Three Essays on Contextual Effects in Traveler's Use of Online Reviews

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ABSTRACT

Tourists' information processing is a dynamic process in that their information use depends on the surrounding context. From tourists' personal characteristics (e.g., age, gender, and travel experience), nature of tourism products (e.g., intangibility and variability), to the development of information technology (e.g., the prevalent usage of mobile devices for information search), a variety of contextual factors are involved when tourists process information for decision-making. Given the importance of online reviews in the hospitality and tourism field as information sources, this dissertation aims to understand the contextual effects of online reviews on tourists' decision-making. By selecting several contextual factors, three independent and interrelated essays examine how tourists' cognitive or behavioral responses to online reviews are affected by those factors.

Considering that local search (e.g., looking for nearby restaurants by using "restaurants near me" as a search query) becomes an important context for using online reviews, both Study 1 and 2 focus on the local search context. Study 1 investigates the role of online reviews in the local search context; specifically, how online reviews are used as ranking factors by local search platforms (LSPs), is examined with an analytical approach. Study 2 investigates tourists' processing of online reviews in the local search context; specifically, how online reviews are differently processed in the local search context (e.g., searching for a restaurant that can be visited immediately) compared with the non-local context (e.g., searching for a restaurant that can be visited in a month), is examined by conducting an experiment. Building on Study 2, Study 3 investigates how tourists' processing of online reviews is affected by another contextual factor, the nature of tourism products; specifically, how the variability of tourism products (i.e., their change in quality over time) influences the way tourists process online reviews, is examined through social media analytics.

Results of the three essays provide empirical support for the underlying argument of this dissertation: understanding tourists' responses to online reviews depends on factors that transcend their information characteristics. As a whole, the findings of this dissertation suggest the need for considering the surrounding context to further understand how online reviews affect tourists' decision-making. As practical implications, this dissertation discusses the importance of leveraging various types of information about tourists' context (e.g., location accessed from smartphones, and physiological condition accessed through smartwatches).

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GENERAL AUDIENCE ABSTRACT

Tourists use online reviews within specific situations. The effects of such reviews on tourists' decision-making are difficult to explain without considering the surrounding contexts. Depending on when (e.g., before or during the trip), where (e.g., at home or destination), or for which products (e.g., restaurants, attractions, or hotels) they use online reviews, even the same online review can be differently perceived by tourists (e.g., how helpful it is). Therefore, the reviews have an increased or reduced influence on their product choices. This dissertation aims to understand the context-dependence of tourist's use of online reviews. The three essays in this dissertation examine how online reviews are used or processed by tourists under certain context: how online reviews affect tourist's decision-making in the local search context (e.g., searching for "restaurants near me" using smartphones during the trip) (Study 1); how tourists process online reviews while relying on reviews for immediately choosing places to visit (Study 2); and how tourists perceive online reviews when they are recently posted (Study 3). The findings confirm the dynamic nature of tourist's use of online reviews and offer several insights for tourism businesses to hone their strategies on marketing online reviews.

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CHAPTER 1. INTRODUCTION

Online reviews refer to any positive or negative statements shared about a product by former consumers on various online platforms (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Since online reviews can reduce potential consumers' uncertainty about product quality, they are influential sources of information that affect consumers' decision-making regarding the choice of products (Mudambi & Schuff, 2010). In particular, the importance of online reviews is recognized in the hospitality and tourism field because it is difficult to assess the quality of intangible tourism products before consumption (Litvin, Goldsmith, & Pan, 2008). Over 80% of tourists do not book hotels without reading online reviews, and over 90% think online reviews as the primary element of consideration while researching accommodation (Bridges, 2019).

When tourists use online reviews to select a product for purchase, various contextual factors are involved. For example, the development of information technology (IT) has fundamentally changed the way tourists access online information (Werthner & Klein, 1999). A variety of technologies (e.g., mobile or location-based search technologies) have offered new affordances for tourists to use online reviews. Nowadays, tourists can use online reviews not only before but also during the trip (Wang, Xiang, & Fesenmaier, 2016). Tourists are exposed to different on-site stimuli while reading online reviews, such as the remaining time until the next scheduled activity, road traffic conditions, the crowdedness of the place of interest, and recommendations from local people or online friends through social media (Tussyadiah & Zach, 2012). Also, while online reviews have been primarily used for long-term decision-making, they are also used for short-term (Gretzel, Fesenmaier, & O'leary, 2006). Furthermore, the different functions or interfaces across online platforms (e.g., online review websites, online travel agents, and social networking sites) could influence tourists' preference for specific platforms, and the potential difference in user bases might affect how online reviews are communicated on certain platforms (Xiang, Du, Ma, & Fan, 2017).

On the other hand, tourism products are complex in nature. Due to their heterogeneity, tourists adopt different rules for decision-making not only across types of products (e.g., restaurants, attractions, or hotels) but also within the same type based on several characteristics (e.g., service level or brand of restaurants) (Kim, Li, & Brymer, 2016). Additionally, since the quality of tourism products varies from one time period to another, the same online reviews could be positively or negatively perceived depending on when tourists access the information (Filieri, Hofacker, & Alguezaui, 2018a). Lastly, tourism products comprise different aspects (e.g., location, staff service, facilities, or cleanliness of a hotel) (McKercher, 1999), and specific aspects become more important factors in decision-making than others under certain situations (e.g., hotel's location during local search or its cleanliness after the outbreak of COVID-19) (Fantozzi, 2021; Ghose, Goldfarb, & Han, 2013). This compound nature makes tourists perceive the information provided in online reviews (e.g., which aspects are evaluated in the reviews) within the particular context (e.g., how important the aspects are at that moment).

Given the effects of the contextual factors created by the today's technological conditions or the complex nature of tourism products, it is argued that they set the basis for understanding the effects of online reviews on tourists' responses (Lamsfus, Wang, Alzua-Sorzabal, & Xiang, 2015). However, online reviews have been treated as non-specific and uniform entities regardless of the context in the hospitality and tourism literature. Specifically, researchers have explained the effects of online reviews on tourists' cognitive or behavioral responses mainly based on their information components (e.g., reviewer's profile, review rating, or text): how the overall rating and number of online reviews affect tourists' interest in (Zhang, Ye, Law, & Li, 2010) or choice of products (Ye, Law, & Gu, 2009), and which information components significantly affects tourists' perceptions of the reviews (Liu & Park, 2015) or the products (Sparks & Browning, 2011; Zhang et al., 2010). Although some studies included several characteristics of tourists and tourism products as contextual factors in their research models (Filieri et al., 2018a; Racherla & Friske, 2012), there are a host of contextual factors that affect tourists' response to online reviews. For example, as described above, the context of use afforded by IT development and the complex nature of

tourism products could affect how tourists process online reviews in their decision-making. To understand the context-dependent nature of online reviews, it is important to consider those contextual factors.

1.1. Summary of Three Essays

The overarching goal of this dissertation is to gain an understanding of the contextual effects of online reviews in the hospitality and tourism field by studying how tourists respond to online reviews under certain contexts. Among a variety of contextual factors, the three independent and interrelated essays focus on the following factors: the context of use and the nature of tourism products.

- Study 1 (Chapter 2): What is the role of online reviews in the local search context?
    - Study 1 aims to understand the role of online reviews in the local search context. This study examines how the ranking results of local search change depending on how online reviews are used as ranking factors. By adopting an analytical approach, the effects of online reviews on the local search ranking of tourism businesses are examined.
- Study 2 (Chapter 3): How does the context of use affect the way tourists process online reviews?
    - Study 2 aims to understand the effects of the context of use on tourists' processing of online reviews. Building on Study 1, Study 2 focuses on the local search context and investigates how tourists perceive online reviews differently in this context when compared to the non-local context. By conducting experiments, this study tests the hypothesis that recent reviews have grater effects on tourists' responses in the local search context when compared to the non-local.
- Study 3 (Chapter 4): How does the nature of tourism products affect the way tourists process online reviews?
    - Building on Study 2, Study 3 aims to understand the effects of another contextual factor on tourists' processing of online reviews, which is the nature of tourism products. Study 3

focuses on review recency and investigates how recent reviews are perceived differently depending on their content. Given the variability of tourism products (i.e., some aspects are more variable in terms of quality), this study tests the hypothesis that recent reviews are perceived as more helpful when they include the information about the aspects whose quality is changeable (e.g., cleanliness or ambiance of a hotel) than those stable (e.g., location or facilities).

1.2. Literature Review

Online reviews refer to any positive or negative statement consumers share on retail, e-commerce, or third-party platforms after experiencing certain products or services (Hennig-Thurau et al., 2004). As peer-generated evaluations, online reviews decrease the level of risk for potential consumers and are perceived as more credible than commercial advertisements or experts' comments (Hu, Liu, & Zhang, 2008). In particular, consumers face a higher risk when they purchase intangible tourism products because their quality is difficult to assess before consumption (Liu & Park, 2015). Therefore, the importance of online reviews in influencing consumers' decision-making is recognized in the hospitality and tourism field (Chen & Xie, 2008).

While the layouts are different for each platform, online reviews typically consist of three information components: evaluation, reputation, and social components (Kwok & Xie, 2016). First, the evaluation components include the review rating and text (Mudambi & Schuff, 2010). As the core information, these components reflect tourists' evaluations in numerical and textual form. While review photos are not mandatory on most platforms, they also represent tourists' evaluations by providing concrete images (Ma, Xiang, Du, & Fan, 2018). Particularly, the evaluations are explained in detail in the review text: which product aspects tourists assess for the evaluation, how they feel about those aspects, and how (dis)satisfied they are with those aspects (Xiang et al., 2017). Also, the information quality of online reviews is represented by the review text, including information quantity, relevancy, understandability, accuracy, completeness, and timeliness (Filieri & McLeay, 2014). These unstructured

textual comments are summarized in the review rating (from 1 to 5, i.e., the worst to the best). As such, the overall rating of online reviews about a business indicates customers' aggregated evaluations of the business. Meanwhile, the number and the variation of online reviews show the business popularity and the consistency of customers' evaluations respectively (Ye, Law, Gu, & Chen, 2011). Many platforms use these indications to rank tourism businesses, which is called review-based business ranking (Ghose, Ipeirotis, & Li, 2012).

Second, the reputation components represent different characteristics of reviewers. Reviewers can verify their identity by providing personal information (e.g., age, gender, home location, or profile pictures) (Forman, Ghose, & Wiesenfeld, 2008). Some platforms such as TripAdvisor and Yelp provide rewards to reviewers (e.g., badges or points) based on their contributions (e.g., the number of reviews written by them), which represent their expertise (Cheung, Luo, Sia, & Chen, 2009). Moreover, several other platforms enable users to become friends or follow each other by adopting social networking functions. In such platforms, the number of friends or followers denote reviewers' popularity (Resnick, Kuwabara, Zeckhauser, & Friedman, 2000). Besides such explicitly displayed characteristics of reviewers, some textual components also represent reviewers' characteristics. For instance, the length of text indicates the level of effort invested by reviewers (Forman et al., 2008) and the choice of words indicate their communication style (Ludwig et al., 2013).

Lastly, social components refer to the information that shows the interaction among tourists, businesses, and platforms. Many platforms enable users to evaluate the usefulness (helpfulness) or enjoyment of reviews by giving votes (e.g., helpful vote on TripAdvisor; useful, funny, and cool vote on Yelp). The voting system helps tourists easily find useful or enjoyable reviews from a huge amount of available information; besides, it also facilitates them to interact with each other by expressing their agreement or gratitude (Bakhshi, Kanuparthy, & Shamma, 2015). As such, the number of votes implies the reactions of other users to focal reviews (Ghose & Ipeirotis, 2010). Also, most platforms offer an opportunity for tourism businesses to interact with tourists by allowing them to respond to customers'

comments (Hennig-Thurau et al., 2010). While they are often used for dealing with customers' dissatisfaction or service failure, managerial responses also indicate how actively tourism businesses engage with tourists (Park & Allen, 2013).

As a bundle of information components, online reviews play a critical role in tourists' decision-making processes by influencing their perceptions and behavior. In the hospitality and tourism literature, a number of online review studies have demonstrated its critical role by examining its effects on tourists' perceptions of online reviews, product attitude or purchase intention, and actual behavior (Schuckert, Liu, & Law, 2015) (Figure 1.1).

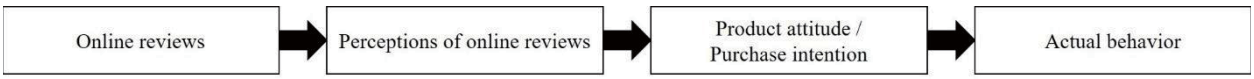

Figure 1.1. Role of online reviews in tourists' decision-making process

Within the chain of reactions, a major stream of the literature has studied tourists' perceptions of online reviews. As it has been found that tourists are not influenced by all reviews, researchers have attempted to understand what kinds of reviews are perceived as helpful or credible for potential tourists (Hlee, Lee, & Koo, 2018). Specifically, these studies have identified the determinant information components that influence tourists' perceptions of online reviews. By examining the effects of reputation (i.e., reviewers' identity disclosure, expertise, reputation, length of text), evaluation (i.e., review rating, readability of text), and social components (i.e., the number of enjoyment votes), Liu and Park (2015) found that all three components significantly affect the perceived usefulness of online reviews. Similarly, Filieri (2016) concluded that tourists assess the trustworthiness of online reviews based on those components. Recent research has provided additional insights into tourists' perceptions of online reviews. The studies with computational content analyses showed that the perceptions are affected by the communication styles reviewers use (Wang, Tang, & Kim, 2019) and the product aspects that are evaluated in the text (Xiang et al., 2017) or photos (Ma et al., 2018). Another group of studies explored the interactions between different information components to provide nuanced explanations. For example,

it has been found that online reviews of the same rating are perceived as more (or less) helpful depending on how recently they are posted (Chen & Lurie, 2013), how long they are (Filieri, Raguseo, & Vitari, 2018b), and which product aspects are mentioned in the text (Shin, Du, Ma, Fan, & Xiang, 2020).

After assessing the helpfulness of online reviews, tourists evaluate the quality of products. Another stream of the literature has studied the next level of tourists' responses: product attitude or purchase intention. These studies have attempted to understand how tourists differently perceive the reviewed products depending on how they are evaluated in online reviews. Vermeulen and Seegers (2009) found that tourists' awareness and consideration of a hotel (i.e., whether to consider it as an option), as well as their attitude to it, are enhanced when there are more positive than negative reviews. Similarly, Sparks and Browning (2011) examined the positive effects of the overall valence of reviews on tourists' level of trust in a hotel and their booking intention.

Lastly, another stream of the literature studied the actual behavior of tourists. By using different performance scales of tourism businesses as response variables, the research has shown how tourists' purchase is affected by online reviews. On a business level, these studies set the overall valence, volume, and variance of online reviews as independent variables and found their significant effects on room sales (Ye et al., 2011) and prices of hotels (Öğüt & Onur Taş, 2012). Zhang et al. (2010) examined the positive effects of the overall valence and volume on the online popularity of restaurants (i.e., the number of page views of their websites). Besides the evaluation, social components have been also found as influential in affecting tourists' purchase, as seen in the positive effects of response rates on the hotel's average daily rate and revenue per available room (Kim, Lim, & Brymer, 2015).

Overall, the existing literature has primarily studied the information components of online reviews and examined their effects on different response variables (Hu & Yang, 2020). However, tourists' information use is a dynamic process wherein different amounts and types of information sources are utilized depending on a variety of contextual factors (Fodness & Murray, 1997). Since tourists' information use occurs within specific contexts, the effects of travel information are not independent from

the surrounding situation. From the tourists' personal to trip characteristics, many contextual factors that influence the way tourists use information (e.g., the choice of the information sources, the time and effort spent, etc.) have been identified (Fodness & Murray, 1997). Luo, Feng, and Cai (2005) showed that tourists' use of the internet is related to their socio-demographics (i.e., gender and household income) and trip characteristics (i.e., travel purpose and party composition). In addition, Lehto, Kim, and Morrison (2006) found that tourists' use of travel-related websites is dependent on their travel expertise: while novice tourists tend to seek general information about destinations from neutral websites (e.g., travel guides or magazines), experts focus on practical information, such as lodging location and price comparisons. In the search engine setting, Xiang and Pan (2011) found that tourists use different search queries for different cities, indicating that tourists' use of the search engine is affected by their knowledge of the destinations.

Like other types of information, understanding the value of online reviews depends on the factors that transcend their information characteristics (Figure 1.2). The dynamic nature of online reviews has been established in other fields with the identification of different contextual factors: when consumers read online reviews (Huang, Tan, Ke, & Wei, 2018; Jin, Hu, & He, 2014), whether they are under time pressure when processing online reviews (Gottschalk & Mafael, 2017), which types of platforms consumers use to process online reviews (Floyd, Freling, Alhoqail, Cho, & Freling, 2014; Gu, Park, & Konana, 2012), which devices they use (Furner & Zinko, 2017), and so on.

