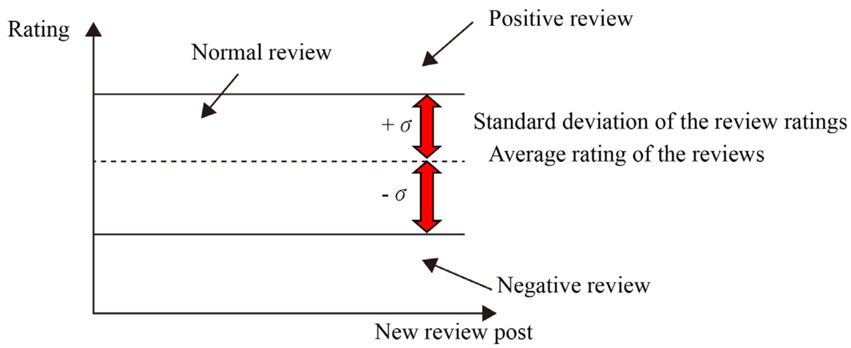
Specifically, for the treatment group with a negative trend, we only considered three recently posted negative reviews for the treatment group (Review 1, Review 2, and Review 3 were all negative), while the fourth posted review was non-negative (Review 4 was non‑negative). Similarly, for the treatment group with a positive trend, we merely considered three recently posted positive reviews (Review 1, Review 2, and Review 3 were all positive), while the fourth review was non-positive (Review 4 was non‑positive). Meanwhile, for the control group, we incorporated three recently posted normal reviews (Review 1, Review 2, and Review 3 were all normal), while the fourth review was non-normal (Review 4 was non-normal).

According to prior literature (Gu and Ye, 2014; Proserpio and Zervas, 2017), management's responses to old reviews have been proven to impact subsequent reviews. Since the management's responses have a confounding effect on posting of new reviews, we minimized the effects by placing a restriction that the reviews in the trend should not have received any management responses (Review 1, Review 2, Review 3, and Review 4). For any trend in the reviews, the same restriction was applied. This produced the initial sets of reviews for the treatment and control groups. For convenience, if there are 3 consecutive positive or negative reviews within the treatment group, we call the grouping "Window 3." <Figure 1> shows the detailed construction of the negative review trend in the treatment group and the normal trend in the control group.

Based on the research designs mentioned above, we defined the following variables. First, we defined a negative review. If the rating of a review was lower than the average rating minus the standard deviation of the review ratings for the hotel, it was considered a negative review. If the rating fell between the average rating minus the standard deviation of the reviews



〈Figure 1〉 Construction of the Treatment and Control groups in Window 3



〈Figure 2〉 Description of Review Categorization

for the hotel and the average rating plus the standard deviation of the reviews for the hotel, we defined the review as a normal review. If the rating of a review was higher than the average rating plus the standard deviation of the review ratings for the hotel, it was considered a positive review. <Figure 2> shows the categorization of the reviews.

Using the definitions of these three variables, we defined positive, negative, and normal trends. In Window 3, if the most recently posted reviews before a new review (Review 0) were all negative, we regarded the trend as negative, if they were all positive, we considered the trend as positive, and if they were all within the normal review threshold, we considered it to be a normal trend.

Given the variables, we calculated the rating distance between the new review (Review 0) and the average of the three most recently posted reviews. The rating distance is calculated as the absolute distance between the most recently posted reviews' rating and the average rating.

$$RatingDistance_{n} = |ReviewRating_0 - AverageRating_{(1,2,3)}|$$

<Table 7> provides definitions of the previously mentioned variables.

