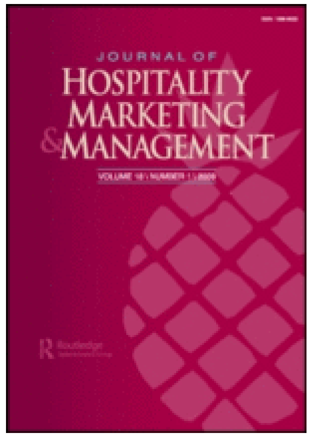
 This is the Pre-Published Version.

This is an Accepted Manuscript of an article published by Taylor & Francis in Journal of Hospitality Marketing & Management on 18 Nov 2023 (published online), available at: https://doi.org/10.1080/19368623.2023.2279166.

Shin, S., & Xiang, Z. (2023). Effect of online review comment recency on information processing: interaction between overall and recently posted individual ratings. Journal of Hospitality Marketing & Management, 33(5), 602–625.



Effect of Online Review Comment Recency on Information Processing: Interaction between Overall and Recently Posted Individual Ratings

Journal:	*Journal of Hospitality Marketing & Management*
Manuscript ID	WHMM-04-2023-3509.R2
Manuscript Type:	Original Article
Keywords:	online reviews, information recency, local search, construal level theory
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1. Introduction

Most consumers often rely on online reviews to make more informed purchase decisions (Lee et al., 2022). Especially when dealing with an experiential product (e.g., a dining experience in a restaurant), consumers feel a greater sense of uncertainty because the product's quality is difficult to assess before consumption (Roy, 2023). Thus, tourists recognize the importance of online reviews (Liu et al., 2022a). Nowadays, over 90% of tourists do not make booking decisions without visiting online review platforms (Minc, 2022).

Online review platforms present not only individual reviews, but also information signals derived from a group of reviews: the average rating of reviews, a list of keywords frequently mentioned in reviews, a collage of photos embedded in reviews, and so on. The availability of different types of information signals enables tourists to process the various signals holistically (Fan & Zhang, 2020). When estimating the overall quality of a hospitality business, based on the average rating of online reviews, tourists check the rating of a recently posted review to determine if the lowest or highest quality ratings have remained unchanged (Pitman, 2022; Ziegele & Weber, 2015). After identifying the attributes of a hospitality business, which are recognized by large numbers of visitors via a list of keywords or a collage of photos (e.g., a signature menu of a restaurant), tourists seek more information about the attributes by reading the individual reviews, paying particular attention to the keywords or photos included in them (Li et al., 2021).

Holistic information processing on an online review platform helps tourists make more informed decisions (Shin et al., 2021). However, holistic processing can also lead tourists to encounter conflicts between information signals (Liu et al., 2022b). For example, it is not unusual for tourists to observe the conflict between the average ratings of online reviews and the rating of a recent individual review, because the quality of a tourism product easily changes over time (Jang, 2004). If aggregated ratings are high but a recent rating is low, how would tourists deal with the conflict? Construal level theory contends that, when individuals are exposed to multiple information signals to make a near-future (or far-future) decision, they are more (or less) likely to rely on up-to-date signals, because these fit with their temporal mindset (Trope et al., 2007). According to the theory, whether tourists adopt an aggregated rating or a recent rating is dependent on whether the review is read for a near-future decision or a far-future decision. In other words, if tourists used online reviews to select a place to visit immediately, they would adopt a recent rating; but for a visit in the distant future, they would adopt an aggregate rating (Shin & Xiang, 2021).

Conflicting information signals offer valuable insights into understanding the intricate process of holistic information processing within individuals. These conflicting signals prompt us to explore factors beyond the signals themselves, shedding light on why an information receiver chooses one signal over another (Siddiqi et al., 2020). Ruiz-Mafe et al. (2020) examined consumers' reactions to products based on both positive and negative reviews and discovered that the order in which the reviews were presented influenced whether consumers leaned towards a positive or a negative review. This highlights the sorting mechanism of online review platforms as a pivotal factor in understanding how consumers process information. Delving into a similar realm, Xu and Jin (2022) investigated consumers' intentions to purchase a product in the face of conflicting online reviews. Their research revealed a correlation between the use of reviews and an individual's propensity for risk-taking. This emphasizes the significance of considering an individual's enduring characteristics when unraveling the complexities of information processing. In the same way that disagreements can arise between individual online reviews, the contrast between an aggregated rating and a recent rating presents an opportunity to delve into situational factors that influence information processing. Notably, the temporal gap between these two ratings allows us to examine how the timing of a purchase affects a consumer's review-processing approach. For instance, a consumer may process online reviews differently based on whether a purchase is immediate or delayed (Kim & Kim, 2022; Luan et al., 2023).

However, the discussion of conflict between an aggregated rating and a recent rating remains limited within the hospitality literature. The vast majority of analogous studies have concentrated on the disparity between an aggregated rating and an individual rating, often disregarding the recency of online reviews (Dai et al., 2019; Naujoks & Benkenstein, 2020; Qiu et al., 2012). Furthermore, as these studies have primarily elucidated tourists' perceptions concerning individual reviews during instances of conflict, there is a lack of comprehensive discussion on the situational factors that empower tourists to navigate such conflicts effectively. This study aims to examine the interaction effect on tourists' perceptions, which is caused by the conflict between an aggregated and a recent rating within the context of restaurant selection. Drawing on construal level theory (CLT) (Trope et al., 2007), we expect that the interaction effect on tourists' perception, which is caused by the conflict between an aggregated and a recent rating, is dependent on tourists' visit timeframe. Specifically, we refer to the CLT's argument of individuals' preference for recent information when dealing with near-future issues to hypothesize that a recent rating would have a greater impact on tourists' perceptions of the review and the reviewed restaurant when tourists use online review platforms to find a restaurant to visit in the near future as opposed to the far future (Shin & Xiang, 2021). The current research would contribute to the literature on tourists' holistic processing on an online review platform by discussing the interaction between conflicting information signals, which frequently occurs in the real world but has been understudied (Qiu et al., 2012; Ziegele & Weber, 2015). Furthermore, this study explained how tourists' visit timeframe affects their usage of an online review platform, a situational factor that must be considered to explain the usage as the platform becomes possible to use anytime (Kim et al., 2022b).

2. Research Background

2.1. Tourist's holistic processing of an online review

Online reviews are defined as statements about a certain product that the product's purchaser writes and uploads to online platforms (Labsomboonsiri et al., 2022). Consumers use online reviews to mitigate the risk of selecting an unsatisfactory product (Roy, 2023). When dealing with an experiential product whose quality is hard to assess without actual consumption, consumers feel a higher level of risk, and, thus, tourists tend to rely primarily on online reviews (Pan et al., 2022). In numerous prior studies, online reviews have been found to determine how tourists perceive and assess tourism products (Zheng et al., 2023).