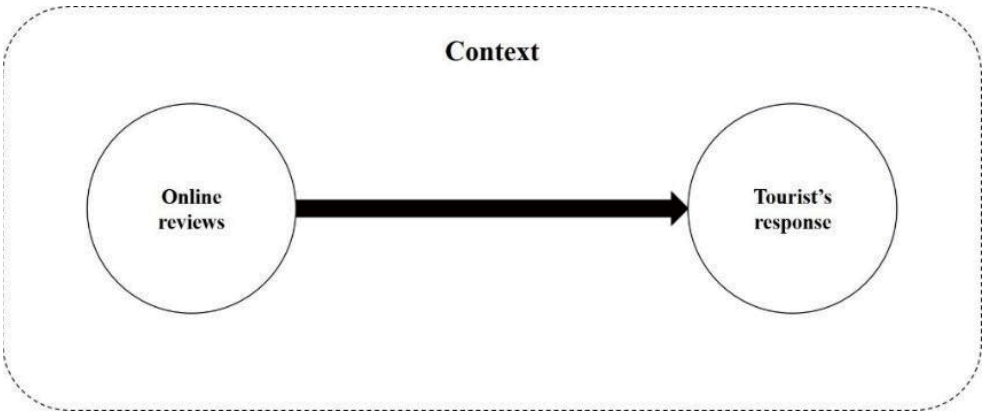

Figure 1.2. Contextual effects of online reviews

However, a majority of the literature on hospitality and tourism has regarded tourists' response to online reviews as independent of its context. Some research has attempted to address this limitation by studying how online reviews have various impacts depending on the characteristics of tourists (e.g., involvement in processing reviews, familiarity with review platforms) (Filieri et al., 2018a; Lim & Van Der Heide, 2015) and tourism products (e.g., type or service level of products) (Racherla & Friske, 2012; Zhang, Ye, & Law, 2011). Nevertheless, there are still a variety of contextual factors that could affect tourists' responses to online reviews, such as when online reviews are used (Shin, Chung, Xiang, & Koo, 2019), by whom (Filieri et al., 2018a), and for what (Racherla & Friske, 2012). To further understand the context-dependent nature of online reviews, it is essential to consider more varied contextual factors.

This dissertation aims to understand the contextual effects of online reviews in the hospitality and tourism field. Three independent and interrelated essays are conducted to understand how tourists respond to online reviews under certain contexts. As indicated in the introduction, the three essays focus on two contextual factors which could influence tourists' responses to online reviews: the context of use and the nature of tourism products (Racherla & Friske, 2012; Uberall, 2020).

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CHAPTER 2. UNDERSTANDING THE ROLE OF ONLINE REVIEWS IN THE LOCAL SEARCH CONTEXT

Abstract

Study 1 aims to understand the role of online reviews in the local search context. When tourists perform local search, their product choices are primarily affected depending on which tourism businesses are high- or low-ranked in the search results. Considering that online reviews are used as ranking factors, this study examines the effects of online reviews on the representation of tourism businesses in the local search platforms (LSPs). By simulating tourists' local search for restaurants on three LSPs (i.e., Google, Bing, and Yelp), how different ranking results are generated across the platforms and how online reviews contribute to the differences is examined. The results showed that the three LSPs' ranking results are different in terms of composition (i.e., which restaurants are included in the ranking) and ranking (i.e., which ones are high- or low-ranked), because of the difference in the way each LSP treats online reviews as ranking factors. This study confirms the context-dependent nature of online reviews, and argues the importance of considering the context of use to understand their impacts on tourists' decision-making.

2.1. Introduction

As one of the essential information sources, online reviews play an instrumental role in consumers' product choices by reducing the uncertainty regarding purchase decisions (Mudambi & Schuff, 2010). In particular, consumers perceive a higher risk when they purchase tourism products due to their intangibility, and the importance of online reviews is recognized in the hospitality and tourism field (Litvin, Goldsmith, & Pan, 2008). Over 75% of tourists are willing to pay a higher price for a hotel with higher rating and almost 90% dismiss services with rating lower than three (Bridges, 2019). Around 80% always consult online reviews before deciding where to eat, visit, and stay (Galov, 2020).

While online reviews play a crucial role in tourists' decision-making, the way they affect tourists' product choices depends on the context in which they are used. For example, in pre-departure search for

restaurants made on a desktop, tourists focus on the top-ranked search results but may not make decisions based solely on the rankings. By reading online reviews, they further evaluate the top-ranked restaurants (e.g., their strengths or weaknesses, their recent evaluations, or customers' feelings about their services). However, it is difficult for tourists to adopt a similar strategy when searching for a nearby restaurant during their trips through a smartphone (e.g., local search) because of the situational constraint (e.g., the small screens of mobile devices or limited time for searching) (Liu, Rau, & Gao, 2010). Thus, in such situations, tourists tend to select the top-ranked ones without further evaluation (Ghose, Goldfarb, & Han, 2013). With respect to the former context, how tourists process online reviews needs to be studied to understand their role in tourists' decision-making. However, given the higher-ranking effect, the role of online reviews in the local search context needs to be explained based on the understanding of their effects on the ranking of tourism businesses.

Understanding the role of online reviews depends on factors that transcend their information characteristics. As indicated in the example, the contextual factors particular to a certain time and place affect tourists' use of online reviews for their decision-making (Furner & Zinko, 2017). To explain the context-dependent nature of online reviews, their role needs to be explored in different contexts. However, the existing literature has studied the role of online reviews primarily in the context of pre-trip planning (Lamsfus, Wang, Alzua-Sorzabal, & Xiang, 2015). Nowadays, on-site decision-making through local search has become a major situation in the hospitality and tourism domain. Local search platforms (LSPs) have become critical information search tools that connect the supply of and demand for hospitality and tourism products, particularly in the on-site context (Raper, Gartner, Karimi, & Rizos, 2007). Given their dominance in the hospitality and tourism field, understanding the role of online reviews is important in the local search context (Shaw, 2020).

Therefore, Study 1 aims to understand the role of online reviews in the local search context. Given the higher-ranking effect in the local search context, this study examines the effects of online reviews on the ranking of tourism businesses. Specifically, it explores how tourism businesses are

differently ranked across different LSPs, depending on how online reviews are utilized as ranking factors on each platform.

2.2. Research Background

2.2.1. Context-dependent nature of online reviews

Online reviews are defined as consumer-generated product evaluations available in the public domain through the Internet (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Since online reviews are shared by former customers based on their own consumption experiences, potential consumers often use them to reduce their uncertainty regarding purchases (Hu, Liu, & Zhang, 2008). Specifically, consumers perceive a higher risk when purchasing intangible tourism products, because their quality is difficult to assess before consumption (Liu & Park, 2015). Thus, online reviews have been essential information sources in the hospitality and tourism field (Chen & Xie, 2008).

Information use by tourists is a dynamic process, wherein a variety of contextual factors are involved. Depending on when and where tourists use information, it can be differently used and have varying impacts on their behavior (Fodness & Murray, 1997). Specifically, as information technology (IT) development enables them to access the Internet at any time or place (Wang, Xiang, & Fesenmaier, 2016), it becomes important to consider the situational influences in order to understand the role of information in their decision-making (Lamsfus et al., 2015). For example, unlike in the pre-consumption stage (i.e., before the trip), they primarily use mobile devices to use the information in the consumption stage (i.e., during the trip). Thus, how the information is presented through mobile devices (e.g., how mobile-friendly it is) needs to be questioned to explain its role in tourists' on-site decision-making (Furner & Zinko, 2017).

Although the context-dependent nature of travel information has been established (Fodness & Murray, 1999), such dynamic nature has been less studied in the online review setting. Since most of the existing literature on online reviews has assumed a particular context (i.e., tourists using online reviews

before the trip through desktops), their effects on tourists' behavior have been examined mainly in the context of pre-trip planning (Lamsfus et al., 2015). To understand the dynamic nature of online reviews, their role in tourists' decision-making has to be studied in various situations, such as in the context of on-site decision-making, which becomes important and prevalent in the hospitality and tourism field (Tussyadiah, 2016).

2.2.2. Online reviews as ranking factors in the local search context

Besides pre-trip decision-making, on-site decision-making becomes a major context of tourists' information use, mainly due to the widespread use of mobile devices (Yoon, Kim, & Connolly, 2018). While tourists' search for activities often happened before the trip in the past, nowadays, 54% of the search occurs at destinations, and 48% of travel experience bookings are made at destinations through mobile devices (Delgado, 2019). Tourists increasingly purchase tourism products during the trip by conducting local search: they search for nearby restaurants at destinations through the search results of "restaurants near me" as main references (i.e., a ranked list of nearby restaurants) (Raper et al., 2007).

While online reviews play an important role in the context of local search as in pre-trip planning, they affect tourists' decision-making in different ways. Once tourists search for tourism businesses, most of the online platforms display a list of businesses ranked according to a variety of factors, including online reviews (e.g., the overall rating and the number of online reviews of a business) (Ghose, Ipeirotis, & Li, 2012). At the pre-trip stage, although tourists focus on the top-ranked businesses, they further evaluate them by reading online reviews. If the evaluations are negative, they might disregard the option despite its higher ranking. However, during local search, tourists have reduced interaction with mobile devices due to the small screen and limited time for the search (Liu et al., 2010). Thus, they tend to skip further evaluation and choose the top-ranked businesses without much consideration (Ghose et al., 2013). Unlike in the former context, online reviews affect tourists' decision-making as ranking factors in this

context. As such, a study of how online reviews influence the ranking of tourism businesses is needed to understand the role of online reviews in the local search context.

This study aims to examine the effects of online reviews on the ranking of tourism businesses in LSPs. Although LSPs employ online reviews as major ranking factors, each platform uses them in different ways. Among the various components of online reviews (e.g., the overall rating and the number of online reviews), each LSP adopts specific components and assigns different weight to each (Long & Chang, 2014). Given the cross-platform difference, this study comparatively examines the ranking results of three major LSPs (Google, Bing, and Yelp), to explain how the results of local search change, depending on how online reviews are used as ranking factors.

2.3. Research Design

To examine comparatively the search results of three major LSPs, an analytical approach was adopted. Particularly, a series of analyses were conducted to understand how different search results are obtained across three LSPs and how online reviews contribute to the differences.

As the major LSPs, Google, Bing, and Yelp were selected. Google and Bing represent over 95% of mobile searches (StatCounter, 2020), and Yelp is one of the top-ranked platforms for discovering local businesses, especially restaurants (Yelp, 2020). As a business domain, this study focused on the restaurant domain, which is top-ranked for local search: according to Google Trends, four out of the top five local search queries are about food (e.g., “Restaurants near me,” “Food near me,” “Pizza near me,” and “Delivery near me”) (Fagan, 2019). As a geographic domain, Los Angeles (LA) was selected because of its large number of restaurants having a wide range of categories (e.g., cuisines, service levels). Thus, LA tourists’ local search for restaurants (i.e., searching “restaurants near me” around popular attractions of LA) was simulated in Google, Bing, and Yelp, and the search results were compared in terms of their composition and ranking.

As for the composition, this study explored how a different set of restaurants is searched on each platform. As for the ranking, it examined how different ranking results are generated in each platform and the extent to which (if any) online reviews cause the differences. After measuring the similarity of the rankings, it examined the impact of online reviews on the rankings in each platform to understand how local search results vary depending on how online reviews are treated as ranking factors.

2.3.1. Data collection

To collect the data, LA tourists' local search for restaurants was simulated. First, local search queries were determined. With the 2020 official visitor map of LA, the places shown as tourist attractions were identified. To cover most areas of the city, all the major areas (i.e., The Valley, Westside, Downtown, Beach Cities, Neighboring Communities) were checked, and 67 places in total were identified (e.g., Union Station, Universal Studios, Griffith Observatory, Venice Boardwalk) (see Appendix 2.A). Using the name of each place, 67 queries were created (e.g., "Restaurants near Union Station," "Restaurants near Universal Studios," "Restaurants near Griffith Observatory," "Restaurants near Venice Boardwalk").

Second, 67 sessions of local search were conducted on each platform. This step had three methodological challenges. First, since a number of search sessions were not feasible through smartphones, they were conducted through desktops. Considering that local search is a mobile-driven phenomenon, the desktop search results might not be valid, because the results could differ with devices. Thus, some queries were randomly sampled, and the search results were compared between desktops and smartphones. The search results were confirmed to be consistent. Second, since the search results could be affected by personalization, the private browsing mode (i.e., incognito) was employed. Given the platforms' capabilities to search and rank local businesses based on user's search history, the search results are likely to be influenced by personalization. To circumvent this challenge, all the browsing data (e.g., search history, download history, cookies, etc.) were removed before each session, and the private

browsing mode was used, which is developed to prevent the association of previous search history with the focal search. Third, since search results can change with time, each search session was conducted at the same time on the same day: for example, the search results of "Restaurant near Union Station" of Google, Bing, and Yelp were collected on the same day.

After conducting the local search on each platform, the restaurant data were collected from each session. The date about top 20 restaurants were collected. From nine sessions, less than 20 restaurants were searched on either Google, Bing, or Yelp e.g., Exchange LA, Row DTLA, The Getty Center, Manhattan Beach Pier, Porsche Experience Center, Van Nuys Airport, Westfield Topanga & The Village, NoHo Arts District, Descanso Gardens. Also, some restaurants appeared on several sessions repeatedly. Thus, 1,079 restaurants in total were collected from Google, 986 from Bing, and 1,107 from Yelp. Although not a part of the main analysis, this discrepancy in the number of searched restaurants across Google, Bing, and Yelp can be the indirect indication of different search results of Google, Bing, and Yelp.

For each restaurant, the following information was collected: restaurant ranking, name, address, mean rating of reviews, number of reviews, distance, price range ($–$$$$), and cuisine. As for the distance between the places used in the search queries and the searched restaurants, the point-to-point straight distance was calculated. With Google Maps Geocoding API, two groups of addresses (i.e., one of 67 places of search queries and another of searched restaurants) were converted into latitudes and longitudes, and nautical miles were calculated. As for the cuisine, while over 60 items were identified, they were grouped into eight categories for easy interpretation of results (i.e., Asian, American, European, Latin, Middle Eastern, Breakfast, Bakery, Café & Dessert, Fastfood, and miscellaneous). All the steps were conducted from April 7 to 22, 2020. All the data were collected through two Web crawling programs (i.e., Botsol and WebHarvy). In the data set, many same restaurants were found to have different names and addresses across the platforms. They were matched through manual inspection.

2.3.2. Data analysis

First, the local search results of Google, Bing, and Yelp were compared in terms of the composition: how a different set of restaurants comes up on each platform. Through descriptive analysis, the restaurants retrieved by Google, Bing, and Yelp were compared in terms of the online reviews, distance, price range, and cuisine. Second, in terms of the ranking: how different rankings are generated in each platform and how online reviews contribute to the differences. On the one hand, the similarity of the rankings was measured. On the other, the impact of online reviews on the rankings was examined.

To measure the similarity of the rankings, Webber's rank-biased overlap (RBO) was used (Webber, Moffat, & Zobel, 2010). Although there are different rank similarity measures, not every measure is appropriate for comparing the ranked lists of the Web search. Webber et al. (2010) has developed the RBO specifically for comparing the ranking results of the Web search. It ranges from zero (totally opposite) to one (perfectly same). If the score between the rankings of two search engines is 0.25, it can be interpreted as two search engines having 25% of their ranking results in common. Since it is designed to compare two rankings, three pairwise comparisons were conducted: Google–Bing, Bing–Yelp, Yelp–Google. All the comparisons were performed through the R programming language. As a rule of thumb, 0.5 has been used as a threshold that separates what is considered to be different and identical (Cardoso & Magalhães, 2011).

To examine the impacts of online reviews on the rankings, a regression analysis was conducted. Each restaurant was treated as one case with its ranking being the dependent variable and its mean rating and number of reviews as independent variables. As the dependent variable (i.e., the ranking of the restaurant) was the rank-ordered variable, ordinal regression was performed (Hair, Black, Babin, & Anderson, 1998). Other than the mean rating and number of reviews, two more independent variables were added: the mean rating and number of recent reviews. Given the arguments of local search experts on the importance of obtaining up-to-date reviews for increasing the ranking, recent reviews were

included (Richard, 2014). All the online reviews uploaded during the two months from the date of data collection (February 1, 2020–March 31, 2020) were defined as recent reviews, and their mean rating and number were added as additional independent variables. As control variables, distance, price range, and cuisine of restaurants were used.

Before the analysis, two assumptions of ordinal logistic regression were tested: proportional odds and the absence of multi-collinearity. First, proportional odds—also known as parallel lines assumption — means that the impacts of the independent variables have to be the same for each level of the dependent variable (Hair et al., 1998). To test this assumption, a parallel lines test was conducted through SPSS and the assumption violated with the 20 levels of dependent variables. By decreasing the levels gradually (i.e., 19, 18, 17, and so on), the test was iterated, and the assumption was found to meet when the 10 levels were used. Thus, the top 10 restaurants were selected for the analysis. Second, to remove the multi-collinearity among the variables, centralization was applied to all the variables. For testing the existence of multicollinearity, all the processed variables' variance inflation factor (VIF) values were checked, and no multi-collinearity was found: all the values were lower than 10 (Table 2.1). Additionally, normalization was conducted to convert all the variables to the same scale.