〈Table 7〉 Definitions of Variables

Variable Name	Definitions of Variables
Window	In the positive/negative review trend, the number of subsequently posted positive/negative reviews. In Window 3, the treatment and control groups contain Review 1, Review 2, and Review 3. For example, the positive review trend consists of 3 positive reviews and one non-positive review. In Window 4, the treatment and control groups contain Review 1, Review 2, Review 3, and Review 4. In Window 4, the below variables are defined similarly.
Positive review	Dummy variable: 1 if the rating of a review is higher than the average of reviews plus a standard deviation of the reviews for the hotel, or if the review rating is 5. 0 otherwise.
Negative review	Dummy variable: 1 if the rating of a review is lower than the average of reviews minus the standard deviation of the reviews for the hotel. 0 otherwise.

〈Table 7〉 Definitions of Variables(Continued)

Variable Name	Definitions of Variables
Normal review	Dummy variable: 1 if the rating of a review is between the average of reviews minus a standard deviation of the reviews for the hotel and the average of review plus a standard deviation of the reviews for the hotel. 0 otherwise.
Positive review trend	Dummy variable for representing a positive trend in the most recently posted reviews: 1 if a certain number of positive reviews are sequentially posted. 0 otherwise. For example, in Window 3, if the 3 most recently posted reviews before the new review (Review 0) are all positive, it is defined as a positive review trend.
Negative review trend	Dummy variable for representing a negative trend in the most recently posted reviews: 1 if a certain number of negative reviews are sequentially posted. 0 otherwise. For example, in Window 3, if the 3 most recently posted reviews before the new review (Review 0) are all negative, it is defined as a positive review trend.
Normal review trend	Dummy variable for representing a normal trend in the most recently posted reviews: 1 if a certain number of normal reviews are sequentially posted. 0 otherwise. For example, in Window 3, if the 3 most recently posted reviews before the new review (Review 0) are all normal, it is defined as a normal review trend.
Difference in review posting dates	The difference in posting dates between Review 0 and Review 1 e.g., In the case of Oct. 11, 2016 and Oct. 09, 2016, the difference in review posting dates is 2.
Average of room score	For Window 3, the average of the room scores from Review 1 to Review 3
Average of service score	For Window 3, the average of the service scores from Review 1 to Review 3
Average of environment score	For Window 3, the average of the environment scores from Review 1 to Review 3
Average of facilities score	For Window 3, the average of the facilities scores from Review 1 to Review 3

Note: Review ratings were calculated by averaging the scores of the four elements: room, service, environment, and facilities.

5.2 Data Description

For Window 3, we used three sets of customer reviews: two for the treatment group and one for the control group. The treatment group comprised both positive and negative trends in customer reviews. The control group comprised only the normal trend in customer reviews. <Table 8> shows the summary statistics for the reviews (Review 1, Review 2, and Review 3) of the sample. The average review rating of the negative review trend was 2.88 and that of the normal review trend was 3.86. Meanwhile, for the positive trend of reviews, it is much higher, up to 4.86. In the case of each element of the review rating (room, service, environment, and facilities), there is also an observable tendency for the average of each element to transform from a negative to a positive trend.

<Table 9> provides the distribution information of the new review (Review 0) for each of the three customer reviewtrends. In the negative review trend, about 57% of customer reviews had ratings higher than or equal to 4.00. Approximately 13% of the reviews had ratings lower than 3.00. Reviews scoring between 4.00 and 5.00 accounted for the largest portion (43.29%). Meanwhile, reviews scoring 1.00 to less than 2.00 made up the smallest percentage (3.28%). In the normal review trend, approximately 58% of the reviews had ratings higher than or equal to 4.00. Approximately 12% of the customer reviews were rated lower than 3.00. Reviews with ratings of 4.00 and less than 5.00

〈Table 8〉 Summary Statistics of the Sample

Variables	Negative Trend	Normal Trend	Positive Trend
Average of review rating	2.88 (.73)	3.86 (.42)	4.86 (.19)
Average of room score	3.03 (.84)	4.00 (.53)	4.93 (.19)
Average of service score	2.80 (.82)	3.88 (.53)	4.90 (.22)
Average of environment score	2.98 (.81)	3.90 (.53)	4.82 (.31)
Average of facilities score	2.72 (.81)	3.66 (.56)	4.80 (.33)

Note: Standard deviations are in parentheses.