Various information components such as the overall rating, reviewer's profile, and review text (review components hereafter) are included in an online review (Wang et al., 2023). Each review component represents a certain aspect of a hospitality business (Shin et al., 2021). The review rating indicates the overall quality of a hospitality business as rated by a former customer (Liu et al., 2020; Valenzuela-Orti et al., 2023). The words written in the review text represent the positive or negative attributes of a hospitality business as perceived by a former customer (Petrescu et al., 2022). Such attributes are depicted visually in an online review's photos (Li et al., 2021). When these review components are derived from a group of online reviews, more diverse aspects of a hospitality business are shown (Siddiqi et al., 2020). While the rating from a single review shows the opinion of a single visitor, the average rating of a group of online reviews may reflect the aggregated evaluation of a large group of visitors. Once the words are extracted from a group of online reviews based on their frequency, they may reveal the popular attributes of a hospitality business that are recognized by large numbers of visitors (Moro & Esmerado, 2020). A collage of photos derived from a group of online reviews can provide a more comprehensive visual description of the attributes of a hospitality business than a few photos from a single review (Băltescu, 2020). An online review platform presents the information derived from a group of online reviews, alongside individual reviews, to help tourists reduce their uncertainty about the hospitality business (Fan & Zhang, 2020).

The information asymmetry between sellers and buyers in a market transaction leads tourists to process different types of information available on an online review platform concurrently (Connelly et al., 2011). Several online review studies showed how tourists interpret individual online reviews and the information signals derived from a group of reviews. Xiao et al. (2022) found that tourists use the following information types, together with individual reviews, when using an online review platform: average rating, number of online reviews, and a collage of photos. Filieri et al. (2021) argued the interaction effect between the number of online reviews and the valence of an individual review on tourists' perceptions in the hotel context: tourists decide whether to take into account a negative hotel review based on the total number of reviews the hotel has received.

By examining the interaction effect between different types of information on tourists' perceptions, the literature emphasized the importance of exploring other potential interaction cases to better understand tourists' holistic processing on an online review platform (Qiu et al., 2012; Ziegele & Weber, 2015). For example, the interaction between the average rating of a group of online reviews and the rating of a single recent review was proposed to be discussed, since these two information types are the ones that tourists often check when using an online review platform (Carter, 2022; Siddiqi et al., 2020): after using an aggregated rating to estimate the overall quality of a hospitality business, tourists check a recent rating to grasp the current quality of the business. However, the interaction effect between an aggregated rating and a recent rating has received scant attention in the hospitality literature, despite being one of the interaction cases that tourists frequently encounter on online review platforms (Pitman, 2022; Ziegele & Weber, 2015). The present study aims to fill a gap in existing research by examining the interaction effect between an aggregated rating and a recent rating on tourists' perceptions.

2.2. Interaction effect between an aggregated and a recent rating on tourists' perceptions

There are two possible scenarios for the interaction between an aggregated and a recent rating: two types of ratings are similar or different in terms of their valence. This research focuses on the latter scenario for several reasons. On the one hand, consumers often encounter the conflict between an aggregated and a recent rating when using an online review platform to look for a hospitality business. While an aggregated rating serves as a comprehensive measure of a product's quality as assessed by large numbers of consumers, a recent rating indicates the quality assessed recently (Kim et al., 2022a). The disparity between an aggregated rating and a recent rating could be easily seen when the rating is for a tourism product whose quality varies easily (Jang, 2004). Considering that tourists frequently experience the conflict between an aggregated and a recent rating, the interaction caused by the conflict should not be overlooked when attempting to explain tourists' holistic processing on an online review platform.

On the other hand, the discrepancy between an aggregated and a recent rating may present an opportunity to identify a situational factor affecting tourists' holistic processing on an online review platform. When information signals are in conflict, the surrounding situation leads consumers to favor a specific signal over another (Spence, 2002). Given the difference between an aggregated and a recent rating in terms of information recency, the temporal aspect of the usage of an online review platform (e.g., whether tourists use the platform to find a place to visit immediately or later) can be suggested as a situational factor (Shin & Xiang, 2021). Specifically, a recent rating might be well adopted in the local search context (i.e., tourists find a restaurant to visit in the near future during the travel) compared to that in the pre-trip search context (i.e., tourists find a restaurant to visit in the far future before the travel). The greater impact of a recent rating on tourists' perceptions in the local search context can be explained by CLT (Trope et al., 2007). CLT accounts for how an individual perceives a piece of information differently depending on its context. Specifically, the theory asserts that the same piece of information can be perceived differently by recipients depending on whether they are dealing with near- or far-future events (Trope et al., 2007). When individuals must make a near-future decision (e.g., find a place to visit immediately), they often utilize a specific mental model (i.e., low construal level), which causes them to rely on recently created information because it fits with the model. This is called the construal fit effect (Trope et al., 2007).

The examination of the impact of time-related factors on tourists' processing could have timely implications because, nowadays, an online review platform can be used anytime (Kim et al., 2022b). That is, the conflict between an aggregated and a recent rating allows us to search for a nuanced explanation of tourists' holistic processing on an online review platform. With this background, the present study aims to examine the interaction effect on tourists' perceptions that is caused by the conflict between an aggregated and a recent rating in the restaurant context. It investigates how the impact of an aggregated rating on tourists' perceptions and that of a recent rating varies according to a time-related factor, namely tourists' visit timeframe: whether a tourist uses an online review platform to find a restaurant to visit immediately or later (Kim et al., 2022b; Shin & Xiang, 2021).

3. Hypothesis Development and Research Design

When an aggregated and a recent rating are in conflict with each other, we hypothesize that a recent rating has a greater impact on tourists' perceptions, especially in the local search context, compared to that in the pre-trip search context, based on the arguments of CLT (Trope et al., 2007). Many studies have offered evidence of the construal fit effect in different settings and examined the context-specific impact of information recency on individuals' perceptions. Jin et al. (2014) found that consumers who need to make near-future consumption decisions are more persuaded by the information created in the recent past, explaining the findings based on the construal fit of temporal distance. Similarly, Shin et al. (2019) argued that tourists departing within a week prefer to read recent online reviews. Kim et al. (2022b) supported the claim by examining the fact that the positive effects of review recency on its usefulness are more prominent when consumers make decisions for the near future than for the distant future.

Drawing on the construal fit effect explained by CLT, this research hypothesizes that a recent rating has a greater impact on tourists' perceptions in the local search context than in the pre-trip context. We develop the overall hypothesis that when a recent rating and the aggregated rating differ, tourists are more likely to rely on the recent rating (as opposed to the aggregated rating) in the local search context than in the pre-trip context. In other words, we should be able to observe the moderating effect of the search context on the impact a recent rating has on tourists' responses to the rating and the reviewed business. A list of types of consumers' responses to a rating has been derived from the literature on individuals' information processing (e.g., involvement and attribution) (Browning et al., 2013; Filieri & McLeay, 2014). Given the selected scenario, the following three types of responses are adopted to examine the extent to which: 1) tourists are sensitive to the difference between a recent rating and the aggregated rating (Lee & Pee, 2018); 2) tourists are interested in processing a recent rating's content (El-Said, 2020); and 3) tourists perceive a recent rating as useful for their decision-making (Racherla & Friske, 2012).

First, tourists would be more sensitive to the difference between the recent rating and the aggregated rating in the local search context compared to that in the pre-trip. If tourists regard a certain two-star rating as more important than another two-star rating because the former is more recent, they accord greater value to the former. Although the rating is the same for both, the recent two-star rating is perceived as more negative than the earlier rating (Fang et al., 2016). In Figure 1, the recent rating (two stars) is lower than the aggregated rating. In such a situation, tourists are sensitive to the disparity because they tend to value the recent rating (Tandon et al., 2021). If the recent rating becomes more important in the local search context, tourists tend to perceive it as more negative, thus making the difference between the recent rating and the aggregated rating more significant.

Hypothesis 1. Once a recent rating conflicts with an aggregated rating, tourists are sensitive to the difference.