Table 2.1. VIF values of variables

	Mean rating of reviews	Number of reviews	Mean rating of recent reviews	Number of recent reviews	Distance	Price range	Cuisine (three dummy variables)		
VIF	1.0583	1.1271	1.2134	1.2232	1.0265	1.1933	1.1926	1.0742	1.0685

Finally, the dependent variable was reversely coded to interpret the results easily: positively significant impacts would mean the higher values of focal independent variables are correlated with the

higher ranking. Additionally, 1,000-times bootstrapping was conducted for each analysis (Google, Bing, and Yelp) as a robust check. All the processes of analysis performed through SPSS.

2.4. Findings

The descriptive statistics of restaurant information are presented in Table 2.2. Compared to Bing (3.81), the mean rating of reviews is higher in Google (4.41) and Yelp (4.12) (Figure 2.1). However, when the recent reviews are considered, the mean rating of Bing (4.12) increases to values similar to those of Google (4.45) and Yelp (4.12) (Figure 2.2). On average, Yelp shows a higher number of reviews (956.65) than Google (649.37) and Bing (558.81) (Figure 2.3), but Google (29.16) is higher than Bing (5.13) and Yelp (5.22) in terms of the number of recent reviews (Figure 2.4). As for the distance, Google (0.77) and Bing (0.76) tend to search for closer local restaurants than Yelp (1.41) (Figure 2.5). In all the three platforms, the cheaper restaurants (price range: $ ~ $$) are frequently ranked on the results (Google: 68.37%, Bing: 84.33%, Yelp: 89.27%) (Figure 2.6). Lastly, as for the cuisine, while Asian, American, Latin, and European restaurants often appear on Google (60.84%), Bing (65.07%), and Yelp (72.99%), Bing and Yelp are skewed toward Asian (Bing: 21.14%, Yelp: 31.40%).

Table 2.2. Descriptive statistics

	Google	Bing	Yelp
Mean rating of reviews (Std.)	4.41 (0.27)	3.81 (0.63)	4.12 (0.44)
Mean number of reviews (Std.)	649.3 (1662.21)	558.81 (788.45)	956.65 (1558.45)
Mean rating of recent reviews (Std.)	4.45 (0.44)	4.12 (0.44)	4.12 (0.44)
Mean number of recent reviews (Std.)	29.16 (29.70)	5.13 (2.48)	5.22 (4.56)
Mean Distance in Nautical Miles (Std.)	0.77 (0.83)	0.76 (1.55)	1.41 (1.48)

Price range (Count)			
-Not available	231 (18.09%)	62 (4.86%)	82 (6.42%)
-$	273 (21.38%)	382 (29.91%)	283 (22.16%)
-$$	600 (46.99%)	695 (54.42%)	857 (67.11%)
-$$$	138 (10.81%)	117 (9.16%)	39 (3.05%)
-$$$$	35 (2.74%)	21 (1.64%)	16 (1.25%)
Cuisine (Count)			
-Asian (Chinese, Japanese, etc.)	216 (16.91%)	270 (21.14%)	401 (31.40%)
-American (Traditional, Southern, etc.)	230 (18.01%)	219 (17.15%)	186 (14.57%)
-European (Italian, French, etc.)	191 (14.96%)	159 (12.45%)	183 (14.33%)
-Latin (Mexican, Cuban, etc.)	140 (10.96%)	183 (14.33%)	162 (12.69%)
-Middle Eastern (Halal, Kosher, etc.)	14 (1.10%)	33 (2.58%)	36 (2.82%)
-Breakfast, Bakery, Café & Dessert	77 (6.03%)	150 (11.75%)	78 (6.11%)
-Fastfood (Pizza, Burger, etc.)	113 (8.85%)	143 (11.20%)	78 (6.11%)
-Miscellaneous (Vegan, Salad, etc.)	296 (23.18%)	120 (9.40%)	153 (11.98%)

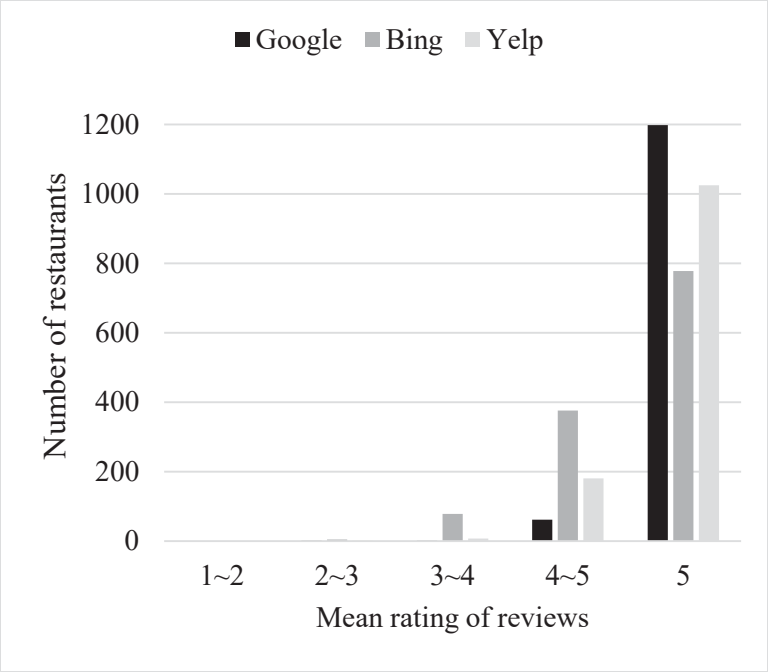

Figure 2.1. Distribution of mean rating of reviews on three platforms

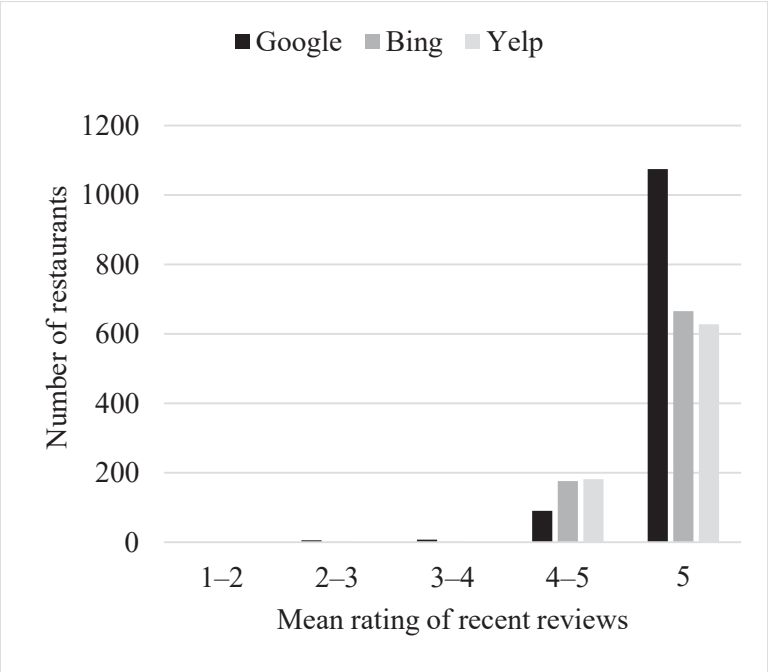

Figure 2.2. Distribution of mean rating of recent reviews on three platforms

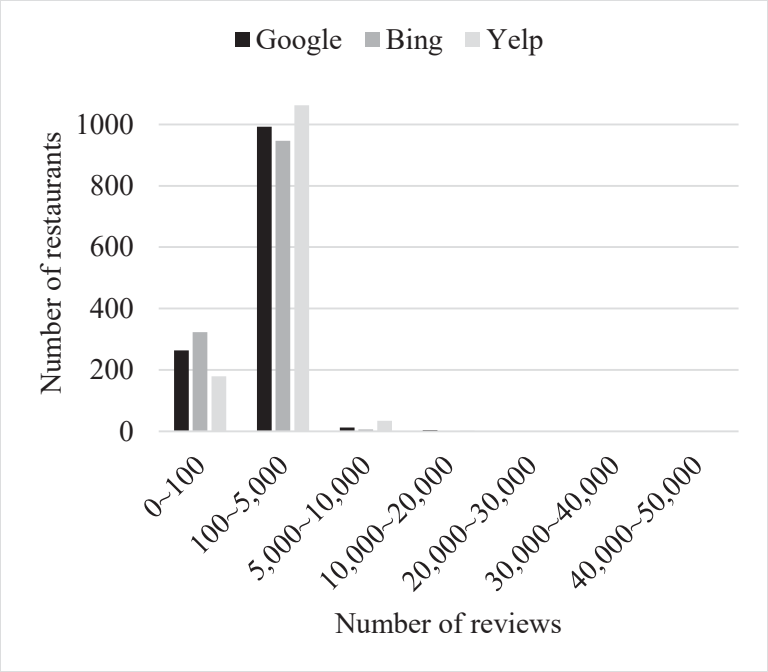

Figure 2.3. Distribution of number of reviews on three platforms

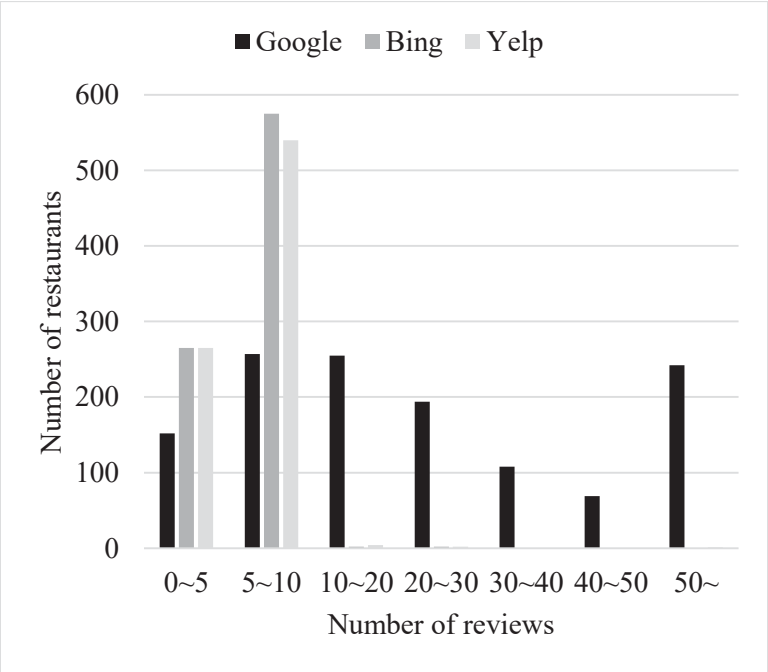

Figure 2.4. Distribution of number of recent reviews on three platforms

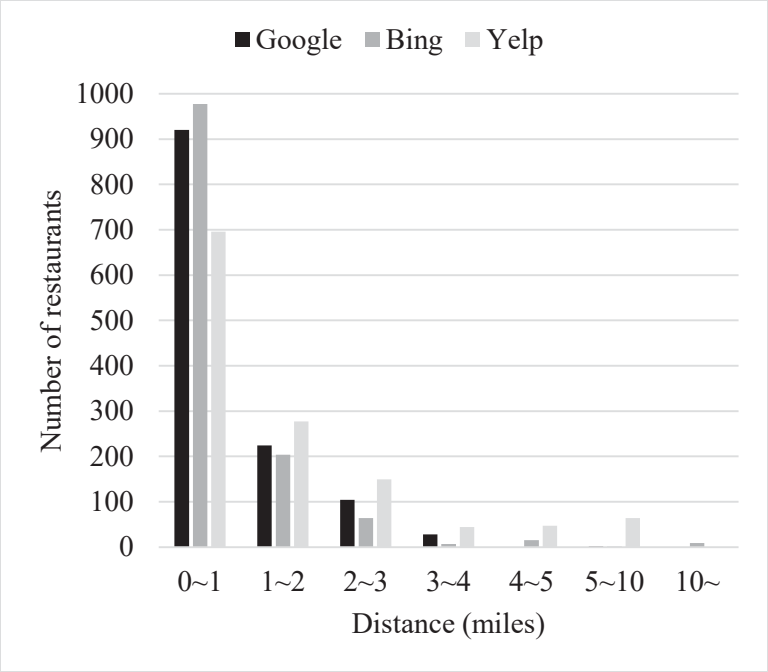

Figure 2.5. Distribution of distance on three platforms

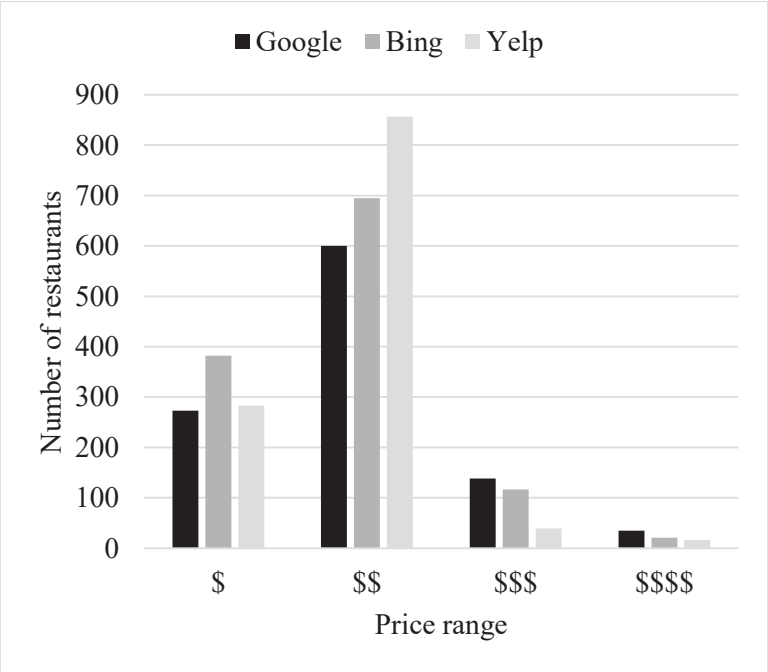

Figure 2.6. Distribution of price range on three platforms

Table 2.3 shows the results of the pairwise rank similarity comparison. It shows that the three LSPs ranking results are significantly different. To show the overall results, 67 RBO scores of each pair

(Google–Bing, Bing–Yelp, Yelp–Google) are averaged. In all three pairs, the average RBO score is about 0.3, significantly lower than 0.5 according to a one-sample t-test ($p < 0.001$). In Figure 2.7, the distribution of RBO scores is presented: among 67 RBO scores, how many cases fall into each interval. Although some comparisons appear quite similar (higher than 0.5), most cases are examined as different (see Appendix 2.A to check 67 RBO scores).

Table 2.3. Average RBO score of three pairwise comparisons

	Google–Bing	Bing–Yelp	Yelp–Google
Mean	0.3391	0.3152	0.3376
Std. Dev.	0.1263	0.0927	0.1247
One-sample t-test	-11.198***	-16.169***	-10.535***

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

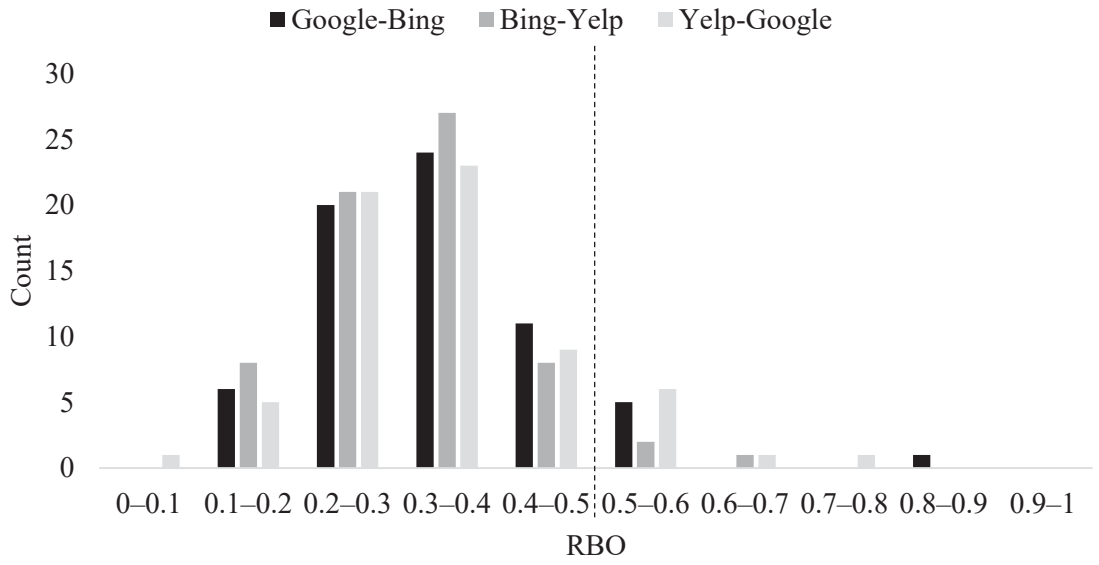

Figure 2.7. Distribution of the RBO scores

Table 2.4 shows the ordinal logistic regression results of Google. The model fits well (chi-square = 56.076, $p < 0.001$), and the test of parallel lines demonstrates insignificant results, indicating that the

assumption is met (chi-square = 111.792, $p = 0.283$). Among the independent variables, only the number of recent reviews is positively significant ($\beta = 0.142$, $p < 0.05$). As for the control variables, distance is negatively significant ($\beta = -0.208$, $p < 0.05$), and two cuisines, Breakfast, Bakery, Café & Dessert ($\beta = -0.902$, $p < 0.05$), and Fastfood ($\beta = -1.521$, $p < 0.001$) are negatively significant, indicating that some cuisines tend to be lower ranked. As for a robust check comparing the original and bootstrap results in terms of significance and direction, all the results appear consistent.