〈Table 9〉 Customer Review Distribution of the Sample (Review 0)

Variables	Negative Trend		Normal Trend		Positive Trend	
	N	Percentage	N	Percentage	N	Percentage
Number of customer reviews	9,273	100.00%	65,127	100.00%	14,540	100.00%
1.00<=Review rating <2.00	304	3.28%	2,159	3.32%	143	0.98%
2.00<=Review rating <3.00	914	9.85%	5,735	8.80%	606	4.17%
3.00<=Review rating <4.00	2,794	30.14%	19,481	29.91%	2,582	17.76%
4.00<=Review rating <5.00	4,015	43.29%	30,501	46.84%	7,096	48.80%
Review rating =5.00	1.246	13.44%	7,251	11.13%	4,113	28.29%

made up the largest portion (46.84%). For the positive review trend, the proportion of reviews with ratings below 3.00, dropped to about 5%, while the number of reviews with ratings higher than or equal to 4.00 rose to about 77%. The largest portion is still comprised of reviews scoring 4.00and less than 5.00 (48.80%). The smallest portion is still comprised of reviews scoring 1.00 and less than 2.00 (0.98%).

Ⅵ. Study 2: Empirical Results

Using the sample described in Section 5.2, we leveraged the following regression model specifications (1) as the baseline model: at the hotel level, we controlled for hotel-level heterogeneity and consideredrobust clustered error terms, which controlled the autocorrelation issue (Bertrand *et al*., 2004).

$$\begin{aligned} AbsoluteDistance_{ig} &= \beta_0 + \beta_1 \times Treatment_{ig} \\ &+ \beta_2 \times Difference\ in\ review\ posting\ dates_{ig} \\ &+ \beta_3 \times Average\ of\ room\ score \\ &+ \beta_4 \times Average\ of\ service\ score \\ &+ \beta_5 \times Average\ of\ environment\ score \\ &+ \beta_6 \times Average\ of\ facilities\ score + \delta_i + \epsilon_{ig} \end{aligned} \quad (1)$$

where $\text{AbsoluteDistance}_{ig}$ is defined as the distance between a review rating (Review 0) and the average of the most recently posted reviews (Review 1, Review 2, and Review 3) and "*g*" represents the treatment and control groups. We regarded both positive and negative review trends as the treatment group, while the normal trend of reviews was used as the control group. If a review belonged to the treatment group, it was 1, otherwise, it was 0. As the difference in posting dates between Review 0 and Review 1 grows, the impact of the previous reviews on the new review post is increasingly dampened. Thus, we considered the difference to be a control variable. Along with this, the trend of previous reviews (Review 1, Review 2, and Review 3) could affect the new review post (Review 0). To control for the effects of the trend, we included the four elements of the review rating as well: average of room score, average of service score, average of environment score, and average of facilities score.

6.1 Negative Trend vs. Normal Trend

<Table 10> provides the empirical results for the negative trend of recent reviews. The dependent variable for the three models was absolute distance, as previously defined. Our primary interest is the variable, "Treatment," which is a dummy variable that represents a new review post in the negative trend of recent reviews. It is 0 when the new review post belongs to the control group, otherwise, it is 1. The first column (1) includes only the independent variable, "Treatment" with hotel-level heterogeneity. In column (2), we include controls representing the trend of the previous reviews. In column (3), we consider clustered error terms at the hotel level. Across all models, the estimated coefficients for "Treatment" were significantly positive ($\beta_{Treatment}$=.51 or .19, *p-value*<0.01). This shows that the new review post (Review 0) in the negative trend is likely to deviate more from the average of recent reviews than from the normal trend of recent reviews. When the ratings of the recently posted reviews are all significantly lower than the long-term average of customer reviews, a prospective review poster is shown to significantly deviate from the trend of recent reviews.