Hypothesis 1a. The difference between the recent rating and the aggregated rating is perceived to be more significant in the local search context than in the pre-trip context.

Second, tourists would be more willing to read the text of a recent rating in a local search context than in a pre-trip context. When individuals deem certain information important for their decision-making, they become more interested in processing it (Petty & Cacioppo, 1984). As depicted in Figure 1, if tourists perceive the recent rating as important, they are willing to read its text (Cialdini, 2016). If tourists regard the recent rating as more important in the local search context, they would be more willing to read the review's text.

Hypothesis 2. Once a recent rating conflicts with an aggregated rating, tourists are interested in processing the content of the recent rating.

Hypothesis 2a. Tourists are more interested in processing the content of the recent rating in the local search context than in the pre-trip context.

Last, tourists would perceive a recent rating as more useful in the local search context than in the pre-trip context. The usefulness of a review has been extensively employed to indicate tourists' responses to a review (Korfiatis et al., 2012). According to the literature, how important an online review is for tourists' decision-making is significantly dependent on the extent to which tourists perceive the review as useful (Purnawirawan et al., 2012). Tourists tend to perceive a recent review as useful for their decision-making (Fu et al., 2011). If the recent rating is more important to tourists in the local search context, its perceived usefulness increases in this context.

Hypothesis 3. Once a recent rating conflicts with an aggregated rating, tourists perceive the recent rating as useful.

Hypothesis 3a. Tourists perceive the recent rating as more useful in the local search context than in the pre-trip context.

Furthermore, we expect that the above-hypothesized effects might also be found in tourists' responses to the reviewed business. With respect to tourists' responses to the reviewed business, we consider two aspects: tourists' attitudes and visit intention (Sparks & Browning, 2011; Vermeulen & Seegers, 2009). Tourists tend to rely more on a recent review than an old review when evaluating a tourism-related business, as the recent review represents the latest performance of the business (Filieri & McLeay, 2014). If a recent rating has a greater impact on tourists' decision-making in the local search context, tourists' attitudes toward and intention to visit the reviewed business are more affected by the recent rating in this context.

Hypothesis 4. Once a recent rating conflicts with an aggregated rating, the recent rating determines tourists' attitudes toward a reviewed business.

Hypothesis 4a. The impact of a recent rating on tourists' attitudes is greater in the local search context than in the pre-trip context.

Hypothesis 5. Once a recent rating conflicts with an aggregated rating, tourists' intention to visit a reviewed business is affected by the recent rating.

Hypothesis 5a. The impact of a recent rating on tourists' visit intention is greater in the local search context than in the pre-trip context.

[Figure 2]

4. Methodology

4.1. Procedure

To test the hypotheses, an experiment was conducted. Figure 3 shows the entire experimental process.

[Figure 3]

According to a between-subjects design, participants were assigned randomly to one of the two distinct search contexts—local and pre-trip. Participants were presented with varying scenarios based on their designated context. In both scenarios, a specific itinerary was assumed: dining at a restaurant after a visit to a renowned museum in the destination. The scenarios exclusively outline the itinerary to prevent any potential confounding influences resulting from specific scenario details (such as travel timing, occasion, and season) (Charafeddine et al., 2015). Similarly, to mitigate such influences, the hypothetical nature of the museum and destination in the scenarios was emphasized. Participants in the local search context were depicted as utilizing their smartphones to search for “restaurants near me” in order to find an immediate restaurant to visit during their ongoing trip. This situation mirrors the common scenario of local searches (Leibson & Shotland, 2018). Conversely, participants in the pre-trip search context were presented with a scenario in which they were planning a trip in a month and intended to visit a museum during the trip. They were portrayed as using desktop computers to explore dining options after their museum visit.

In both search contexts, participants researched five fictitious restaurants after reading the scenarios. Two result pages for a fictitious restaurant were shown to the participants, which are “Overview” and “Reviews” (Appendix A). The “Overview” page contained general information about the restaurant, including its name, an aggregated rating, the price range, distance, and dining options. On the “Review” page, both a recent (uploaded a week ago) and an aggregated rating were included. In light of a consumer survey on online review usage conducted by an online marketing company, it was found that consumers tend to perceive online reviews posted within two weeks as recent (Murphy, 2020). In light of these findings, we have chosen a stricter criterion for review recency in our stimuli, opting for a one-week timeframe. The reviewer information and text of the recent rating were omitted to avoid their unexpected effects.

Although the five restaurants had the same aggregated rating (i.e., three stars), the recent rating varied from one star to five stars. Each participant was exposed to five restaurants that had varying gaps between the recent and aggregated ratings: One restaurant had the same recent and aggregated rating; two restaurants had a higher recent rating (positive difference cases: recent rating = 4 or 5 vs. aggregated rating = 3); and the other two had a higher aggregated rating (negative difference cases: recent rating = 1 or 2 vs. aggregated rating = 3). To give the same number of restaurants with positive and negative difference cases, the aggregated rating was set at three stars.

To avoid the unexpected effects of the cuisine of a restaurant, all five restaurants were presented as Mexican because it was one of the most popular ethnic cuisines in the US at the time of the study, where all the participants resided (Williams, 2020). Furthermore, the price level and dining options were uniformly maintained across all restaurants. Given the challenge of locating more than two nearby restaurants with identical numbers of reviews and distances, we opted to maintain a high degree of similarity in these parameters (number of reviews: 220, 222, 224, 226, or 228; proximity: 0.6, 0.7, or 0.8 miles). This approach was taken to mitigate potential confounding effects stemming from significant disparities while enhancing the authenticity of the stimuli, following the method outlined by Hu and Yang (2020). It is worth noting that the sequence of the five restaurants was randomly determined.

4.2. Measures and data collection

As for the questions that participants were asked to answer for each restaurant, a single-item measure was used. While a multi-item measure was preferred to a single-item measure specifically due to the former's higher predictive validity, it was found that there is no difference in the predictive validity between the measures (Bergkvist & Rossiter, 2007; Hoeppner et al., 2011). Furthermore, as a single-item measure that has been shown to be effective in controlling common method bias, its use has increased in various research fields, including hospitality and tourism (Dolnicar, 2018). Especially, a single-item measure is recommended when an item can adequately describe the main dimension of the construct (i.e., when items are semantically redundant) (Diamantopoulos & Riefler, 2011). Hence, we used a single-item measure for each dependent variable of this research, as was the case in previous studies involving a similar construct: how different are the recent and aggregated ratings? (Sensitivity: 1 = very similar, 7 = very different) (Grinberg, 2012); if possible, would you like to read the text of the recent rating? (Interest: 1 = definitely not, 7 = definitely yes) (Changchit & Klaus, 2020); how useful was the recent rating to your decision? (Usefulness: 1 = not useful, 7 = very useful) (Purnawirawan et al., 2015); what do you think about this restaurant? (Attitude: 1 = dislike, 7 = like) (Bergkvist & Rossiter, 2007); would you like to try out this restaurant? (Visit intention: 1 = definitely not, 7 = definitely yes) (Lu et al., 2020). At the end of the survey, two manipulation check questions were presented along with those regarding demographics: how recent was the rating posted a week ago? (1 = very old, 7 = very recent); when will your restaurant visit happen? (1 = very soon, 7 = long after).