Table 2.4. Ordinal logistic regression analysis of Google

	Estimate	Bootstrap Median (95% CI)	Std.	df	Sig.
Mean rating of reviews	-0.124	-0.140 (-0.466~0.186)	0.151	1	0.412
Number of reviews	0.046	0.044 (-0.095~0.183)	0.073	1	0.529
Mean rating of recent reviews	0.060	0.066 (-0.139~0.271)	0.097	1	0.537
Number of recent reviews	0.142	0.137 (-0.021~0.295)	0.074	1	0.049
Distance	-0.208	-0.218 (-0.354~-0.081)	0.061	1	0.001
Price range	0.045	0.041 (-0.194~0.276)	0.112	1	0.689
Cuisine					
Asian	-0.273	-0.268 (-0.700~0.165)	0.212	1	0.197
American	-0.054	-0.034 (-0.441~0.373)	0.207	1	0.795
European	-0.032	-0.023 (-0.519~0.474)	0.227	1	0.888
Latin	-0.128	-0.137 (-0.687~0.413)	0.264	1	0.628
Middle Eastern	0.728	0.723 (0.635~0.811)	0.801	1	0.363
Breakfast, Bakery, Café & Dessert	-0.902	-0.917 (-1.540~-0.294)	0.318	1	0.005
Fastfood	-1.521	-1.541 (-2.111~-0.97)	0.286	1	0.000
Miscellaneous	0			0	

Pseudo R-Square (Model Fit)	0.082 (Chi-Square = 56.076, $p < 0.001$)
Test of Parallel Lines	Chi-Square = 111.792 ($p = 0.283$)

Table 2.5 shows the results of Bing. The model is significant (chi-square = 40.046, $p < 0.001$), and the parallel lines assumption is met (chi-square = 101.606, $p = 0.548$). The number of reviews is positively significant ($\beta = 0.170$, $p < 0.05$), and distance is negatively significant ($\beta = -0.537$, $p < 0.001$). Also, Asian ($\beta = -0.511$, $p < 0.05$) is negatively significant. All the original and bootstrap results are consistent.

Table 2.5. Ordinal logistic regression analysis of Bing

	Estimate	Bootstrap Median (95% CI)	Std.	df	Sig.
Mean rating of reviews	-0.035	-0.036 (-0.170~0.098)	0.059	1	0.546
Number of reviews	0.170	0.171 (0.034~0.307)	0.071	1	0.016
Mean rating of recent reviews	0.042	0.031 (-0.157~0.219)	0.079	1	0.593
Number of recent reviews	0.131	0.109 (-0.173~0.391)	0.113	1	0.248
Distance	-0.537	-0.575 (-0.866~-0.284)	0.112	1	0.000
Price range	0.205	0.207 (-0.028~0.442)	0.117	1	0.080
Cuisine					
Asian	-0.511	-0.512 (-1.011~-0.012)	0.259	1	0.049
American	0.013	0.013 (-0.522~0.548)	0.261	1	0.961
European	-0.160	-0.153 (-0.673~0.368)	0.279	1	0.565
Latin	-0.073	-0.054 (-0.667~0.559)	0.294	1	0.803
Middle Eastern	0.202	0.259 (-0.668~1.186)	0.431	1	0.638
Breakfast, Bakery, Café & Dessert	-0.217	-0.216 (-0.787~0.356)	0.295	1	0.461

Fastfood	-0.074	-0.046 (-0.623~0.532)	0.299	1	0.804
Miscellaneous	0			0	
Pseudo R-Square (Model Fit)	0.059 (Chi-Square = 40.046, $p < 0.001$)				
Test of Parallel Lines	Chi-Square = 101.606 ($p = 0.548$)				

Table 2.6 shows the results of Yelp. The model is significant (chi-square = 25.523, $p < 0.05$), and the parallel lines assumption is met (chi-square = 28.342, $p = 0.860$). The number of reviews is positively significant ($\beta = 0.224$, $p < 0.05$). The mean rating of recent review is positively significant ($\beta = 0.375$, $p = 0.042$). The distance is negatively significant ($\beta = -0.196$, $p < 0.05$). The bootstrap results show the same findings.

Table 2.6. Ordinal logistic regression analysis of Yelp

	Estimate	Bootstrap Median (95% CI)	Std.	df	Sig.
Mean rating of reviews	-0.043	-0.047 (-0.19~0.096)	0.071	1	0.544
Number of reviews	0.224	0.234 (0.089~0.378)	0.074	1	0.002
Mean rating of recent reviews	0.375	0.373 (-0.059~0.804)	0.191	1	0.042
Number of recent reviews	0.091	0.108 (-0.155~0.370)	0.111	1	0.414
Distance	-0.196	-0.199 (-0.326~-0.071)	0.063	1	0.002
Price range	0.114	0.100 (-0.176~0.376)	0.144	1	0.429
Cuisine					
Asian	-0.219	-0.224 (-0.685~0.238)	0.231	1	0.343
American	0.014	0.026 (-0.502~0.554)	0.263	1	0.958
European	0.014	0.042 (-0.525~0.609)	0.267	1	0.957
Latin	-0.156	-0.179 (-0.719~0.362)	0.289	1	0.590

Middle Eastern	-0.368	-0.349 (-1.044~0.347)	0.445	1	0.409
Breakfast, Bakery, Café & Dessert	-0.148	-0.185 (-0.919~0.549)	0.354	1	0.675
Fastfood	-0.168	-0.153 (-0.786~0.481)	0.354	1	0.636
Miscellaneous	0			0	
Pseudo R-Square (Model Fit)	0.039 (Chi-Square = 25.523, $p < 0.05$)				
Test of Parallel Lines	Chi-Square = 28.342 ($p = 0.860$)				

2.5. Discussion

To understand the role of online reviews in the local search context, this study conducts an analytical research and examines how tourism businesses are differently represented across LSPs depending on how online reviews are used in each platform. By simulating LA tourists' local search for restaurants, it compares the local search results of Google, Bing, and Yelp in terms of composition and ranking. While all three LSPs provide the rankings of local restaurants according to tourists' location, it is found that a different set of restaurants is brought up and different rankings are generated across the platforms. Specifically, the findings show that the restaurant domain is differently represented across three LSPs in terms of popularity, service quality, distance, price, and cuisine. It is also found that the different search results are on account of the differences in the way each LSP treats online reviews. On Google, the number of recent reviews is examined as positively significant: the restaurants that receive many recent reviews tend to be highly ranked. However, the number of reviews, not the recent ones, has a positive impact on Bing: the restaurants that have received many reviews so far tend to be highly ranked. Moreover, on Yelp, the number of reviews and the mean rating of recent reviews are examined as having positive effects: the restaurants that receive many reviews so far and are positively evaluated in recent times tend to be highly ranked. The distance is the only common factor that has a significant impact on the ranking in all three LSPs. These findings reveal that the ranking of tourism businesses in the local

search results significantly depends on how online reviews are used as ranking factors. These findings indicate that the three major LSPs differently define which local businesses have to be higher ranked. Every platform aims to provide valid ranking results: the local businesses that have to be higher ranked are actually higher ranked and vice versa. However, each platform differently defines which restaurants should be highly ranked. While Bing and Yelp regard the cumulative popularity of restaurants as an important aspect together with the proximity, Google values the recent popularity. Moreover, Yelp considers the recent business quality of restaurants an additional aspect.

2.5.1. Theoretical implications

First, this study contributes to the tourism literature on online reviews by examining their context-dependent nature. Although the contextual effects of travel information have been explored, such varying impacts have been limitedly examined in the online review setting. Furthermore, since the characteristics of tourists and tourism products have been mainly studied as contextual factors, the situational influences have been sparsely investigated, such as when and where tourists use travel information (Filieri, Hofacker, & Alguezaui, 2018; Racherla & Friske, 2012). Nowadays, online reviews are used in various situations with IT development and are expected to affect tourists' decision-making in different ways in each situation (Lamsfus et al., 2015). However, most existing studies have overlooked the dynamic nature of online reviews. This study addresses this limitation by arguing and confirming that the role of online reviews needs to be understood differently in the local search context.

Second, this research can serve as a basis for understanding tourists' on-site decision-making. Although meaningful contributions are present, the studies of online representation of travel information have focused on the pre-trip information search context (Fodness & Murray, 1997; Vogt & Fesenmaier, 1998; Xiang & Gretzel, 2010). While pre-trip decision-making is a major context of tourists' information search, tourists' on-site decision-making also gains importance (Tussyadiah & Zach, 2012). Considering

that LSPs are influential information sources for tourists' on-site decisions, this research can serve as a reference for future research on tourists' on-site information search and decision-making.

Third, this research is one of the earliest studies about LSPs in the hospitality and tourism field. A major information channel connecting tourists and service providers, such as search engines, has been an important research topic in the field (Xiang, Wöber, & Fesenmaier, 2008). The literature has made substantial contributions to tourists' information search by examining the impacts of information channels on their perceptions (Pan & Li, 2011) or behavior (Li, Pan, Law, & Huang, 2017). Further, it has provided important insights into online tourism marketing by investigating the roles of information channels in presenting the domain (Xiang & Gretzel, 2010). However, existing literature has been limited in that it has focused on general search engines despite the increasing significance of LSPs in the hospitality and tourism field (Pedrana, 2014). The current research fills this gap by discussing the importance of LSPs in representing the domain.

Finally, this research contributes to the literature on socio-technical systems by suggesting that studies using a single data source have to consider the potential "biases" in the data. According to the results, there are discrepancies in the representation of tourism domain on three major LSPs. Such "biases" created by inherent aspects of socio-technical systems have been found in other types of systems, such as online review websites (Xiang, Du, Ma, & Fan, 2017). Although existing hospitality and tourism literature on socio-technical systems has usually utilized a single platform to collect data, most studies have not discussed the potential "biases" in the data (Li, Xu, Tang, Wang, & Li, 2018). By showing the cross-platform difference in the context of LSP, the findings support the importance of considering the unique characteristics of each socio-technical system in drawing implications from the results based on single-source data.

2.5.2. Practical implications

The current research offers several practical implications for LSPs and local tourism businesses. The findings show that each LSP treats specific ranking factors more importantly. Considering that each tourist has different criteria for the desired products, it would be differently defined by individuals, which aspects need to be primarily considered for ranking tourism businesses: while some tourists would select the place to visit based on its popularity, others choose with its quality (Tsaur & Tzeng, 1996). By promoting which ranking factors are prioritized, LSPs can let tourists choose the platforms that fit their preferences. Without any knowledge about LSPs (e.g., how their rankings are determined), tourists might choose a platform simply because it is familiar or available. Indeed, a recent survey found 77% of respondents use Google Maps for local search (Sterling, 2019). Based on the findings, each LSP can differentiate itself with respect to the ranking algorithms, and help tourists select the platform with a specific reason.

In addition, it is found that restaurants are differently ranked across LSPs even when the search occurs at the same location: when 'restaurants near Chinatown' is searched, one restaurant is ranked 2nd in Google, 8th in Yelp, and 12th in Bing. This finding indicates that tourism businesses have to consider the differences in the rankings to manage their online reputation in LSPs. Especially for local independent businesses, online reputation is an essential factor in capturing and reaching customers (Tsai, 2013). To accurately measure their online reputation, tourism businesses must check their different rankings in LSPs. Further, the findings provide hints to tourism businesses on how to improve their rank in each LSP. Based on the different set of important ranking factors of each platform, tourism businesses can implement specific strategies to improve their rank on a target platform.

2.6. Conclusion

This study seeks to explain the role of online reviews in the local search context. By comparatively examining the local search results of Google, Bing, and Yelp, this study finds that local restaurants around particular geographic regions are differently searched and ranked across three LSPs

because of the way online reviews are treated as ranking factors on each platform. This study contributes to the research areas related to the contextual effects of online reviews.

However, there are several limitations. First, Google, Bing, and Yelp are considered representative of LSPs. While they are the top-ranked platforms for local search, there are other popular LSPs, including Apple Maps (Shaw, 2020). Further, this study considers a particular tourism domain around a specific area (i.e., restaurants in LA). Thus, the findings are difficult to be generalized. By adopting various LSPs or targeting different domains, future research needs to improve the generalizability of the results. Second, some potential ranking factors are not considered in the analysis. According to an industrial report, there are several important ranking factors of LSPs, which are not included in the analyses, such as mentions in social media, domain authority of website, or quantity of inbound links to website (Shaw, 2020). By taking into account those ranking factors, future research would be able to provide a full picture of the ranking algorithms of LSPs. Lastly, as tourists' response to the ranking results are not considered, this study is limited in that the role of online reviews in the local search context is partially explored. Although it is not the main goal of this study, analyzing tourists' response to the difference in local search results is necessary to understand the effects of online reviews on tourists' decision-making. Therefore, future research needs to analyze the further process of tourists' local search: how tourists choose a tourism business in the local search context.

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Appendix

Appendix 2.A. RBO scores of 67 three pairwise of comparisons

No.	**Restaurants near ~**	**Google-Bing**	**Bing-Yelp**	**Yelp-Google**
1	Chinatown	0.3121	0.4362	0.2313
2	Union Station	0.2887	0.3751	0.5442
3	Cathedral of Our Lady of The Angels	0.3669	0.2964	0.2861
4	LA City Hall	0.2071	0.3169	0.3813
5	Japanese American National Museum	0.3470	0.2334	0.3706
6	The Walt Disney Concert Hall	0.3155	0.1403	0.5086
7	Grand Central Market	0.3168	0.1940	0.3332
8	OUE Skyspace LA	0.3501	0.3256	0.2758
9	Los Angeles Visitor Information Center Downtown	0.5289	0.1940	0.5318
10	Exchange LA	0.2533	0.1864	0.4717
11	Row DTLA	0.3981	0.4431	0.2125
12	Whole Foods	0.4593	0.4220	0.4114
13	The GRAMMY Museum at L.A. LIVE	0.4033	0.2996	0.3038
14	Belasco Theatre	0.3657	0.5329	0.3447
15	Los Angeles Convention Center	0.4023	0.1977	0.3246
16	Universal Studios	0.3172	0.2438	0.5560
17	Warner Bros. Studio (Warner Bros. New York Street)	0.4634	0.3913	0.2526
18	Los Angeles Zoo	0.3782	0.3131	0.2400
19	Griffith Park	0.2574	0.2624	0.2949
20	Hollywood Bowl	0.4534	0.1463	0.1876

21	Griffith Observatory	0.2145	0.2292	0.3734
22	Go Los Angeles (Go Los Angeles Pass)	0.2935	0.3646	0.3913
23	Pantages Theatre	0.2310	0.1961	0.3100
24	Barnsdall Park	0.2310	0.3791	0.4978
25	Mak Center	0.1609	0.2986	0.3555
26	Skirball Cultural Center	0.3731	0.3035	0.1327
27	The Getty Center	0.2316	0.3079	0.6711
28	UCLA (Meyer and Renee Luskin Conference Center)	0.3745	0.2159	0.2280
29	Rodeo Drive (Rodeo Drive Walk Of Style)	0.5411	0.3897	0.2939
30	The Orginal Farmers Market	0.2595	0.2234	0.2544
31	Westside Pavilion	0.1463	0.2389	0.3327
32	Sony Pictures Studios	0.3354	0.3646	0.3253
33	Westfield Culver City	0.4463	0.3692	0.0889
34	Pacific Park	0.4134	0.3668	0.3782
35	Venice Boardwalk	0.2340	0.3538	0.4397
36	Marian Del Rey (Marina Del Rey Hotel)	0.3696	0.1424	0.4143
37	Los Angeles International Airport	0.3033	0.3117	0.3203
38	The Forum	0.3169	0.2914	0.3093
39	Manhattan Beach Pier	0.1567	0.3469	0.3366
40	King Harbor (King Harbor Marina)	0.2180	0.3072	0.3339
41	Torrance Cultural Arts Center	0.2180	0.2565	0.2076
42	Porsche Experience Center	0.3211	0.2761	0.2761
43	Point Vicente Interpretive Center	0.3245	0.3011	0.2879
44	Wayfarers Chapel	0.4748	0.2671	0.1685
45	Trump National Golf Club	0.5706	0.4134	0.3326

46	Cabrillo Marine Aquarium	0.2421	0.3611	0.2058
47	Battleship USS Iowa Museum	0.3081	0.2558	0.2313
48	Banning Residence and Museum	0.2313	0.3657	0.3742
49	Mission San Fernando Rey de España	0.3179	0.2849	0.5019
50	California State University, Northridge	0.2827	0.2602	0.4144
51	Van Nuys Airport	0.2824	0.3213	0.3620
52	The Japanese Garden	0.1952	0.3594	0.3643
53	Westfield Topanga & The Village	0.1514	0.4360	0.4018
54	Orcutt Ranch Horticulture Center	0.1901	0.3254	0.2878
55	Hollywood Burbank Airport	0.3148	0.2267	0.2313
56	NoHo Arts District	0.8314	0.6080	0.7864
57	Tujunga Village (Elizabeth Mestnik Acting Studio)	0.4266	0.2428	0.3062
58	Disney Studios	0.5019	0.5267	0.1975
59	LA Equestrian Center	0.2328	0.2255	0.4922
60	Glendale Galleria	0.2131	0.4155	0.4095
61	Descanso Gardens	0.4492	0.3390	0.3486
62	Rose Bowl	0.2085	0.4195	0.1502
63	Old Town Pasadena (Old Pasadena)	0.3293	0.3063	0.2331
64	The Huntington Library, Art Museum, and Botanical Gardens	0.5301	0.2987	0.2645
65	Westfield Santa Anita	0.3959	0.3911	0.2927
66	Heritage Square Museum	0.3376	0.4330	0.5215
67	Mission San Gabriel de Arcangelo	0.4863	0.3157	0.2264

CHAPTER 3. TOURISTS' PERCEPTIONS OF RECENT ONLINE REVIEWS IN THE LOCAL SEARCH CONTEXT

Abstract

Study 2 aims to understand how tourists process online reviews in the local search context. Building on Study 1, this study investigates how the context of use affects tourists' processing of online reviews. Given the situational characteristics of local search, how tourists perceive online reviews differently is examined in the context (i.e., searching for a restaurant that can be visited immediately) in comparison with its counterpart, non-local search context (i.e., searching for a restaurant that can be visited in a month). Based on construal level theory (CLT), this study hypothesizes the greater effects of recent reviews on tourists' cognitive and behavioral responses within the local search context, and conducts an experiment to test the hypothesis. The results showed that recent reviews have greater effects on tourists' cognitive and behavioral responses in the local search context than in non-local. Based on the findings, this study discusses tourists' contextual information processing in the online review setting as an implication and provides several directions for future research.