6.2 Positive Trend vs. Normal Trend

<Table 11> provides the possible influences of positive reviews on the new review post (Review 0). Each

〈Table 10〉 Negative Trend vs. Normal Trend

Variables	AbsoluteDistance Model (1)	AbsoluteDistance Model (2)	AbsoluteDistance Model (3)
Treatment	$.51^{***}$ (.01)	$.19^{***}$ (.01)	$.19^{***}$ (.01)
Difference in review posting dates	No	Yes	Yes
Average of room score	No	Yes	Yes
Average of service score	No	Yes	Yes
Average of environment score	No	Yes	Yes
Average of facilities score	No	Yes	Yes
Hotel FE	Yes	Yes	Yes
Cluster Standard Errors (hotel level)	No	No	Yes
R-Squared	8.13%	9.70%	9.70%
Observations	74,400	74,400	74,400

Note: The standard errors are shown in parentheses. $^{**}p < 0.05$ and $^{***}p < 0.01$.

〈Table 11〉 Positive Trend vs. Normal Trend

Variables	AbsoluteDistance Model (1)	AbsoluteDistance Model (2)	AbsoluteDistance Model (3)
Treatment	$.18^{***}$ (.01)	$.16^{***}$ (.01)	$.16^{***}$ (.01)
Difference in review posting dates	No	Yes	Yes
Average of room score	No	Yes	Yes
Average of service score	No	Yes	Yes
Average of environment score	No	Yes	Yes
Average of facilities score	No	Yes	Yes
Hotel FE	Yes	Yes	Yes
Cluster Standard Errors (hotel level)	No	No	Yes
R-Squared	1.39%	1.56%	1.56%
Observations	79,667	79,667	79,667

Note: The standard errors are shown in parentheses. $^{**}p<0.05$., and $^{***}p<0.01$.

model included the same variables as in <Table 10> We also focus on the independent variable, "Treatment" which represents a new review post in the positive trend of recent reviews. The estimated coefficients for the "Treatment" are all significantly positive ($\beta_{\text{Treatment}}$ = .18 or .16, *p-value* < 0.01). When a new review poster looks at a positive trend in recent reviews, he or she tends to assign ratings, which significantly deviate from the average rating of recent reviews. Thus, the deviation behavior in review posting is confirmed in case of both the negative and the positive trend of recent reviews.

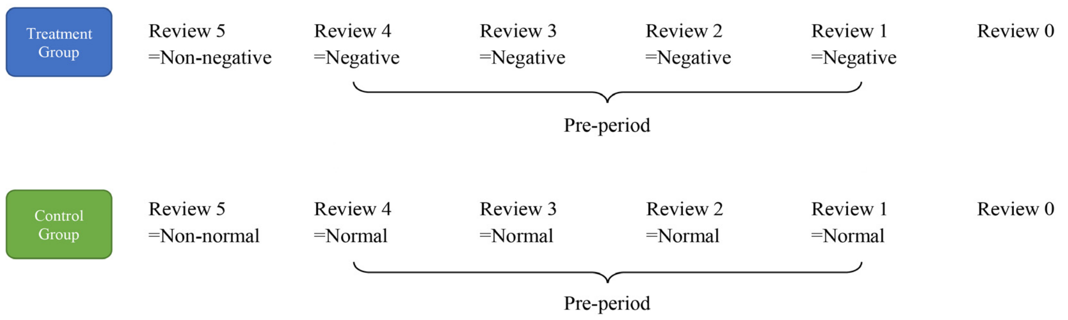
Regarding negativity bias in the review generation and consumption processes, we compared the estimated coefficients to check the differences between two regression models based on Clogg *et al.* (1995).[1] In this comparison, the null hypothesis is the equality of the regression coefficients. When we considered the estimated coefficients of Model (3) in <Tables 10> and <Table 11>, the equality of the regression coefficients was rejected at the 95% confidence level. This implies that the review trends have differential impacts on subsequent reviews, and in case of a negative trend of reviews, new review posters tend to assign ratings that significantly deviate from the trend than in case of a positive trend. Thus, H2 and H3b are supported.