We used Amazon's Mechanical Turk (MTurk). Within five days of February 20, 2021, 500 adults in the U.S. participated. Our participant selection focused on adults in the U.S. with prior experience using local searches to discover restaurants. We also specifically included individuals whose historical survey approval rates exceeded 95%. Furthermore, we employed two validation queries to enhance data reliability: 1) What cuisine was offered at the restaurant? 2) Were you able to read the text in the online reviews? A total of 265 responses were disregarded because they were not valid for analysis (145 from the local context and 120 from the pre-trip search context). The demographic composition of the sample is presented in Table 1.

[Table 1]

5. Findings

The manipulation was well achieved. A recent rating was perceived as recent in both contexts (M_{local} = 5.62, t = 17.747, p < 0.001; $M_{pre\text{-}trip}$ = 5.83, t = 21.665, p < 0.001). The participants in the local (pre-trip) search context perceived that their restaurant visit happened in the near (far) future (M_{local} =1.92, $M_{pre\text{-}trip}$ = 6.75, $t = -42.195$, $p < 0.001$).

We conducted a 2 × 3 ANOVA with review recency (recent > aggregated rating vs. recent = aggregated rating vs. recent < aggregated rating) and search context (local vs. pre-trip search). As for the first hypothesis, the dependent variable was sensitivity—the extent to which tourists are sensitive to the difference between a recent and an aggregated rating. As shown in Table 2, the main effect of review recency was statistically significant ($F = 100.593$, $p < 0.001$): when the recent rating differs from the aggregated rating, the participants sensitively react to the difference. Hypothesis 1 was supported. The main effect of search context was also statistically significant ($F = 32.015$, $p < 0.01$): the difference perceived by the participants in the local search context was greater than that in the pre-trip context (Table 2 and Figure 4). Thus, Hypothesis 1a was also supported. No interaction effect was found ($F = 1.267$, $p = 0.282$).

[Table 2]

[Figure 4]

As for the second hypothesis, the dependent variable was interest, i.e., the extent to which tourists are interested in processing a recent review's content. The main effect of review recency was statistically significant ($F = 5.181$, $p < 0.05$) (Table 3); when the recent rating differs from the aggregated rating, the participants are interested in processing the recent review's content. Hypothesis 2 was supported. However, this was not the case for the search context ($F = 0.133$, $p = 0.715$). The participants in both search contexts had a higher interest in the processing, meaning there is no significant difference based on the search context. Hypothesis 2a was not supported by the evidence. No interaction effect was found ($F = 0.344$, $p = 0.709$) (Table 3).

[Table 3]

As for the third hypothesis, the dependent variable was usefulness—the extent to which tourists perceive a recent review as useful for their decision-making. Both the main effects of review recency ($F = 1.348$, $p = 0.260$) and search context ($F = 0.528$, $p = 0.468$) were not significant (Table 4). The recent rating was perceived as useful regardless of its difference from the aggregated rating and the search context. Thus, both hypotheses 3 and 3a were not supported. No interaction effect was found ($F = 1.532$, $p = 0.216$).

[Table 4]

The dependent variable for the fourth hypothesis was attitude. Both the main effects of review recency ($F = 70.716$, $p < 0.001$) and search context ($F = 8.083$, $p < 0.05$) were significant (Table 5). Participants' attitudes were more affected by a recent rating in the local search context compared to those in the pre-trip context. Hypothesis 4a was supported. No interaction effect was found ($F = 0.541$, $p = 0.582$).

[Table 5]

[Figure 5]

H5 and H5a were also supported, which pertain to visit intention. The participants were willing or unwilling to visit the restaurant when the recent rating was higher or lower than the aggregated rating, respectively ($F = 69.508$, $p < 0.001$). Especially, the participants in the local search context showed higher or lower visit intention than those in the pre-trip when the recent rating was higher or lower than the aggregated rating, respectively ($F = 9.885$, $p < 0.01$) (Table 6 and Figure 6). No interaction effect was found ($F = 0.663$, $p = 0.516$).

[Table 6]

[Figure 6]

We conducted a secondary analysis using a different aggregate rating of 4.5. Given that Womply's 2019 data indicates that more than 90% of restaurants fall within the overall rating range of 3.5 to 4.9 (Womply, 2019), our choice of a 4.5 rating aligns with a more representative scenario for this supplementary analysis. Out of 500 newly collected responses, 280 invalid cases were disregarded (local search: 130, pre-trip search: 150). Two conditions for review recency were adopted: positive (i.e., recent rating = 5 vs. aggregated rating = 4.5) and negative (i.e., recent rating = 1, 2, 3, or 4 vs. aggregated rating = 4.5). Thus, a 2 × 2 ANOVA with the search context and the review recency was conducted. The results were similar to those of the main analysis in that H1a, H4a, and H5a were supported (Appendix A). However, contrary to the main analysis, hypotheses 2a and 3a were also supported: the participants in the local search context had more interest in processing the recent rating's content ($F = 6.081$, $p < 0.05$) and considered the recent rating more useful than those in the pre-trip context ($F = 13.983$, $p < 0.001$) (Figure 7).

[Figure 7]

6. Discussion

To examine the context-specific effect of review recency on tourists' decision-making, this study investigated how a recent review was differently adopted in the local search context in comparison with the pre-trip context. Following CLT, we hypothesized that tourists would be more sensitive to a recent rating when choosing a restaurant to visit in the local search context than in the pre-trip context. As hypothesized, a context-specific effect of review recency on tourists' decision-making is supported in the restaurant domain: when a recent rating differs from the aggregated rating, tourists tend to adopt the former to evaluate the restaurant, and the impact of the former becomes pronounced in the local search context. Aligned with the previous online review research adopting CLT, this study found that the perception of temporal dimension of the review by consumers varies depending on whether they are dealing with a near-future purchase or far-future purchase (Jin et al., 2014; Kim et al., 2022b).

Tourists' responses to a review appeared not to be influenced by the search context, contrary to our expectations. Regardless of whether they are in the local search context or the pre-trip context, tourists are interested in reading the text of a recent review (H2a) and regard it as useful (H3 and H3a). However, this was not the case in the secondary analysis. Tourists were more willing to further process a recent review and considered it more useful in the local search context than in the pre-trip context. These mixed findings could be attributed to tourists' involvement in a restaurant. Consumers tend to be less interested in a product whose aggregated rating is lower than three stars (Clark, 2019). When we set the aggregated rating at three stars in the main analysis to expose the participants to the same number of difference cases (i.e., two cases each of positive and negative differences between a recent and an aggregated rating), such manipulation might lower the participants' involvement in the restaurant. In fact, individuals' involvement in a subject was examined as a boundary condition for the effect of construal fit in previous studies (Park & Morton, 2015; Wang & Lee, 2006).

6.1. Theoretical implications

First, this study examines the importance of investigating the recency of online reviews and the visit timeframe of tourists to explain tourists' usage of the reviews in the local search context. Although a local search has become one of the major contexts for tourists' usage of online reviews, most previous research has primarily focused on the pre-trip search context (Chong et al., 2018; Filieri & McLeay, 2014; Hwang et al., 2018;

Xie et al., 2016; Zhao et al., 2015). Our findings examined the primary role of review recency in tourists' decision-making in the local search context and attributed the context-specific role to tourists' visit timeframe. This research contributes to the literature by indicating a specific information aspect and situational characteristic that must be considered to explain how tourists use online information to make purchase decisions during local searches (García-Milon et al., 2021; Liu et al., 2022c; Tussyadiah, 2016).