3.1. Introduction

Online reviews are influential sources of information that support consumers' product choices by reducing their uncertainty about product quality (Mudambi & Schuff, 2010). Consumers feel greater uncertainty when purchasing intangible tourism products whose quality is hard to assess before consumption; thus, the effects of online reviews on consumers' purchase intention are prominent in the hospitality and tourism field (Litvin, Goldsmith, & Pan, 2008). Over 70% of tourists value the overall rating of the reviews over a hotel's brand, and 81% always or usually reference the reviews before selecting a hotel (Bridges, 2019).

Tourists process online reviews in different ways depending on the context of use, such as when and where they use the reviews. The same reviews can be differently perceived depending on the surrounding situation. For example, while tourists prefer the recently uploaded reviews in general because the quality of tourism products varies greatly from one time period to another, recent reviews could be more influential under a certain context such as local search (e.g., looking for a nearby restaurant during the trip by searching for "Restaurants near me" using smartphones) (Shin & Xiang, 2021). When conducting local search, tourists are likely to visit the place of interest soon after the search; notably, about 80% of consumers visit a business within a day after performing local search (Think with Google, 2019). According to the construal level theory (CLT), individuals' preference for up-to-date information increases when they are dealing with near-future events (Trope, Liberman, & Wakslak, 2007). Considering that tourists often deal with near-future visit when performing local search, it is expected that their decision-making would be more affected by recent reviews in the context (Lamsfus, Wang, Alzua-Sorzabal, & Xiang, 2015).

Understanding tourists' processing of online reviews needs to include an analysis of factors that transcend their information characteristics. The effects of the reviews on tourists' perceptions may become more (or less) pronounced depending on when (Shin, Chung, Xiang, & Koo, 2019), by whom (Filieri, Hofacker, & Alguezaui, 2018a), and for what they are processed (Racherla & Friske, 2012). Given the dynamic nature of online reviews, it is important to consider the context of use in developing our understanding of how tourists process them. However, the existing tourism literature treats tourists' processing of online reviews as static. Other than some research studying the characteristics of tourists and tourism products as contextual factors (Filieri et al., 2018a; Racherla & Friske, 2012), a majority of the literature has argued that tourists process the reviews independently of the context.

To address this limitation, Study 2 aims to understand how the context of use affects tourists' processing of online reviews. This study examines how tourists process online reviews differently in the local search (e.g., searching for a restaurant that can be visited immediately) in comparison with the non-

local context (e.g., searching for a restaurant that can be visited in a month). Given the potential contextual effects of review recency indicated in the aforementioned example, this study tests the hypothesis that recent reviews are more influential in affecting tourists' decision-making in the local search context as compared to its non-local counterpart based on CLT which explains individuals' fluctuating perceptions of information as dependent upon the surrounding environment.

3.2. Research Background

Tourists' information processing is a dynamic process in that various contextual factors are involved. It always occurs within a certain context and, thus, is affected by different situational supports or constraints of that environment (Fodness & Murray, 1997). Many studies supported the context-dependence after examining the situational influences on tourists' information processing. This research found that information can be perceived differently depending on tourists' personal (e.g., gender, age, or knowledge of destinations) (Lehto, Kim, & Morrison, 2006; Luo, Feng, & Cai, 2005), or trip characteristics (e.g., travel purpose, length, or party composition) (Fodness & Murray, 1998). Based on these findings, it has been argued that it is important to consider the effects of different contextual factors to explain how tourists process information before making decisions (Fodness & Murray, 1997).

As online reviews become an influential source of information in the hospitality and tourism field, they have been a major topic in the literature on tourists' information processing (Schuckert, Liu, & Law, 2015). However, a majority of the literature has assumed that tourists process the reviews as independent of their context. The existing literature has explained tourists' processing of online reviews to be mainly based on the reviews' information components (e.g., reviewer's profile, review rating, or text): which components tourists consider when processing the reviews (Filieri, 2016; Liu & Park, 2015) or how they affect tourists' perceptions (Chen & Lurie, 2013; Filieri, Raguseo, & Vitari, 2018c; Shin, Du, Ma, Fan, & Xiang, 2020). Only some research has included tourists' and tourism products' characteristics as moderators of the relationship between the components and tourists' perceptions to explain contextual

information processing of tourists in the online review setting (Lim & Van Der Heide, 2015; Racherla & Friske, 2012). However, there are still a host of potential contextual factors that could affect tourists' processing of online reviews, such as the context of use—whether tourists process the reviews in the local or non-local search context (Shin et al., 2019).

Nowadays, many travel decisions are made not only before but also during the trip through local search; over half of tourists' search for attractions or activities occurs during their trip, and about 50% of travel experience bookings are made at destinations through local search (Delgado, 2019). Online reviews play an influential role in tourists' decision-making in the local search context as they do in the pre-trip situation. However, in contrast to the pre-trip planning context, tourists tend to visit the place of interest right after processing the reviews, so they often deal with short-term decision-making in the local search context (Think with Google, 2019). Given the argument of CLT, such situational characteristics could make a specific aspect of reviews more prominent in the local search context, such as review recency (Jin, Hu, & He, 2014).

The CLT explains individuals' fluctuating perceptions of information as dependent upon the surrounding environment. It argues that the same piece of information can be differently perceived by recipients depending on whether they think the subject of the information (e.g., events or objects) is temporally, spatially, or socially close or far (Trope et al., 2007). Specifically, according to CLT, when processing information regarding near-future (far-) events, individuals tend to use a particular mental model called low-construal (high-) level, and the mindset makes them more (less) sensitive to temporal dimension of information. Thus, their preference for up-to-date information tends to be prominent when the temporal distance between individuals and focal subjects is close and vice versa (Liberman & Trope, 1998; Trope & Liberman, 2000).

Given the situational characteristics of local search and the argument of CLT, it is expected that the effects of review recency on tourists' decision-making (i.e., how influential tourists think recent

reviews are as they select the place to visit) become more pronounced when tourists use online reviews during local search. This study aims to examine the moderating effect of the context of use on the relationship between review recency and tourists' cognitive and behavioral responses. Specifically, this research compares the effects of review recency in two different contexts: local search and non-local context.

3.3. Research Hypotheses

This research proposes that recent reviews are more influential in affecting tourists' decision-making in the local search context as compared to its non-local counterpart, indicating the moderating effects of the context of use on the relationship between review recency and tourists' perceptions of the reviews and reviewed products. To examine the moderating effects, this research assumes a particular situation, that is, when the rating of a recent review (recent rating) is different from that of all the reviews (overall rating). While tourists' product choices are more affected by the recent rating than the overall rating because of its up-to-date nature, this research hypothesizes that the higher effects of recent rating become pronounced in the local search context. To test this, five hypotheses are developed (Figure 3.1).

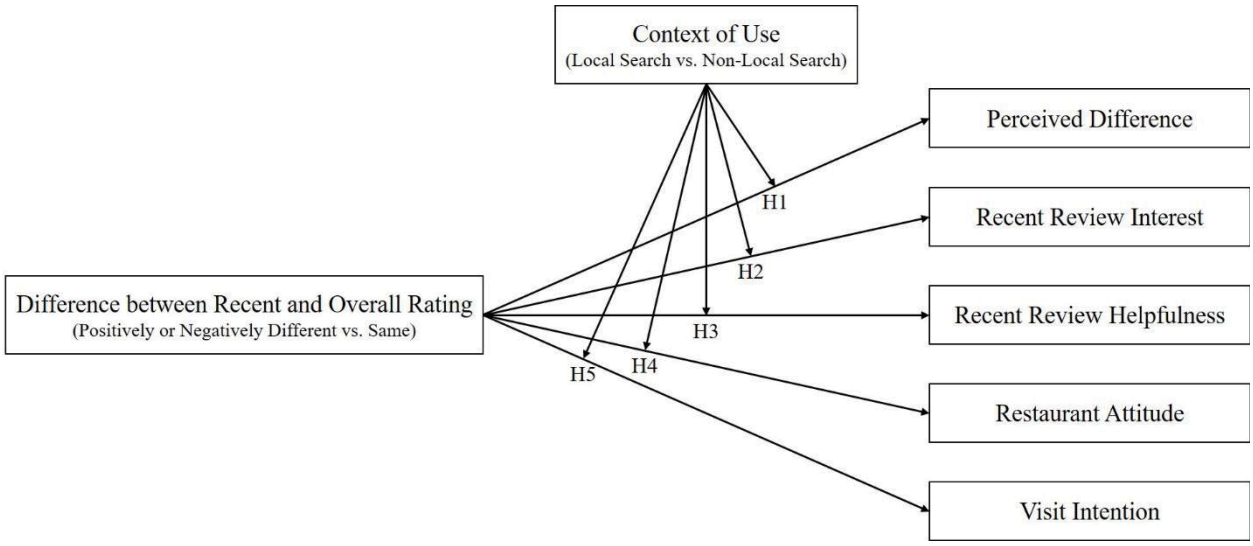

Figure 3.1. Research model

First, the extent to which tourists are sensitive to the difference between recent and overall rating can be more pronounced in the local search than the non-local context. Consumers react more sensitively to the information about the aspect that matters to them (Mosteller & Poddar, 2017). Low-income consumers are highly sensitive to the price information (Guy, Henson, & Dotson, 2015), just as the deal-prone are to the promotion (Palazon & Delgado-Ballester, 2011). If recent reviews are more importantly considered in the local search context, tourists can be more sensitive to the evaluation of recent reviews. As such, if the recent rating is different from the overall rating, the difference might be perceived as larger in the local search context.

Hypothesis 1. If the recent rating is different from the overall rating, tourists perceive the difference as larger in the local than in the non-local search context.

Second, tourists' interest in recent reviews is expected to increase in the local search context. When individuals have an interest in specific information, they tend to take more time and effort to process it (Cialdini, 2016). How interested tourists are in recent reviews can indicate how much the latter is influential in affecting tourists' decisions (Singh et al., 2017). As such, the greater effects of recent reviews in the local search context can be examined by looking at the increase in tourists' interest in recent reviews, such as how much they want to read the review text. When the recent rating is different from the overall rating, tourists are likely to focus on the recent review because of its up-to-date nature (Ziegele & Weber, 2015), and such interest is expected to increase in the local search context.

Hypothesis 2. If the recent rating is different from the overall rating, tourists have a higher interest in the recent review in the local than in the non-local search context.

Along with tourists' interests in recent reviews, their perceptions regarding the helpfulness of the reviews can be another antecedent (Filieri, McLeay, Tsui, & Lin, 2018b). To impact tourists' decisions, online reviews need to be perceived as helpful (Chevalier & Mayzlin, 2006). The more helpful they are to tourists, the more influential in affecting their decisions. A recent review is perceived as helpful when its

rating is different from the overall rating because it shows the latest change in the quality of the reviewed product (Ziegele & Weber, 2015). If recent reviews are more influential in the local search context, their helpfulness would be more prominent in the situation.

Hypothesis 3. If the recent rating is different from the overall rating, tourists perceive the recent review as more helpful in the local than in the non-local search context.

Other than tourists' perceptions of online reviews, those of reviewed products are also important to explain the impact of reviews, such as attitude or visit intention (Sparks & Browning, 2011; Vermeulen & Seegers, 2009). If a certain review is more influential in consumers' decision-making than others, their product attitude and purchase intention would be more affected by the evaluation of the former compared to the latter (Ghosh, 2018). If recent reviews are more influential in the local search context, their effects on tourists' attitude toward the reviewed place and visit intention would increase.

Hypothesis 4. If the recent rating is different from the overall rating, tourists' attitude toward the focal product is more affected by the recent review in the local than in the non-local search context.

Hypothesis 5. If the recent rating is different from the overall rating, tourists' visit intention is more affected by the recent review in the local than in the non-local search context.

3.4. Research Design

To test the hypotheses, an experiment was conducted. Participants were assigned randomly to one of the two different contexts—local search or non-local context. Those of local search (non-local) context were asked to imagine that they are going to search for a restaurant, that this search will be made during (before) the trip, and that they will visit the restaurant right after the search (in a month). In both conditions, participants checked five hypothetical restaurants to make decisions. For each restaurant, two mock result pages were presented: "Overview" and "Reviews." The "Overview" page contained general information about the restaurant, including name, a summary of online reviews (i.e., the overall rating and

number of reviews), price range, distance, and dining options. In addition to the summary of the reviews, the “Reviews” page included a single recent review uploaded the previous week. Although the five restaurants had the same overall rating, three out of five-star rating, the recent rating varied from one- to five-star rating. In other words, the participants were exposed to restaurants having varying gaps between the recent and overall rating—they were the same in one case (e.g., recent 3 vs. overall 3) but different in others (e.g., positive difference: recent 5 vs. overall 3; negative difference: recent 1 vs. overall 3). To give the same number of the cases of positive (i.e., two cases: recent 5 or 4 vs. overall 3) and negative difference (i.e., two cases: recent 2 or 1 vs. overall 3), the overall rating was set as three-star. Except for the difference between recent and overall rating, all other information was either the same (price range, distance, dining options) or similar (the number of reviews) (Figure 3.2). To avoid the unexpected effects of the cuisine of a restaurant, all five restaurants were presented as Mexican ones. The order of the five restaurants was randomly set.