6.3 Robustness Check

In this robustness check, we considered Window 4, because the number of posted reviews displayed to customers varies from three to four, depending on the service platform. In Window 4, as the trend of previous reviews, Review 1, Review 2, Review 3, and Review 4 were included both in the treatment and control groups. For the treatment group, both the negative and positive trend of customer reviews were considered. For the control group, the normal trend in customer reviews was considered. Based on the research design explained in Section 5.1, we constructed the treatment and control groups by selecting the trend

1) Clogg *et al.* (1995) suggested the following z-test:

$$Z=\frac{\hat{\beta}(Treatment\ in\ Negative\ Trend)-\hat{\beta}(Treatment\ in\ Positive\ Trend)}{[(S.E.(\hat{\beta}(Treatment\ in\ Negative\ Trend))^2+(S.E.(\hat{\beta}(Treatment\ in\ Positive\ Trend)))^2]^{1/2}}$$



〈Figure 3〉 Construction of the treatment and control groups in Window 4

of reviews corresponding to the design. This is illustrated in <Figure 3>.

The treatment group for the negative trend of recent reviews consists of 3,091 reviews, and the treatment group for the positive trend of recent reviews is composed of 5,691 reviews. The control group consisted of 38,464 reviews.

6.3.1 Negative Trend vs. Normal Trend

In this robustness check, we explored how a review poster is affected by the trend of recent reviews. As shown in <Table 11>, we examined the influence of the negative trend in recent reviews on a new post compared to that of a normal trend. Each model was set up in the same way as described in Section 6.1. The dependent variable was the absolute distance between the rating of a new post and the average rating of recent reviews. We focusedon the effects of "Treatment" in this section as well. Across all models, the estimated coefficients for "Treatment" were all significantly positive ($\beta_{\text{Treatment}}$=.49 or .25, *p-value* <0.01). As found in Section 6.1, a new review poster assigns a review rating with a large difference if there exists a negative trend in recent reviews compared

〈Table 12〉 Negative Trend vs. Normal Trend

Variables	AbsoluteDistance Model (1)	AbsoluteDistance Model (2)	AbsoluteDistance Model (3)
Treatment	$.49^{***}$ (.01)	$.25^{***}$ (.02)	$.25^{***}$ (.02)
Difference in review posting dates	No	Yes	Yes
Average of room score	No	Yes	Yes
Average of service score	No	Yes	Yes
Average of environment score	No	Yes	Yes
Average of facilities score	No	Yes	Yes
Hotel FE	Yes	Yes	Yes
Cluster Standard Errors (hotel level)	No	No	Yes
R-Squared	4.67%	5.57%	5.57%
Observations	41,555	41,555	41,555

Note: The standard errors are shown in parentheses. $^{**}p < 0.05$ and $^{***}p < 0.01$.

〈Table 13〉 Positive Trend vs. Normal Trend

Variables	AbsoluteDistance Model (1)	AbsoluteDistance Model (2)	AbsoluteDistance Model (3)
Treatment	$.17^{***}$ (.01)	$.19^{***}$ (.01)	$.19^{***}$ (.01)
Difference in review posting dates	No	Yes	Yes
Average of room score	No	Yes	Yes
Average of service score	No	Yes	Yes
Average of environment score	No	Yes	Yes
Average of facilities score	No	Yes	Yes
Hotel FE	Yes	Yes	Yes
Cluster Standard Errors (hotel level)	No	No	Yes
R-Squared	0.88%	1.02%	1.02%
Observations	44,155	44,155	44,155

Note: The standard errors are shown in parentheses. $^{**}p<0.05$, and $^{***}p<0.01$.

to when there is a normal trend in recent reviews. This greater deviation behavior was also confirmed in case of a negative trend in recent reviews. This is shown in <Table 12>.