Second, this research contributes to the literature on the role of information recency in shaping tourists' decision-making. Most previous studies have examined the direct impact of information recency on tourists' perceptions to explain the role of recency in their decision-making. However, our findings revealed that tourists' preference for up-to-date information is dependent on the timeframe of their intended visit. According to our results, it is important to consider the factors that could moderate the impact of information recency on tourists' perceptions. Together with the studies identifying the factors moderating the impact of review recency on tourists' review perception (Filieri et al., 2018; Tandon et al., 2021), this research underlines the need for research on information recency to explore different factors that could interact with it in affecting tourists' decision-making. Furthermore, from a methodological perspective, this research proposes a plausible situation that could be adopted to examine the impact of review recency on consumer perception, namely the difference between recent and aggregated ratings.

Third, this research contributes to the literature on tourists' processing of online reviews in particular and of travel information in general by providing empirical support for its context-dependence. While individuals' information processing has been found to be affected by different situational factors (e.g., the type of product being considered or device being used) (Furner & Zinko, 2017; Mudambi & Schuff, 2010), the varying impact of information on consumers' perception has not been sufficiently studied in the hospitality and tourism fields. The existing literature has adopted either the socio-demographics of tourists or the types of tourism products as potential moderators (Lehto et al., 2006; Racherla & Friske, 2012). Temporal or spatial factors have been scarcely adopted as potential moderators that explain the context-dependent nature of tourists' information processing (Huang et al., 2015; Jin et al., 2014). This research addressed the limitation by discussing a temporal factor that could affect tourists' processing of online reviews.

6.2. Practical implications

First, hospitality businesses can use our findings to improve their online review monitoring strategy. The main finding indicates that tourists are more sensitive to recent reviews when checking them on local search platforms (LSPs) than other online review platforms. The availability of online reviews on various platforms (e.g., TripAdvisor, Yelp, Google, and so on) necessitates that hospitality businesses prioritize which platforms to monitor (Nau, 2019). The findings of this research indicate that hospitality businesses need to monitor online reviews uploaded on LSPs more closely than those on other platforms. Such prioritization would make hospitality businesses' review monitoring more effective in improving their online reputation and attracting more customers (Beddow, 2020).

Second, based on our research, it is worth considering whether the successful response strategies employed on online review platforms can be effectively adapted for LSPs. Our study reveals a noteworthy trend where recent reviews hold significant sway in capturing the attention of tourists, even when accessed through smartphones. This contrasts with prior research, which suggested consumers were generally disinclined to engage with written content on mobile devices (Furner & Zinko, 2017; Jin et al., 2019). Building upon these insights, the hospitality sector stands to benefit from incorporating a crucial tenet of review response strategy—timely engagement—into their approach to LSPs. This practice, which has already proven effective on established online platforms, can be seamlessly adapted to LSPs. Leveraging the aforementioned implication, restaurants should not only prioritize LSPs for monitoring purposes but also consider them a pivotal channel for actively engaging with and responding to online reviews.

Lastly, this research provides LSPs with guidelines on how to improve the user experience. Our findings suggest that recent reviews become powerful decision cues for users of LSPs. LSP users tend to make decisions within a main page quickly because of situational constraints (e.g., small screens on mobile devices or environmental distractions from on-site stimuli) (Ghose et al., 2013). However, most existing LSPs do not present the relevant information (e.g., the average rating of recent reviews) on their main page. Based on the findings of this research, LSPs can reflect the needs of users by adding the information that they rely on in the local search context, such as recent reviews.

6.3. Limitations and future research directions

Despite these contributions, this study had several limitations. While the main focus of this research was the role of the information recency of an online review in tourists' decision-making, the recency cannot fully explain how tourists use the review for their purchase decisions because there are other informational features of the review (Hu & Yang, 2021). Future research should extend the model by studying the context-specific effects of other informational features of an online review. Second, we used hypothetical situations to collect participants' answers. While we controlled several exogenous factors (e.g., the restaurant's proximity or the type of devices used), the participant's answers were not free from the other potential exogenous factors. For instance, even slight disparities in the number of reviews and proximity presented in the stimuli could potentially impact the results. Future research should set up a more controlled experiment to validate the findings. Third, as for the difference between a recent and an aggregated rating, we adopted only two possible cases. Although this was done to make the differences realistic (93% of restaurants have an overall rating between 3.5 and 4.9) (Womply, 2019), other differences can be possible as well (recent rating: 1–5 vs. aggregated rating: 1–5). Thus, future research should adopt such manipulations to account for various possible scenarios. Fourth, while they were not the main points of this research, other situational influences are required to further understand how tourists process online reviews in an increasingly mobile and dynamic context. Other situational characteristics (e.g., limited time for searching) should be addressed in future research. Finally, future research ought to delve into survey data reliability and the broader applicability of our discoveries. This could be accomplished by sourcing samples from professional agencies or other notably dependable channels, surpassing the reliance on Amazon MTurk. Moreover, diversifying the sample by incorporating participants from various countries or cultural contexts will enhance the generalizability of our findings.

Disclosure statement

The authors report there are no competing interests to declare.

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Tables

Table 1. Participants' demographics

Demographic Variables	Freq.	%
Gender		
• Male	153	57.74
• Female	112	42.26
Age		
• 18–24	30	11.32
• 25–34	158	59.62
• 35–44	40	15.09
• 45–54	19	7.17

• 55 and above	18	6.79
Education		
• Less than high school	2	0.75
• High school graduate	21	7.92
• Some college but no degree	22	8.30
• Associate degree (2-year)	21	7.92
• Bachelor's degree (4-year)	159	60.00
• Master's degree	36	13.58
• Doctoral degree	4	1.51
Occupation		
• Management, professional, and related	95	35.85
• Service	30	11.32
• Sales and office	36	13.58
• Farming, fishing, and forestry	11	4.15
• Construction, extraction, and maintenance	23	8.68
• Production, transportation, and material moving	8	3.02
• Government	13	4.91
• Student	9	3.40
• Retired	5	1.89
• Unemployed	21	7.92
• Etc.	14	5.28
Total	265	100

Table 2. ANOVA result for testing H1(a)

	Sum of Squares (df)	Mean	Mean Square (F)
Review recency	629.926 (2)		314.963 (100.593***)
• Recent > Aggregated rating		4.85	
• Recent = Aggregated rating		3.00	
• Recent < Aggregated rating		4.56	
Search context	32.015 (1)		32.015 (10.225**)
• Local search		4.53	
• Pre-trip search		4.19	
Review recency · Search context	7.934 (2)		3.967 (1.267)

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 3. ANOVA results for testing H2(a)

	Sum of Squares (df)	Mean	Mean Square (F)
Review recency	20.549 (2)		10.275 (5.181*)
• Recent > Aggregated rating		5.75	
• Recent = Aggregated rating		5.42	
• Recent < Aggregated rating		5.58	
Search context	0.264 (1)		0.264 (0.133)
• Local search		5.59	
• Pre-trip search		5.56	
Review recency · Search context	1.364 (2)		0.682 (0.344)

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 4. ANOVA result for testing H3(a)

	Sum of Squares (df)	Mean	Mean Square (F)
Review recency	3.749 (2)		1.874 (1.348)
• Recent > Aggregated rating		5.79	
• Recent = Aggregated rating		5.73	
• Recent < Aggregated rating		5.67	
Search context	0.734 (1)		0.734 (0.528)
• Local search		5.75	
• Pre-trip search		5.70	
Review recency · Search context	4.262 (2)		2.131 (1.532)