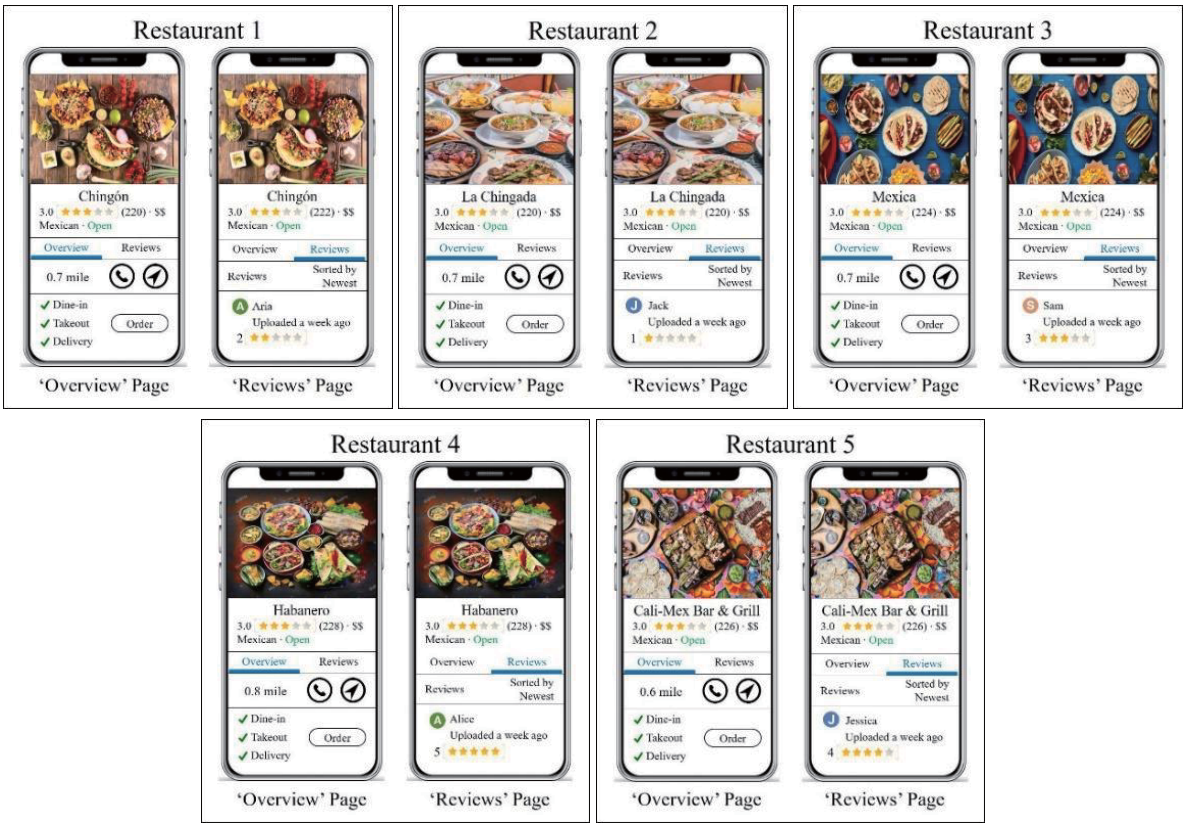

Figure 3.2. Mock pages of five restaurants

After checking the mock pages of each restaurant, participants were asked to answer five questions for testing the five hypotheses respectively: how different are the overall rating and "a-week-ago" rating? (1: very similar ~ 7: very different); if possible, would you like to read the text of "a-week-ago" review? (1: definitely not ~ 7: definitely yes); how useful was the "Reviews" page for your decision? (1: not useful ~ 7: very useful); what do you think about this restaurant? (1: bad ~ 7: good; 1: dislike ~ 7: like; 1: undesirable ~ 7: desirable); would you like to try out this restaurant? (1: definitely not ~ 7: definitely yes). Finally, several questions were followed for manipulation check, and demographics were asked at the end of the survey.

Participants were recruited through Amazon's Mechanical Turk (MTurk). A total of 500 people took part in the experimental survey during February 23–24, 2021. Due to incomplete or untrustworthy responses, several cases were removed, resulting in 265 cases (local search: 145, non-local search: 120) for analysis (Table 3.1). A Chi-square test was conducted to check whether two groups are similar in terms of demographics, and the results showed that two groups are comparable in terms of gender (x^2 = 0.320, p = 0.858), age (x^2 = 9.062, p = 0.060), education (x^2 = 9.126, p = 0.167), and occupation (x^2 = 4.803, p = 0.904).

Table 3.1. Demographics of the participants of local search context and non-local

Demographic Variables	Local search (n = 145)		Non-local search (n = 120)		Chi-Square (Significance)
	Freq.	%	Freq.	%	
Gender					0.320 (0.858)
• Male	83	57.2	70	58.3	
• Female	62	42.8	50	41.7	
Age					9.062 (0.060)
• 18–24	22	15.2	8	6.7	

• 25–34	83	57.2	75	62.5	
• 35–44	24	16.6	16	13.3	
• 45–54	6	4.1	13	10.8	
• 55 and above	10	6.9	8	6.7	
Education					
• Less than high school	2	1.4	0	0.0	
• High school graduate	14	9.7	7	5.8	
• Some college but no degree	11	7.6	11	9.2	9.126
• Associate degree in college (2-year)	16	11.0	5	4.2	(0.167)
• Bachelor's degree in college (4-year)	83	57.2	76	63.3	
• Master's degree	18	12.4	18	15.0	
• Doctoral degree	1	0.7	3	2.5	
Occupation					
• Management, professional, and related	52	35.9	43	35.8	
• Service	18	12.4	12	10.0	
• Sales and office	22	15.2	14	11.7	
• Farming, fishing, and forestry	5	3.4	6	5.0	
• Construction, extraction, and maintenance	14	9.7	9	7.5	4.803
• Production, transportation, and material moving	5	3.4	3	2.5	(0.904)
• Government	6	4.1	7	5.8	
• Student	3	2.1	6	5.0	
• Retired	3	2.1	2	1.7	
• Unemployed	11	2.1	10	8.3	

• Etc.	6	4.1	8	6.7	
Total	145	100	120	100	

3.5. Findings

The following questions were used as manipulation checks: how recent is "a-week-ago" review? (1: very old ~ 7: very recent); according to the situation that you are asked to imagine, when will your restaurant visit happen? (1: very soon ~ 7: long after). The manipulation was well achieved. As for the first question, the manipulated review as recent was perceived as intended in both contexts. By using the midpoint of rating scale of one to seven, one-sample t-test was conducted, and the sample mean was significantly higher than four in both contexts (M_{local} = 5.62, t = 17.747, $p < 0.001$; $M_{non\text{-}local}$ = 5.83, t = 21.665, $p < 0.001$). As for the second question, the results showed that the participants of local search context think that they are to visit the restaurant in near future, and those of non-local consider their visit to be a far-future event (M_{local} =1.92, $M_{non\text{-}local}$ = 6.75, t = -42.195, $p < 0.001$). Additionally, another question was asked to check whether the two groups are similar in terms of the preference for Mexican food to avoid the unexpected effects of the cuisine of the restaurant: how much do you like Mexican food? (1: not at all ~ 7: very much). The results indicated that two groups have similar degree of preferences (M_{local} =5.62, $M_{non\text{-}local}$ =5.71, t = -0.522, $p = 0.602$).

To test the five hypotheses, a 2 X 3 analysis of variance (ANOVA) with the context of use (local search vs. non-local) and the difference between recent and overall rating (positive vs. negative difference vs. none) was conducted. As for the first hypothesis, the dependent variable was perceived difference. The main effect of context of use ($F = 10.225$, $p < 0.01$) and difference were significant ($F = 100.593$, $p < 0.001$), but no interaction effect was found ($F = 1.267$, $p = 0.282$) (Table 3.2). As shown in Figure 3.3, the difference perceived by the participants of local search context was higher than that of non-local in all three cases of difference. Hypothesis 1 was supported.

Table 3.2. Descriptive statistics and ANOVA result for Hypothesis 1

	Type III Sum of Squares	Mean	df	Mean Square	F
Context of use	32.015		1	32.015	10.225**
• Local search		4.53			
• Non-local search		4.19			
Difference	629.926		2	314.963	100.593***
• Positive (Recent > Overall)		4.85			
• None (Recent = Overall)		3.00			
• Negative (Recent < Overall)		4.56			
Context of use · Difference	7.934		2	3.967	0.282
Error	4129.863		1319	3.131	

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

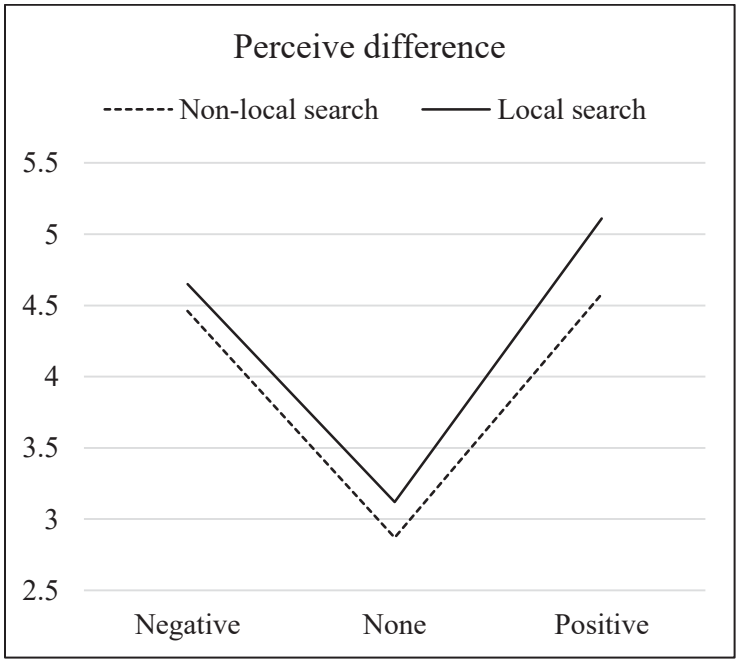

Figure 3.3. Means for perceived difference across difference manipulation

As for the second hypothesis, the dependent variable was recent review interest. While the main effect of difference was significant ($F = 5.181$, $p < 0.05$), that of context of use was not ($F = 0.133$, $p = 0.715$). No interaction effect was found ($F = 0.344$, $p = 0.709$) (Table 3.3). As shown in Figure 3.4, the participants of both contexts had a higher interest in the recent rating when it is different from the overall than when they are same. However, the results showed that there is no significant difference based on the context of use. Thus, Hypothesis 2 was not supported.

Table 3.3. Descriptive statistics and ANOVA result for Hypothesis 2

	Type III Sum of Squares	Mean	df	Mean Square	F
Context of use	0.264		1	0.264	0.133
• Local search		5.59			
• Non-local search		5.56			
Difference	20.549		2	10.275	5.181*
• Positive (Recent > Overall)		5.75			
• None (Recent = Overall)		5.42			
• Negative (Recent < Overall)		5.58			
Context of use · Difference	1.364		2	0.682	0.344
Error	2615.889		1319	1.983	

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

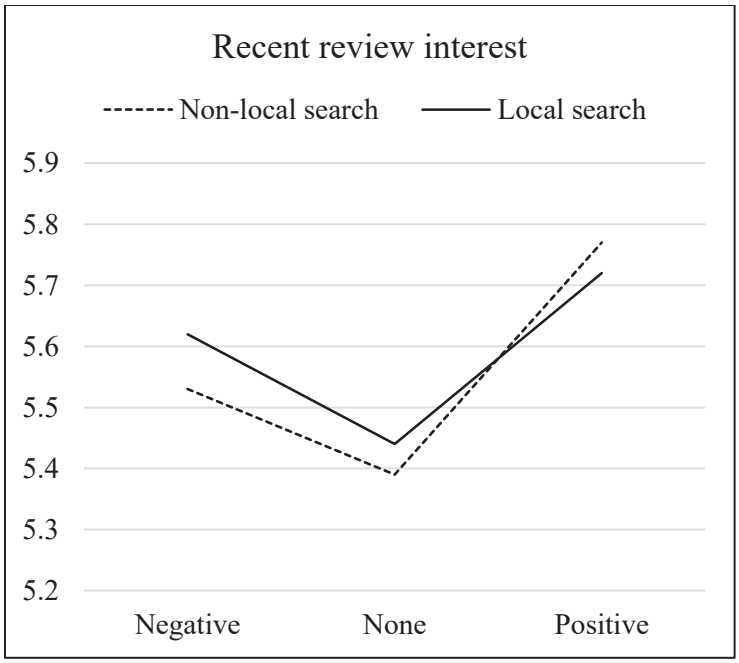

Figure 3.4. Means for recent review interest across difference manipulation

As for the third hypothesis, the dependent variable was recent review helpfulness. The main effect of context of use ($F = 0.528$, $p = 0.468$) and difference ($F = 1.348$, $p = 0.260$) were not significant. No interaction effect was found ($F = 1.532$, $p = 0.216$) (Table 3.4). Figure 3.5 showed that the recent rating is perceived as helpful regardless of the context of use and its difference from the overall rating. Thus, Hypothesis 3 was not supported.

Table 3.4. Descriptive statistics and ANOVA result for Hypothesis 3

	Type III Sum of Squares	Mean	df	Mean Square	F
Context of use	0.734		1	0.734	0.528
• Local search		5.75			
• Non-local search		5.70			
Difference	3.749		2	1.874	1.348
• Positive (Recent > Overall)		5.79			

• None (Recent = Overall)		5.73			
• Negative (Recent < Overall)		5.67			
Context of use · Difference	4.262		2	2.131	1.532
Error	1834.356		1319	1.391	

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

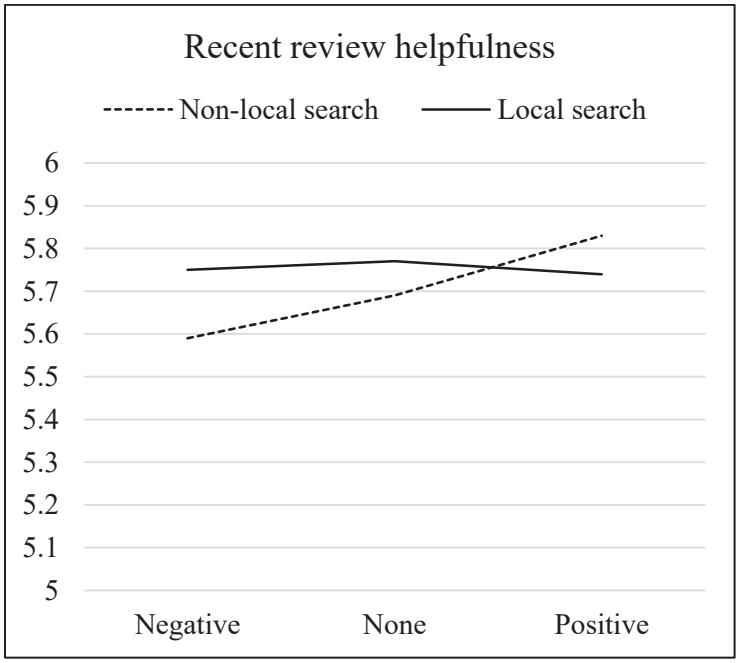

Figure 3.5. Means for recent review helpfulness across difference manipulation

As for the fourth hypothesis, the dependent variable was restaurant attitude. Since three questions were asked (i.e., what do you think about this restaurant? 1: bad ~ 7: good; 1: dislike ~ 7: like; 1: undesirable ~ 7: desirable), the mean value of the three answers was used for the analysis. Both the main effect of context of use ($F = 8.083$, $p < 0.05$) and difference ($F = 70.716$, $p < 0.001$) were significant. There was no interaction effect ($F = 0.547$, $p = 0.852$) (Table 3.5). As shown in Figure 3.6, the results showed that the participants of both contexts have a positive attitude toward the focal restaurant when the recent rating is higher than the overall and vice versa. However, those of local search context (i.e., the change in means for restaurant attitude: 1.09) showed a higher degree of change than those of non-local

(0.92). Furthermore, the negative change (i.e., the decrease from the mean of 'None' to that of 'Negative') was greater than the positive one (i.e., the increase from the mean of 'None' to that of 'Positive) in both contexts, meaning the participants of both contexts strongly reacted to the negative difference compared to the positive. In conclusion, Hypothesis 4 was supported.

Table 3.5. Descriptive statistics and ANOVA result for Hypothesis 4

	Type III Sum of Squares	Mean	df	Mean Square	F
Context of use	15.712		1	15.712	8.083*
• Local search		5.10			
• Non-local search		4.87			
Difference	274.934		2	137.467	70.716***
• Positive (Recent > Overall)		5.42			
• None (Recent = Overall)		5.13			
• Negative (Recent < Overall)		4.41			
Context of use · Difference	2.105	-	2	1.052	0.547
Error	2564.044		1319	1.944	

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

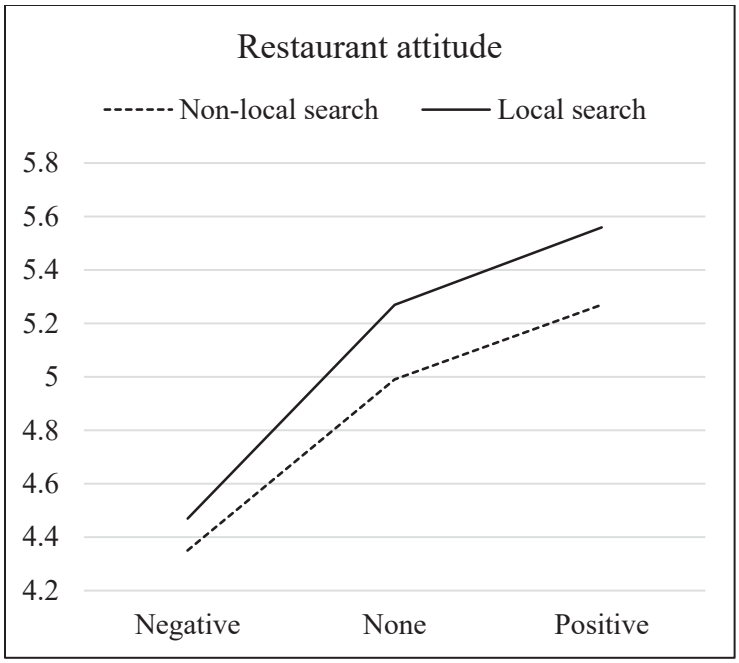

Figure 3.6. Means for restaurant attitude across difference manipulation

As for the last hypothesis, the dependent variable was visit intention. The main effect of context of use ($F = 9.885$, $p < 0.01$) and difference ($F = 69.508$, $p < 0.001$) were significant. No interaction effect was found ($F = 0.663$, $p = 0.516$) (Table 3.6). As shown in Figure 3.7, it was similar to the findings of Hypothesis 4: 1) participants of both contexts have higher visit intention when the recent rating is higher than the overall rating and vice versa; 2) those of local search context (1.21) showed a higher degree of change than those of non-local (1.01); and 3) the negative change was greater than the positive one. Hypothesis 5 was supported.