As shown in <Table 13>, we examined the influence of the positive trend of recent reviews on a new review post. If the trend in recent reviews is positive, "Treatment" becomes 1. If the trend of recent reviews is normal, "Treatment" becomes 0. Similar to the results shown in <Table 11>, the estimated coefficients for "Treatment" are all positive and significant ($\beta_{\text{Treatment}}$ =.17 or .19, *p-value* < 0.01). Based on the results presented in <Tables 10> and <Table 11>, we confirm that, in cases of both negative and positive trend of recent reviews, a new review poster will tend to assign significantly deviated ratings from the previous trend, intentionally leaving a review rating that is far from the average of the recent reviews. These results were compared with those in the normal trend of recent reviews. However, the temporal aberration from the average rating of recent reviews cannot last long because review generation has the tendency to adjust the temporal deviation.

Ⅶ. Discussion and Conclusions

7.1 Major Findings

This study explores the relative impacts of the average ratings and ratings of the most recently posted reviews on online review generation and consumption. To identify the relative impacts, we conducted two studies: experimental designs for online review consumption and empirical analyses for online review generation.

Review consumetrs (readers) tend to follow recent reviews by actively adjusting their decision-making with temporary aberrations (a trend of recent reviews) when they observe two conflicting pieces of information. The effect is different with respect to whether the trend of recent reviews is negative or positive. When people observe a positive trend in recent reviews, their intention to book a hotel room increases, while their evaluations of the true quality of hotel services do not move toward the trend significantly. However, when people observe a negative trend in recent reviews, their intention to book a hotel room decreases and their evaluations of the true quality of hotel services move towards the trend. This result is confirmed by the impact of negativity bias on online review consumption. The significant impact of a negative trend on review consumption might be caused by the objective of review consumers (to avoid the worst case): the purchase decision of experience goods (i.e., hotel reservation) involves decision-making to reduce commission errors (i.e., booking a bad hotel) rather than omission error (i.e., missing a good hotel). As the uncertainty of product characteristics and the risk of purchasing a product are more salient in experience goods, individuals are more likely to make purchase decisions based on product reviews (Zhu and Zhang, 2010). To reduce the risk of making a bad choice (purchase decision), they are more likely to be hypersensitive to negative reviews and timely information. Thus, people generally tend to actively mirror recent reviews when they make a purchase decision, and consider a negative trend in recent reviews more seriously than positive information.

In contrast, in case of online review generation, our results show that subsequent review ratings tend to deviate from the ratings of recent reviews. This result indicates that when review posters observe an inconsistency between the average rating and the most recently posted review ratings, they use the average rating as the initial anchor and adjust the inconsistency using the ratings of the most recently posted reviews, in order to deviate from the most recent trend, regardless of whether the direction is positive or negative. Since the objective of review generation is to capture the attention of review readers, review posters sometimes deviate from the temporary aberration. This is also confirmed by the impact of negativity bias on online review generation. In other words, review posters decide their ratings by deviating more from recent reviews when their trend is negative rather than the trend is positive. This indicates that review posters recognize that review readers value a negative trend more than a positive trend. Thus, they leave more distanced ratings to catch the attention and belief of their peers.

In summary, both review consumers and producers actively adjust their opinions to reflect additional information when they observe two different kinds of information. However, the way they do this varies depending on their objective, and thus leads to different behavioral consequences. While review consumers want to book a good hotel, review producers want to gain attention of the readers. Review consumers actively adjust their opinions and use timely information to choose a good hotel. However, review posters actively adjust their reviews by deviating from recent reviews to receive attention from review readers. Their goals being different makes a difference in the direction of adjustments brought on by recent reviews. However, despite the differing objectives of review readers and posters, we can confirm that a negativity bias exists in both the decision-making processes, review generation and review consumption.