$*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Table 5. ANOVA result for testing H4(a)

	Sum of Squares (df)	Mean	Mean Square (F)
Review recency	274.934 (2)		137.467 (70.716***)
• Recent > Aggregated rating		5.42	
• Recent = Aggregated rating		5.13	
• Recent < Aggregated rating		4.41	
Search context	15.712 (1)		15.712 (8.083*)
• Local search		5.10	
• Pre-trip search		4.87	
Review recency · Search context	2.105 (2)	-	1.052 (0.541)

$*p < 0.05$; $**p < 0.01$; $***p < 0.001$

824 Table 6. ANOVA result for testing H5(a)

	Sum of Squares (df)	Mean	Mean Square (F)
Review recency	335.168 (2)		167.584 (69.508***)
• Recent > Aggregated rating		5.37	
• Recent = Aggregated rating		5.00	
• Recent < Aggregated rating		4.26	
Search context	23.832 (1)		23.832 (9.885**)
• Local search		5.01	
• Pre-trip search		4.73	
Review recency · Search context	3.196 (2)		1.598 (0.663)

825 *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Figures

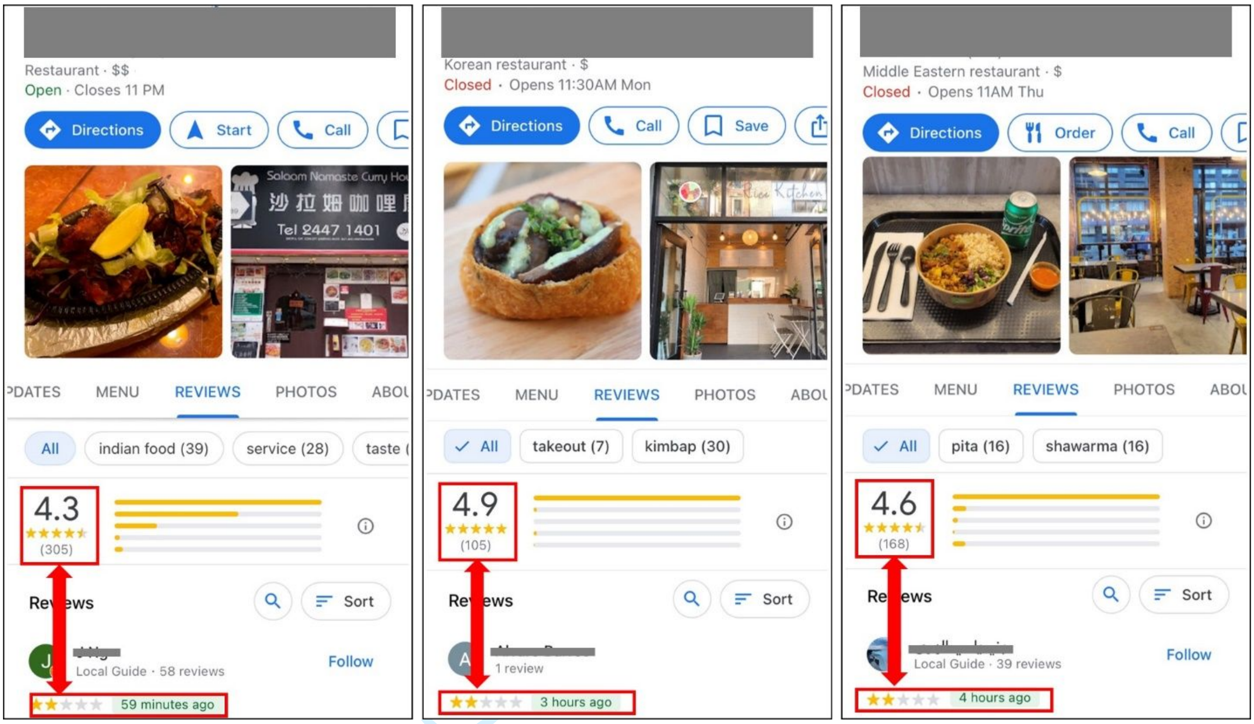


Figure 1. Conflict between a recent rating and an aggregated rating in terms of valence