Table 3.6. Descriptive statistics and ANOVA result for Hypothesis 5

	Type III Sum of Squares	Mean	df	Mean Square	F
Context of use	23.832		1	23.832	9.885**
• Local search		5.01			
• Non-local search		4.73			

Difference	335.168		2	167.584	69.508***
• Positive (Recent > Overall)		5.37			
• None (Recent = Overall)		5.00			
• Negative (Recent < Overall)		4.26			
Context of use · Difference	3.196		2	1.598	0.663
Error	3180.114		1319	2.411	

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

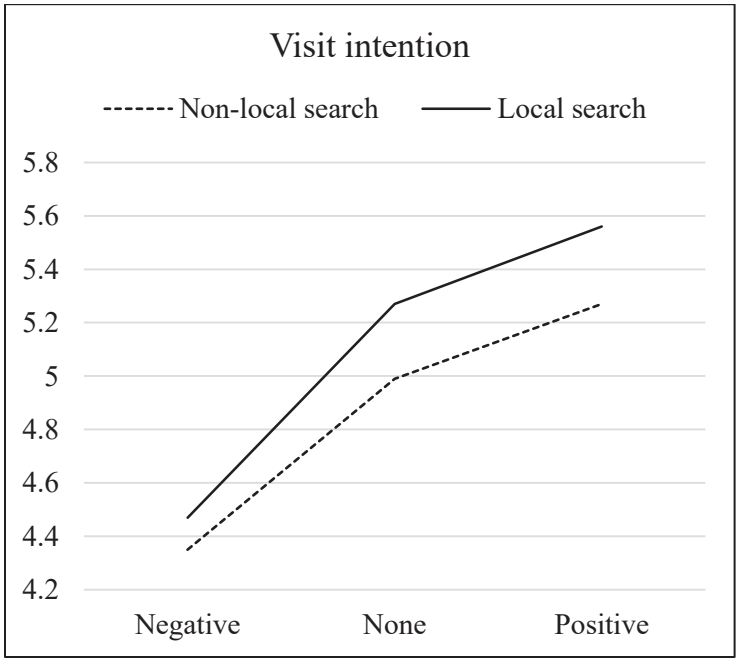

Figure 3.7. Means for visit intention across difference manipulation

As a robust check, the same process of analysis was repeated in a different scenario (i.e., the overall rating of a restaurant is 4.5). A different group of participants was recruited through Amazon's MTurk. A total of 500 people participated during February 25–26, 2021. Among the collected surveys, 220 valid cases were used for analysis (local search: 120, non-local search: 100). Two groups were considered comparable in terms of gender ($x^2 = 0.121$, $p = 0.785$), age ($x^2 = 5.639$, $p = 0.228$), education ($x^2 = 5.119$, $p = 0.645$), and occupation ($x^2 = 6.680$, $p = 0.727$) (Appendix 3.A). The manipulation checks

were well achieved. Since the overall rating was set as 4.5, there were two conditions for the difference between recent and overall rating: positive (i.e., recent 5 vs. overall 4.5) and negative difference (i.e., recent 1, 2, 3, or 4 vs. overall 4.5). Thus, a 2 X 2 ANOVA with the context of use (local search vs. non-local) and the difference between recent and overall rating (positive vs. negative difference) was conducted. Most findings were supported (Hypothesis 1 and 4, and 5): the participants of local search context perceived the higher difference ($F = 7.234$, $p < 0.05$), and their restaurant attitude ($F = 5.211$, $p < 0.05$) and visit intention ($F = 2.727$, $p < 0.05$) were more affected by the recent rating compared to those of non-local (Appendix 3.B). However, contrary to the main analysis, Hypothesis 2 and 3 were supported: the participants of local search context had more interest in the recent rating ($F = 6.081$, $p < 0.05$) and considered it more helpful than those of non-local ($F = 13.983$, $p < 0.001$) (Figure 3.8).

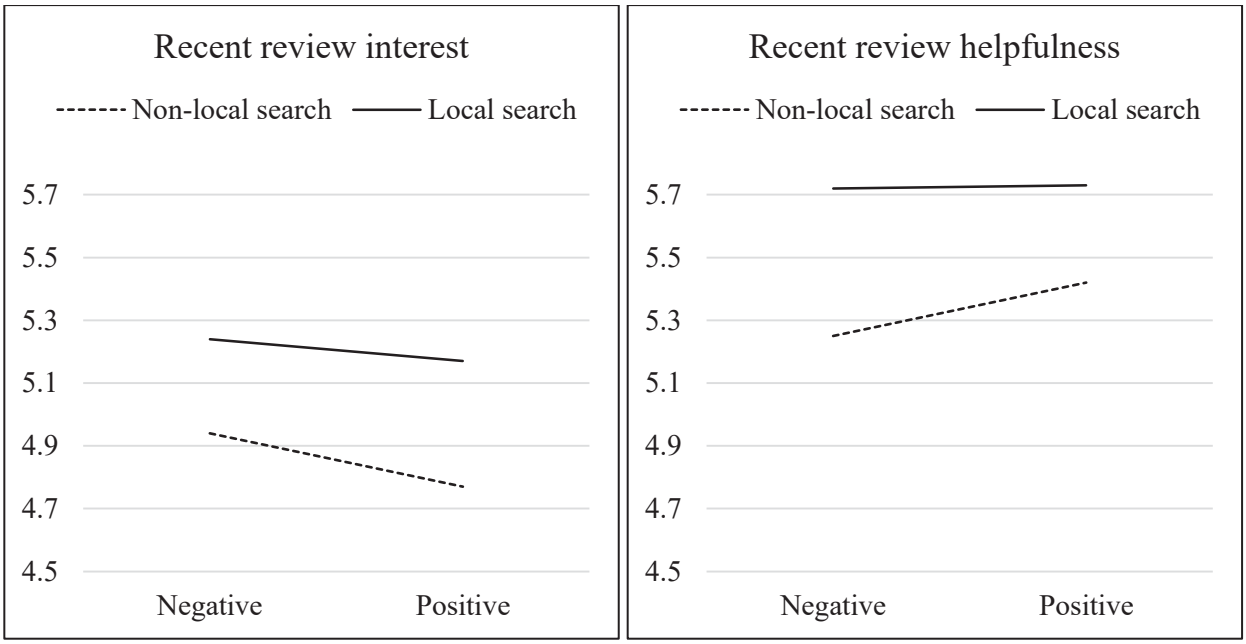

Figure 3.8. Means for recent review interest (left) and helpfulness (right) across difference manipulation

3.6. Discussion

To understand how the context of use affects the way tourists process online reviews, this study conducts experiments and examines how tourists process reviews differently in the local search context in

comparison with the non-local. Based on CLT, this study hypothesizes that recent reviews are more influential in tourists' decision-making in the local search context as compared to the non-local.

As hypothesized, the contextual effects of review recency on tourists' responses are supported in the restaurant domain. When the evaluations of recent reviews are different from the aggregated evaluations, tourists tend to focus on the former for their decision-making. However, the effects of recent reviews become pronounced in the local search context. Tourists become more sensitive to, and their attitude toward and intention to visit the focal restaurants are more affected by the recent evaluations when they are in the local search context compared to the non-local. Aligned with the previous online review research adopting CLT, this study examines that a specific information dimension (i.e., timeliness) can be more (less) importantly considered by consumers depending on whether they are dealing with a near-future (far-future) purchase (Jin et al., 2014; Shin & Xiang, 2021).

Furthermore, although it is not the focus of this study, it is also found that the effects of recent reviews on tourists' restaurant perceptions become strong when recent reviews show negative evaluations. While tourists have positive (negative) attitude and higher (lower) visit intention when recent reviews have higher (lower) ratings, they react more strongly to the lower ratings of the recent reviews than they do to the higher ones. These results can be well explained by one of the main arguments of prospect theory—people tend to be more sensitive to losses than gains (Kahneman & Tversky, 2013). By comparing the negative change in tourists' product perceptions driven by the lower rating of recent reviews to the positive by the higher rating, this study confirms the loss aversion property similar to the previous online review studies adopting prospect theory (Mellinas, Nicolau, & Park, 2019; Park & Nicolau, 2015).

Contrary to the hypothesis about recent review interest and helpfulness, the results show that tourists' review perceptions are not significantly affected by the context of use. Regardless of whether they are in the local search context or the non-local, tourists are interested in checking the evaluations of

recent reviews and regard them as helpful. However, interestingly, the results of the robust check analysis show the significant effects, that is, tourists of local search context have significantly higher interest in recent reviews and consider them more helpful compared to those of non-local. The mixed results can be explained by tourists' involvement in a restaurant. According to a current consumer report, over 80% of consumers do not consider products with less than a three-star rating (Clark, 2020). This indicates that consumers' involvement in a product is low when its overall rating is similar to or lower than three-star. Due to the difference in the overall rating of a restaurant, participants of the experiment for the main analysis might have lower involvement in the restaurant compared to those for the robust check. In a previous study on CLT, individuals' involvement was identified as an important boundary condition for construal fit, that is, individuals' information preferences vary according to their construal level. It was found that the effect of construal fit can be observed or absent depending on how much individuals are involved in the focal subject (Park & Morton, 2015; Wang & Lee, 2006). Therefore, the weak effect of construal fit in the results of the main analysis (i.e., significant only on tourists' product perceptions) compared to those of the robust check (i.e., both on tourists' product and review perceptions) might be attributed to the difference in participants' level of involvement in the focal subject.

3.6.1. Theoretical implications

First, this study contributes to the literature of tourists' processing of online reviews by providing empirical support for its context-dependence. While the processing is expected to be affected by different contextual factors (Floyd, Freling, Alhoqail, Cho, & Freling, 2014; Gu, Park, & Konana, 2012), the varying effects of online reviews on consumers' perceptions have been limitedly studied in the hospitality and tourism field. Specifically, as IT development has enabled tourists to use the reviews both before and during the trip, the timing of decision-making has been regarded as an important contextual factor, that is, the same reviews can be perceived differently depending on whether tourists read them for short-term or long-term decision-making (Shin et al., 2019). By examining the effects of decision-making timing on

tourists' processing of reviews, this study confirms the contextual effects of online reviews on tourists' decision-making.

Second, this study examines the importance of review recency in understanding tourists' perceptions of online reviews. Given the variable nature of tourism products (i.e., their quality varies from one time period to another), consumers' preference for recent reviews is expected to be higher in the hospitality and tourism domain (Filieri et al., 2018a). Although several online review studies have examined the effects of different information components, relatively little research has studied the time dimension of reviews (Filieri & McLeay, 2014; Xie, Chen, & Wu, 2016). By examining the effects of review recency on tourists' perceptions, this study suggests another important component to be considered in future research.

Third, this study provides empirical support for CLT and prospect theory. By taking advantage of the situational characteristic of local search, this study attempts to examine how individuals' information preferences change depending on whether they deal with near- or far-future events and confirms the effect of the temporal distance (Trope et al., 2007). Furthermore, this study shows the findings that are aligned with one of the arguments of prospect theory: tourists strongly react to the negative evaluations of recent reviews compared to the positive. With the findings, this study confirms the loss aversion property of prospect theory—people are more sensitive to losses than gains (Kahneman & Tversky, 2013). This study contributes to the theories by corroborating their arguments in the context of tourists' use of online reviews during local search.

Finally, this study contributes to the literature on tourists' information use by validating the need for considering the timing of decision-making as a contextual factor. Although several factors have been examined as significantly affecting the way tourists use information for their decision-making, most are related to the characteristics of tourists (e.g., socio-demographics) (Lehto et al., 2006; Luo et al., 2005) or tourism products (e.g., types of tourism products) (Filieri et al., 2018a; Racherla & Friske, 2012).

Notably, the factors that are specific to a time or place have been comparatively understudied in the hospitality and tourism field (Huang, Tan, Ke, & Wei, 2018; Jin et al., 2014). Especially, when tourists use information has been suggested as an important contextual factor (Lamsfus et al., 2015). By examining the potential effects, this study confirms the importance of considering the temporal dimension for understanding tourists' information use for decision-making.

3.6.2. Practical implications

The results of the current study can be a guideline for improving the online marketing strategies of tourism businesses. The main finding indicates that tourism businesses should prioritize local search platforms (LSPs) for monitoring online reviews. Since there are several platforms where online reviews are available (e.g., Google, TripAdvisor, Facebook, and so on), tourism businesses have to decide which platforms they should check at first or focus on for providing timely managerial responses to recent reviews (Nau, 2019). Given the higher impact of recent reviews in the local search context, tourism businesses could make the monitoring more effective in improving their online reputation by prioritizing LSPs. For example, they can check LSPs at first on every cycle of the monitoring or shorten the cycle, particularly for the platforms. Moreover, since people tend to have a higher visit intention when performing local search (Beddow, 2020), prioritizing LSPs for the monitoring could be also effective in attracting more customers.

Other than tourism businesses, LSPs can improve their usability based on the findings. Due to the situational constraints (e.g., small screens of mobile devices or limited time for search), people try to make it as simple as possible when performing local search (Liu, Rau, & Gao, 2010). For example, they want to choose a place to visit within the main result page without further clicks, such as those that would take them to another page displaying further information, reviews, or photos of the place (Ghose, Goldfarb, & Han, 2013) (Figure 3.9).

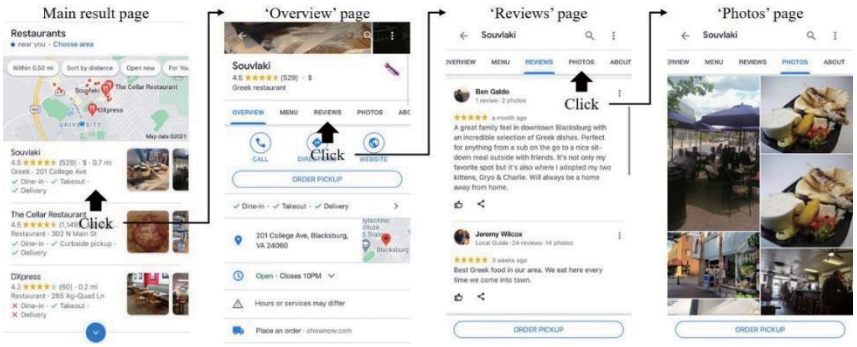

Figure 3.9. Main result page of local search and other pages (mobile version of Google)

To be useful, LSPs should enable users to easily make decisions by presenting helpful information on the main result page. Given the findings that consumers' product perceptions are more affected by recent reviews in the local search context, the information about recent reviews (e.g., the rating of recent reviews) could be one that LSPs need to present. Considering that most LSPs do not provide any information about recent reviews on the main result page (Figure 3.10), the higher impacts of recent reviews can suggest a specific direction to improve their usability, that is, which information needs to be included in the main result page to enable users to make decisions without further clicks.

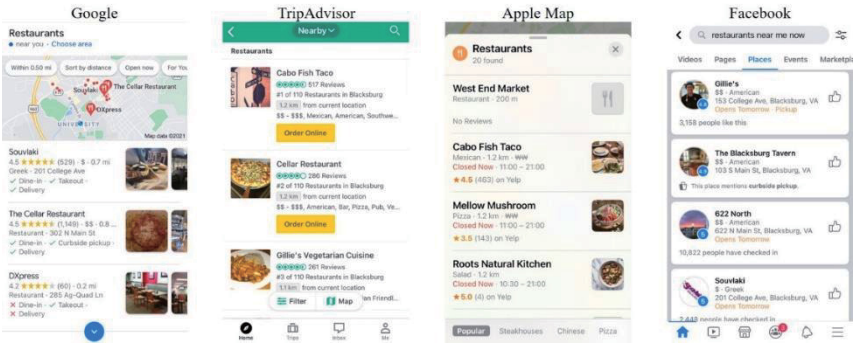

Figure 3.10. Main result page of major LSPs (mobile version)

3.7. Conclusion

This study seeks to explain tourists' processing of online reviews in the local search context. By examining the effects of recent reviews on tourists' decision-making in two different contexts, this study finds that tourists are more affected by recent reviews in the local search context compared to non-local.

This study contributes to the literature on the tourists' information use by confirming its context-dependence in the online review setting.