7.2 Theoretical Implications

Our findings have several theoretical implications for online review literature. While OTAs tend to provide these two types of information in practice, scholars have paid relatively scant attention to their influence on both review consumers and producers. We sequentially observed different types of information as anchoring and adjustment processes, based on the behavioral decision theory, and identified the different effects of positive and negative trends inrecent reviews on adjustment information processes. This study thus enhances our understanding by emphasizing the importance of timely information and the interaction between average ratings and recent reviews. Moreover, we call for research on the interplay between multiple information sources in the realm of online reviews. For example, in practice, OTAs provide multiple kinds of information, such as ratings of room, service, environment, and facilities. Considering the interactions of these multiple kinds of information, we can partially answer the call for research by enhancing the understanding of the mechanism and process of online review consumption and generation (King *et al.*, 2014).

While some research has attempted to understand prior reviews in the context of online reviews, they lack a theoretical foundation. We adopted a theoretical lens of behavioral decision theory to understand online review generation and consumption, as well as suggest additional theoretical perspectives to explain and interpret previous findings regarding the impacts of prior reviews. Based on the findings of previous studies on this subject and a theoretical lens, we examined the presence of herding behavior in review consumption and reactance behavior in review generation in the context of online reviews, providing a hint to explain the underlying mechanism behind these behaviors. Both review posters and consumers anchor their decision at the average rating and adjust it with recent reviews, while the way they adjust it differs depending on their objective. Moreover, its effect can vary depending on whether the temporary aberration is positive or negative. Furthermore, this study confirms the existence of negativity bias in online review consumption and generation, and applies it to the trend of recent reviews. This also calls for research on the replication and extension of our understanding of negativity bias in the context of online reviews.

We considered the generation and consumption of online reviews. While these two activities are closely connected (Yang *et al.*, 2012), there is a lack of studies examining both activities. By exploring the interplay between average rating and recent reviews, which affect online review generation and consumption differently, we can identify the relative effects of the two types of information more thoroughly. Moreover, our findings imply that the processing mechanism of these two types of information is based on behavioral decision theory, with different objectives of online review generation and consumption. Future studies can expand our findings by shedding light on the underlying psychological mechanisms of information processing for other types of individuals' decision-making behaviors.

7.3 Managerial Implications

This study provides practical insights for hotel managers. First, in online review generation, subsequent review ratings tend to deviate from the preceding trend. That is, the review rating system shows resilience to an aberration in extreme review trends because there exists a tendency to converge toward the average rating. This implies that management response is not a requirement to control the dynamics of the flow of customer reviews. However, reducing the negative trend is important for online review consumption, as it directly affects the sales in the hotel industry (Chevalier and Mayzlin, 2006). Thus, it would be better for managers to consider how to deal with the negative trend in recent reviews. For example, armed with a combination of previous findings, managers should act strategically to quickly reduce the damage of a negative trend using management responses (Wang and Chaudhry, 2018). Our study also provides insights into OTAs. While OTAs already provide various kinds of information to users, we suggest focusing on the trend of recent reviews. For instance, similar to the moving average in the stock market, OTAs can provide information about the tendency of online reviews to help consumers' decision-making processes. However, because too much information can at times be harmful due to information overload (O'Reilly III, 1980; Schick *et al.*, 1990), OTAs should consider providing adequate amount of information and design how to deliver the information properly to users (Lamest and Brady, 2019).