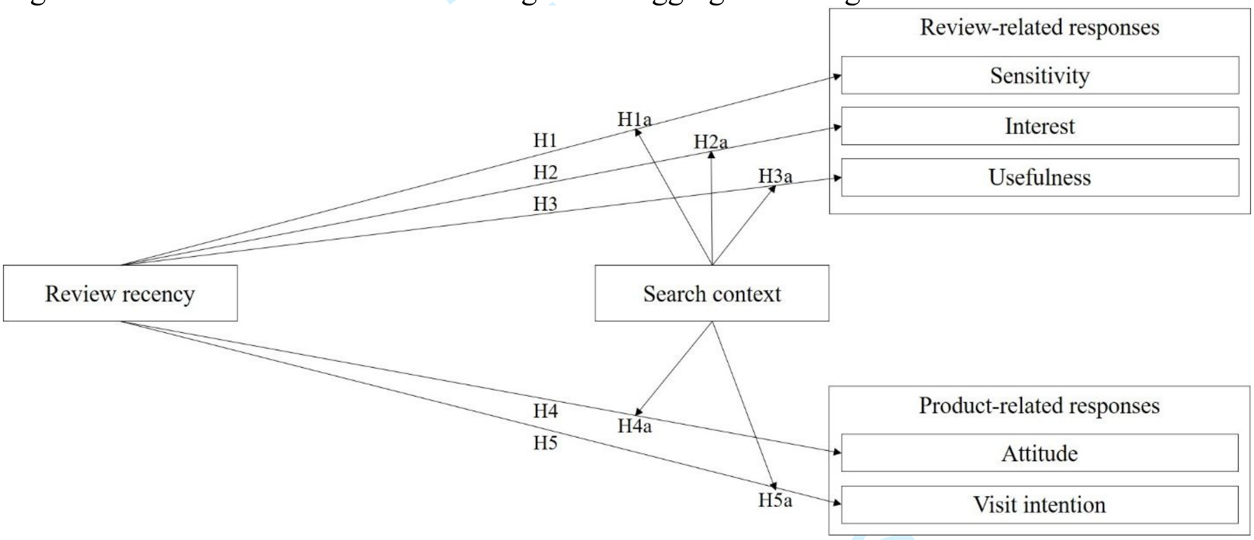


Figure 2. Research model

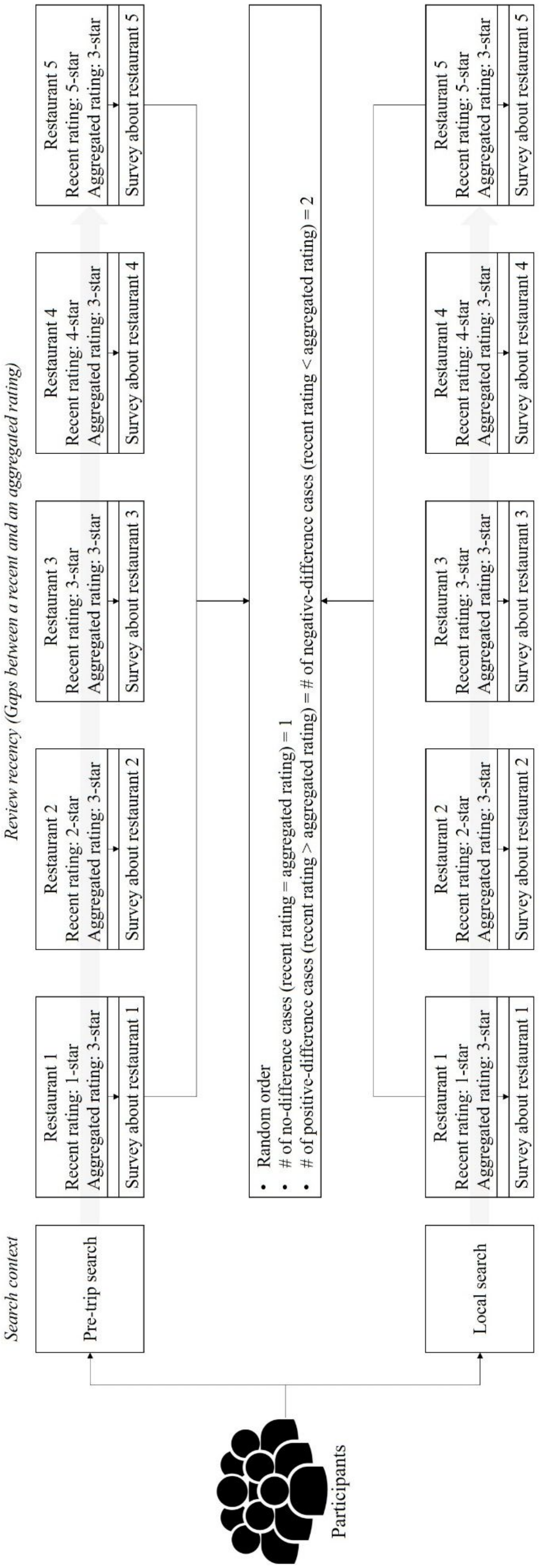


Figure 3. Experiment procedure

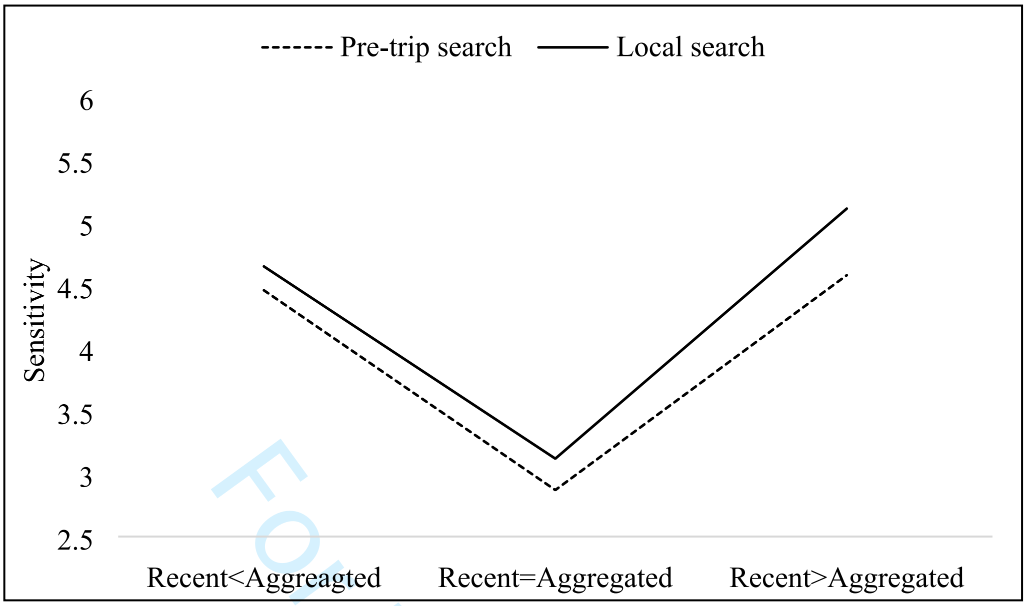


Figure 4. Means for sensitivity across review recency manipulation

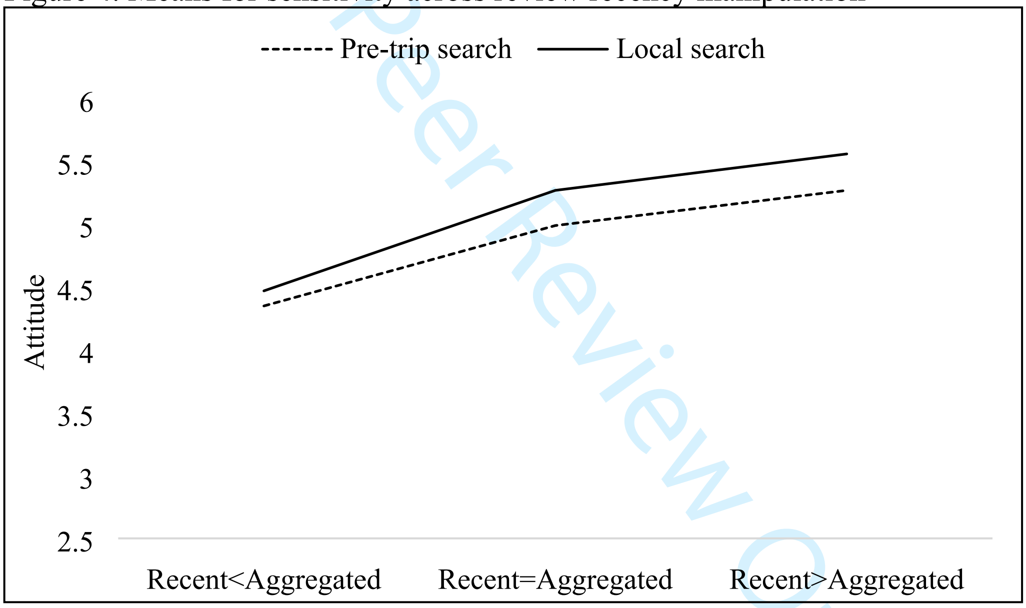


Figure 5. Means for attitude across review recency manipulation

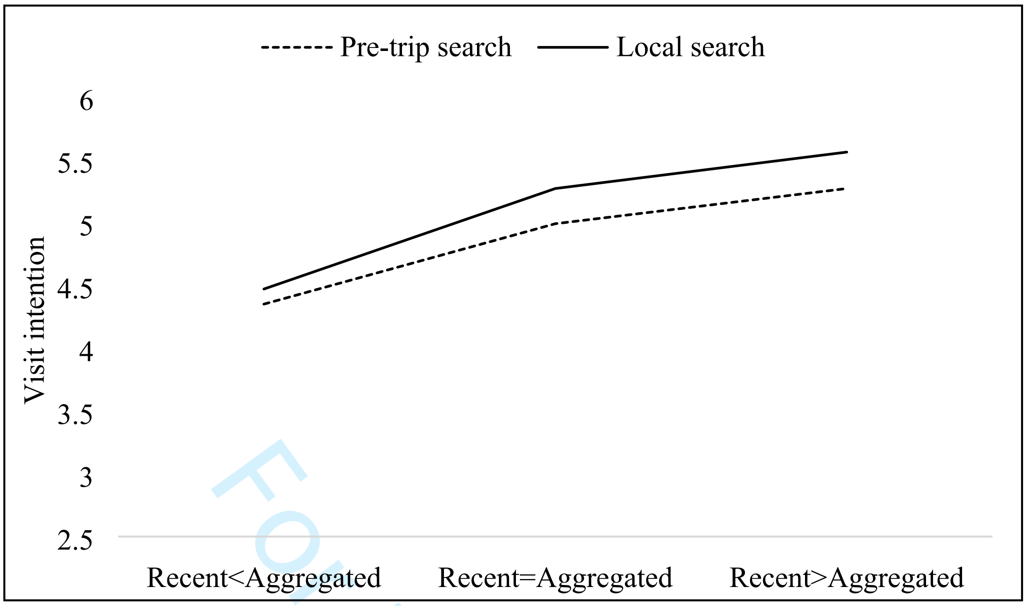
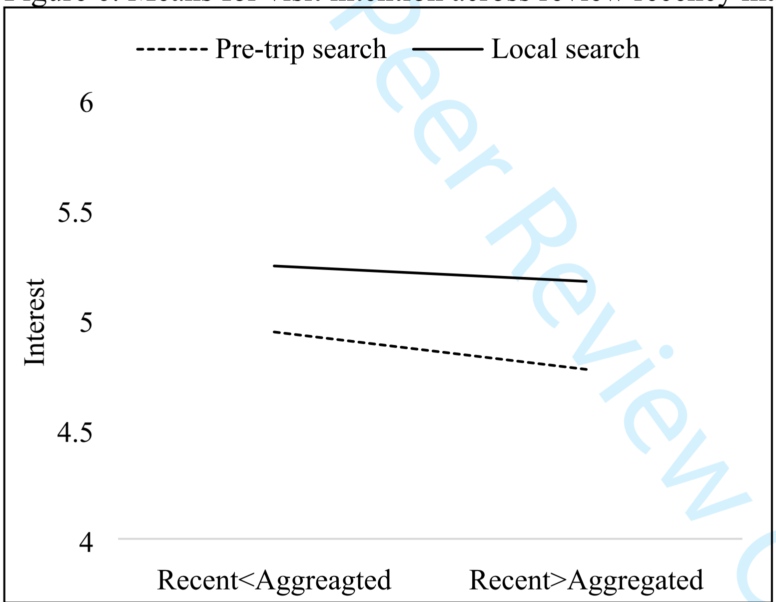
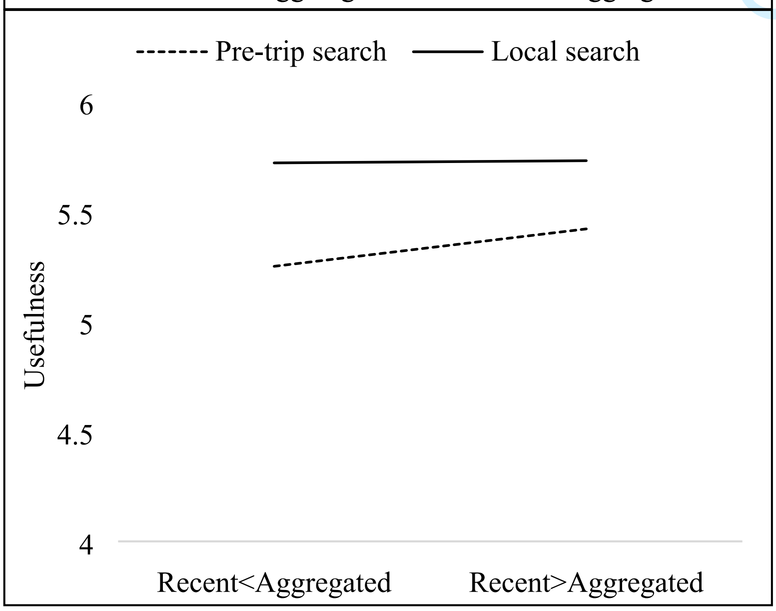


Figure 6. Means for visit intention across review recency manipulation