7.4 Limitations and Future Research Opportunities

This study calls for future research to address the limitations of and validating and expanding the findings of our study. First, our study is limited in that it only considers quantitative aspects, such as the average rating and the ratings of recent reviews. To provide more rigorous findings by reflecting on the practical aspects, future research should consider other dimensions of reviews, including review content. Relatedly, the hotel search process may include various variables such as room availability, price fluctuation, and irregular promotions, which were not considered in our research. If these aspects are considered in future research, the generalizability of the results can be improved. Thus, observational research can be helpful in future research. Second, we conducted separate studies to explore both online review generation and consumption behavior. However, because the behaviors have synergy, considering both generation and consumption simultaneously can provide an integrated understanding (Yang *et al.*, 2012). Third, we used empirical data from only the hotel reservation service platform. Future research considering other types or multiple types of products or services can have more generalizability by providing empirical results with more dramatic variations or differences. In addition, empirical data were collected from China, and the experimental data were collected from South Korea. Since these two nations share Eastern culture (collectivism), our findings can ensure data consistency from the sample; however, the results of our study can be different for Western culture (individualism) (e.g., Hong *et al.*, 2016). Future research with cross-cultural data can generalize or enhance our findings by comparing the similarities or differences between cultures.

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〈Appendix〉 Measurement Items for Study 1

Construct	Questionnaire	Source
Intention to book the hotel	To what extent do you intend to book the hotel based on the most recently posted reviews? (1 = definitely not book the hotel, 7 = definitely book the hotel).	Xie *et al.* (2011)
Perceived helpfulness	To what extent do you consider the most recently posted reviews could be helpful to you? (1 = not at all, 7 = to a great extent)	Guilding (1999)
Perceived credibility	(1) the ratings of the most recently posted reviews are convincing (2) the ratings of the most recently posted reviews are believable (3) the ratings of the most recently posted reviews are credible (1 = strongly disagree, 7 = strongly agree)	Sinkovics *et al.* (2012)
Perceived value	(1) the ratings of the most recently posted reviews are useful (2) the ratings of the most recently posted reviews are valuable (3) the ratings of the most recently posted reviews are important (1 = strongly disagree, 7 = strongly agree)	Sinkovics *et al.* (2012)
True quality	Using the 6 options provided, please click the box which most accurately represents where the true quality lies. (1 = the cumulative rating, 6 = the rating of the most recently posted reviews)	

Information Systems Review
Volume 23 Number 3
August 2021

The Differential Impacts of Temporary Aberration on Online Review Consumption and Generation

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Abstract

Many online travel agencies (OTAs) provide average ratings and time-relevant information or the most recently posted reviews regarding hotels to satisfy customers. To identify these two factors' relative influence on behavioral decision-making processes, we conducted two studies: (1) an experimental research design to explore the relative influence of the two on online review consumption and (2) an empirical approach to examine their relative impact on online review generation. The results show that when review posters observe an inconsistency between average ratings and recent reviews, they tend to deviate from the recent reviews regardless of the overall direction (reactance behavior). Meanwhile, review consumers tend to conform to the opinions presented in recent reviews (herding behavior). Additionally, in both cases, the effects are amplified in case of a negative aberration. Based on the findings, this study provides theoretical and practical implications regarding the relative influences of average rating and recently posted reviews and their different impacts on online review consumption and generation.

Keywords: Online Reviews, Average Rating, Recent Reviews, Temporary Aberration, Review Generation, Review Consumption

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현재 한국기술교육대학교 산업경영학부 조교수로 재직 중이다. KAIST 경영대학에서 박사 취득 후 중국과학기술대학 조교수를 역임하였다. 주요 관심분야는 collective dynamics and human behaviors in IS이다. Journal of Business Ethics, International Journal of Information Management, Communications of the ACM 등 주요 저널에 논문을 발표하였다.

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현재 명지대학교 미래융합경영학과 조교수로 재직 중이다. KAIST 경영대학에서 박사학위를 취득하였다. 주요 관심분야는 CRM, 뉴미디어전략, 정보보안 등이다. Journal of Intellectual Capital, Information Technology & People, Computers & Security 등 주요 저널에 논문을 발표하였다.

논문접수일 : 2021년 04월 27일 게재확정일 : 2021년 06월 22일
1차 수정일 : 2021년 06월 19일