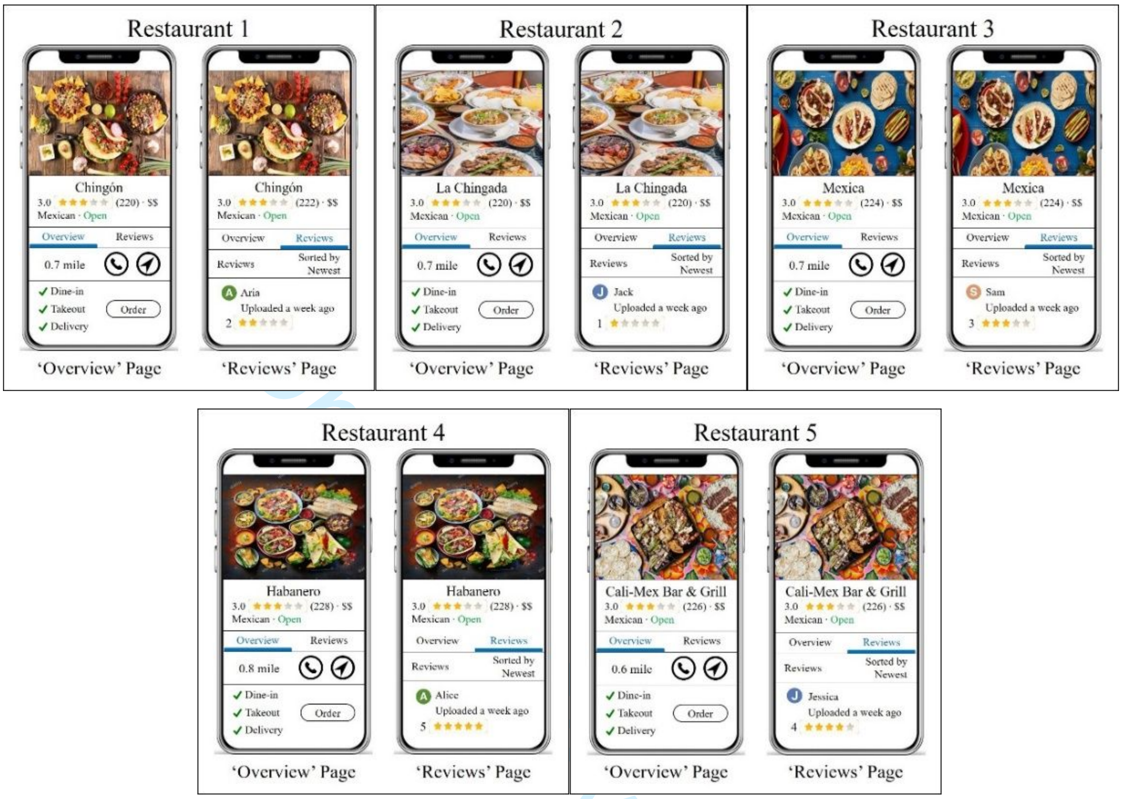




841 Figure 7. Means for interest and usefulness across review recency manipulation

Appendices

Appendix A. Mock pages of five restaurants



Appendix B. ANOVA results of H1a, H2a, and H2b in supplementary analysis

	Recent review sensitivity (*F*-statistic)	Attitude (*F*-statistic)	Visit intention (*F*-statistic)
Visit timeframe (Local vs. Pre-trip search)	7.234*	5.211*	2.727*
Review recency (Positive vs. Negative difference)	83.049***	75.538***	65.839***
Visit timeframe · Review recency	0.752	0.025	0.496

848 $*p < 0.05$; $**p < 0.01$; $***p < 0.001$