Despite the contributions, this study has several limitations. Even though the participants were well informed about the situations they had to imagine for taking the survey, their answers were based on hypothetical situations. Thus, there can be exogenous factors that were not controlled during the experiments. Although this study tried to control some potential factors (e.g., number of reviews, distance, and cuisine of restaurants, and type of devices used for the search), future research needs to validate the findings in a more realistic or controlled environment. Also, this study simulated a limited range of differences between recent and overall rating (e.g., recent: 1 ~ 5 vs. overall: 3 or 4.5). Although it was done so for making the differences realistic (e.g., 93% of restaurants have an overall rating between 3.5 and 4.9) (Womply, 2019), other differences can be possible as well (e.g., recent: 1 ~ 5 vs. overall: 1 ~ 5). Particularly, some surprising cases might be effective in discovering the nuanced effects of review recency (e.g., recent: 5 vs overall: 1), so future research could consider such manipulations in the survey. Furthermore, although there are other situational characteristics of local search, this study focused on a specific characteristic. While this study aimed to examine the effects of the timing of tourists' decision-making, other situational influences are required to further understand how tourists process online reviews in the local search context. As such, future research needs to consider other situational characteristics of local search (e.g., limited time for the search task). Lastly, the sample was limited especially in terms of country and culture—all the participants are residents of the United States. By expanding the sample, future research could improve the generalizability of the results.

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Appendix

Appendix 3.A. Robust check analysis: Demographic information of the participants

Demographic Variables	Local search (n = 120)		Non-local search (n = 100)		Chi-Square (Significance)
	Freq.	%	Freq.	%	
Gender					
• Male	70	58.3	56	56.0	0.121 (0.785)
• Female	50	41.7	44	44.0	
Age					
• 18-24	35	29.2	18	18.0	
• 25-34	63	52.5	53	53.0	5.639
• 35-44	7	5.8	8	8.0	(0.228)
• 45-54	9	7.5	12	12.0	
• 55 and over	6	5.0	9	9.0	
Education					
• Less than high school	1	0.8	0	0.0	
• High school graduate	4	3.3	3	3.0	
• Some collage but no degree	6	5.0	3	3.0	
• Associate degree in college (2-year)	6	5.0	6	6.0	5.119 (0.645)
• Bachelor's degree in college (4-year)	59	49.2	50	50.0	
• Master's degree	39	32.5	34	34.0	
• Doctoral degree	3	2.5	0	0.0	
• Professional degree (JD, MD)	2	1.7	4	4.0	

Occupation					
• Management, professional, and related	44	36.7	40	40.0	
• Service	11	9.2	10	10.0	
• Sales and office	25	20.8	18	18.0	
• Farming, fishing, and forestry	7	5.8	2	2.0	
• Construction, extraction, and maintenance	9	7.5	7	7.0	6.680
• Production, transportation, and material moving	4	3.3	5	5.0	(0.727)
• Government	1	0.8	4	4.0	
• Student	3	2.5	1	1.0	
• Retired	3	2.5	3	3.0	
• Unemployed	8	6.7	4	4.0	
• Etc	5	4.2	6	6.0	
Total	120	100	100	100	

Appendix 3.B. Robust check analysis: Descriptive statistics and ANOVA result for hypothesis 1, 4, and 5

	Perceived difference (*F*-statistic)	Restaurant attitude (*F*-statistic)	Visit intention (*F*-statistic)
Context of use (Local vs. Non-local search)	7.234*	5.211*	2.727*
Difference (Positive vs. Negative difference)	83.049***	75.538***	65.839***
Context of use · Difference	0.752	0.025	0.496

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

CHAPTER 4. MODERATING EFFECTS OF RECENCY AND CONTENT ON HELPFULNESS OF ONLINE HOTEL REVIEWS

Abstract

Building on Study 2, Study 3 aims to examine the contextual effects of review recency on tourists' perception. By regarding the nature of tourism products as a potential contextual factor, this study investigates how it affects tourists' perceptions of recent reviews. While the quality of tourism products varies over time, some aspects are more changeable (e.g., a hotel's cleanliness or ambiance) than others (e.g., location or facilities). Given the variability of tourism products, this study hypothesizes that recent reviews are perceived more helpful when they include information about aspects whose quality changes easily. With hotel review data collected from TripAdvisor, the moderating effect of review recency on the relationship between content (i.e., the extent to which certain hotel aspects are mentioned in the text) and helpfulness is examined. The results showed significant effects of interaction between review recency and content: the helpfulness of recent reviews is dependent on the mentions of particular aspects in the text. Based on the findings, this study proposes the need to consider various interactions between different information components of online reviews to understand their contextual effects.

4.1. Introduction

Online reviews are an essential source of information, which guide consumers' decision-making process as they reduce uncertainty regarding product purchases (Mudambi & Schuff, 2010). Consumers perceive a higher risk when dealing with intangible tourism products because their quality normally cannot be assessed before consumption (Litvin, Goldsmith, & Pan, 2008). For this reason, online reviews are considered influential, particularly in the hospitality and tourism field (Liu & Park, 2015). Over 90% of tourists consider reading online reviews a necessary part of hotel search, and 80% will use review rating to narrow down their hotel choices (Hotel Minder, 2020).

Online reviews consist of a bundle of different information components, such as the reviewer's profile, review rating, posting date, and text. Since tourists consider these components together when processing the reviews, some establish the context for others (Shin, Du, Ma, Fan, & Xiang, 2020). If a hotel review was posted a few days before, tourists expect information on the recent status of the establishment (e.g., whether its service quality remains high) and how it is dealing with current issues (e.g., whether it is following the COVID-19 safety guidelines strictly) (Fantozzi, 2021). If this information is mentioned in the text as expected, tourists will perceive the recent review to be more timely and helpful; if lacking, its recency may be less valued. Although tourists generally prefer recent reviews because they reflect the current performance of the business, their recency will be appreciated more (or less) depending on their content (Shin & Xiang, 2021).

Tourists' processing of online reviews is context-specific. As indicated in the above example, specific components, such as the posting date, can act as contextual factors that will affect the way tourists process other components (Chen & Lurie, 2013). To understand the context-dependent nature of online reviews, potential interactions between the different components need to be examined. However, existing studies have considered tourists' processing of online reviews as static. Specifically, the majority of the literature examines the effect of the components in isolation, leaving much to be desired in terms of examining the potential effects of certain components on others (Shin et al., 2020).

Study 3 aimed to examine the interaction effects between different information components of online reviews on tourists' perceptions. Tourism products consist of different aspects (e.g., location, staff service, facilities, and ambiance) (McKercher, 1999), and some aspects are more changeable than others in terms of quality; for example, staff service and ambiance will vary more than location and facilities. Given the variability of tourism products, this study investigates how tourists perceive recent reviews differently, depending on their content. Specifically, this study tests the hypothesis that recent reviews are perceived as being more or less helpful depending on which product aspects are mentioned in the text.

4.2. Research Background

Online reviews facilitate consumers' purchase decisions by reducing uncertainty about product quality (Mudambi & Schuff, 2010). In particular, the importance of online reviews is recognized in the hospitality and tourism field because consumers tend to experience a higher level of risk when purchasing intangible tourism products whose quality is hard to assess prior to consumption (Litvin et al., 2008). As the impact of online reviews on tourists' decision-making has been examined (Sparks & Browning, 2011; Ye, Law, Gu, & Chen, 2011), it has been a major topic in the literature; namely, how tourists process the reviews for their decision-making (Liu & Park, 2015).

Online reviews contain various information components, and tourists consider them simultaneously when processing the reviews. As a result, some components become the context for others, meaning that the interpretation of the latter can depend on the former (Shin et al., 2020). For example, if both the pros and cons of a product are described, the review text tends to be perceived as objective. However, that objectivity may be valued less if the review rating is extremely high or low because the readers may perceive the review to be incoherent (Schlosser, 2011). Together with the empirical findings, the contextual processing of online reviews has been explained by several theoretical frameworks, including the elastic capacity model (ECM) (Kahneman, 1973) and the heuristic-systematic model (HSM) (Chaiken, 1980). By arguing that individuals process both the main and the auxiliary components of information together, these models have emphasized the importance of considering possible interactions between different components when understanding individuals' capacities of parallel information processing (Lord, Lee, & Sauer, 1995).

However, the existing literature on tourists' processing of online reviews has regarded the different components of the reviews as independent entities. Most of the previous studies have documented tourists' perceptions of online reviews in terms of each component's individual effect (Hlee, Lee, & Koo, 2018). The possible interactions between them, and the resulting holistic effects on the tourists' perceptions, have not been well understood in the hospitality and tourism literature (Shin et al., 2020). Although some research has attempted to address this limitation, it has primarily studied the

interaction between review rating and text: reviews whose rating and text valence are consistent tend to be perceived as more helpful than those that are inconsistent (Schlosser, 2011; Zhang, Yu, Li, & Lin, 2016; Zhou & Guo, 2015). Nevertheless, the review rating is not the only the component that can establish the context and interact with others.

Like the review rating, the recency of the review can be the basis for interpreting the other components. Review recency refers to the degree to which an online review is current in terms of its posting date (Filieri & McLeay, 2014). If there is a recently-uploaded review about a hotel (e.g., within the last week), tourists will expect to receive information about its current status. The helpfulness of the recent review might depend on whether up-to-date information is provided in the text as expected. While the reviews uploaded yesterday are often perceived as being more helpful than ones a few months ago, their higher recency will be appreciated more when their content is actually up-to-date (Jatowt, Kawai, & Tanaka, 2011). To understand tourists' contextual information processing in the online review setting, this study aims to investigate how specific components of online reviews become the context for others by examining the moderating effect of review recency on the relationship between its content and helpfulness.

4.3. Research Hypotheses

This research aims to examine the moderating effects of review recency on the relationship between the content of the text and its helpfulness. When writing online reviews, tourists evaluate different aspects of tourism products (Phillips, Barnes, Zigan, & Schegg, 2017). Although the evaluation of each aspect helps potential tourists to know about the product, as time passes, the information relating to certain aspects will become less helpful faster than that relating to other aspects (Fu, Bin, Xie, Liuli, & Yu, 2011). For example, the location or the facilities of a hotel are comparatively more stable in terms of quality than service, ambiance, or cleanliness. This means that an evaluation of the former aspects will remain valid information for potential tourists even though it was posted a month or two before. Conversely, the quality of the latter aspects is highly variable, so their evaluation will not be considered

valid unless a review was uploaded within the last week or two (Shin & Xiang, 2021). If there is a week-old hotel review, its greater recency will be recognized by tourists when it includes an evaluation of aspects whose quality quickly changes. If the recent review speaks only about those aspects whose quality is not highly variable (e.g., the facilities of a hotel), its recency may be less valued. By pointing to the limitations of a timestamp on online information in reflecting its recency, Jatowt et al. (2011) argue that it is not only the posting date but also the content that makes the information fresh and relevant. Therefore, this study hypothesizes that review recency has a moderating effect on the relationship between its content and helpfulness: while information about each aspect is helpful for tourists wishing to assess the product, information about certain aspects will be appreciated either more or less depending on the review recency.

Hypothesis 1. Review recency moderates the effect of its content on helpfulness. The information of certain aspects written in review text will be perceived as either more or less helpful depending on review recency.

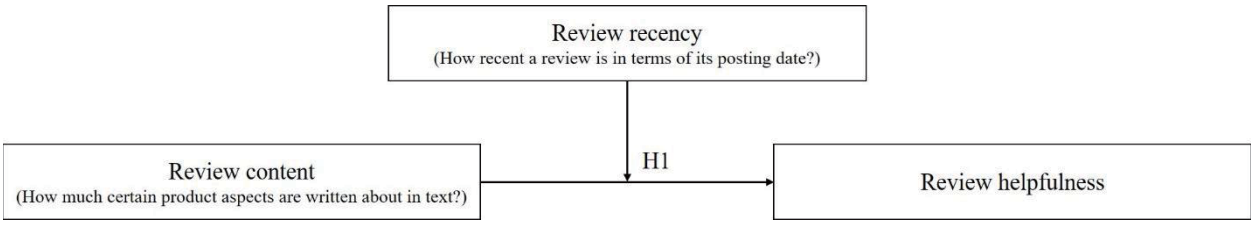

Figure 4.1. Research Model

4.4. Research Design

To test the hypothesis, social media analytics was implemented, which combines Web crawling, text mining, and statistical analysis with a large set of social media data (Fan & Gordon, 2014). Web crawling was conducted to collect online review data from a major review website. Text mining was conducted to measure review content: aspect-level text mining analysis was used to measure how much certain aspects were written about in the text (Hu, Chen, & Chou, 2017). Together with the content, the measures for other key variables (i.e., review recency, helpfulness) and control variables (i.e., reviewer's

expertise and contribution, review rating, length, sentiment, and readability of text) were also developed. Finally, a hierarchical regression analysis was performed to examine the moderating effect of review recency on the relationship between content and helpfulness.

4.4.1. Data collection

The data collection took place in March 2021. The top ten US cities in terms of the number of annual visitors in 2019 were selected: New York, Miami, Los Angeles, Orlando, San Francisco, Las Vegas, Honolulu, Washington D.C, Boston, and Chicago (Haqqi, 2020). The reviews written in English about all searchable hotels in those ten cities were collected from TripAdvsior. Hotel reviews posted between July 2020 and February 2021 were collected. There was a specific reason for selecting this time period for data collection, which will be explained in the next section. For each review, the following information components were collected: the number of reviews that a reviewer had written (reviewer's expertise), helpful votes that a reviewer had received (reviewer's contribution), review rating, posting date, text, and the number of helpful votes that a review had received. A Web crawling program (WebHarvy) was used for the collection. In total, 20,165 reviews of 1,357 hotels were collected (Table 4.1). TripAdvisor enables reviewers to indicate the date of their visit when writing a review: even though a review may be posted in July 2020, it can be about an experience in March 2020. By using this feature, the reviews were removed if the time gap between the posting and visiting date was over a month.

Table 4.1. Summary of data collection

	Cities	Number of hotels searchable on TripAdvisor	Number of reviews collected from TripAdvisor
1	New York, New York	335	3,487 from 262 hotels
2	Miami, Florida	130	1,117 from 92 hotels
3	Los Angeles, California	177	1,574 from 150 hotels
4	Orlando, Florida	338	4,289 from 219 hotels

5	San Francisco, California	132	903 from 105 hotels
6	Las Vegas, Nevada	184	3,140 from 131 hotels
7	Honolulu, Hawaii	44	363 from 37 hotels
8	Washington D.C.	124	1,995 from 113 hotels
9	Boston, Massachusetts	95	1,404 from 80 hotels
10	Chicago, Illinois	158	1,893 from 133 hotels
Total		20,165 reviews from 1,357 hotels	

4.4.2. Development of measures

A dependent variable, review helpfulness, is defined as the degree to which online reviews are perceived as helpful by tourists. Many online review studies measure this by the number of helpful votes that each review has received (Hong, Xu, Wang, & Fan, 2017). Since the current study focuses on the effect of review recency on helpfulness, it is necessary to bear in mind that old reviews are likely to have received more votes than recent ones due to their longer availability (Krishnamoorthy, 2015). To mitigate this accumulation trend, the study tried to scale the number of votes by dividing it by the number of months elapsed since the posting date of the review.

An independent variable, review content, refers to how much certain hotel aspects are mentioned in the text. To measure this variable, the hybrid approach of aspect extraction was used (Yadav & Roychoudhury, 2019). The hybrid approach uses two different aspect detection methods: frequency (detecting the main aspects of the text based on the frequencies of single or compound nouns) and syntax (based on the adjectival relationship between sentiment and aspect words). First, review text was preprocessed using several basic procedures: tokenization (splitting text into tokens, such as words or sentences), stop words removal (removing insignificant words in terms of meaning), and lemmatization (converting a word to its base form). Second, parts of speech (PoS) were tagged using the Apache

OpenNLP MaxEnt PoS tagger, which is available in the natural language processing package of R software (Toutanova, Klein, Manning, & Singer, 2003). Third, all nouns were collected, and their support values were calculated (the total number of appearances of a noun divided by the total number of online reviews). By following a rule of thumb, all nouns whose support values were higher than 1% were selected as frequent and thus, as important aspects (Bagheri, Saraee, & de Jong, 2013). Fourth, nouns that were infrequent but can be important were detected using the syntax method. Nouns that had an adjectival relationship with the frequent nouns identified in the previous step were considered as possible aspects of interest. All the extracted aspects were then grouped, based on their meanings, and each group was categorized as "Staff service", "Cleanliness & Safety", "Location", "Food & Event", "Facilities", "General experience", "Value", and "Atmosphere" (Table 4.2). Regarding review content, each review was assigned eight values indicating how many times the words of each aspect group appeared in the text: giving a ratio for each group's word frequency (i.e., the number of appearances of the words of each aspect group) in relation to all aspect words (i.e., the number of all aspect words written in the text).

Table 4.2. Words identified and grouped using aspect extraction

Staff service	Cleanliness & Safety	Location	Food & Event	Facilities	General experience	Value	Atmosphere
Staff	Clean(liness)	Location	Food	Room	Hotel	Price	Accommodating
Service	COVID	View	Breakfast	Bed	Stay	Rate	Welcoming
(Front) Desk	Safe(ty)	City	Restaurant	Bathroom	Experience	Worth	Quiet
Check (in/out)	Pandemic	Close	Bar	Lobby	Place		Noise
Customer	Housekeep(er/ing)	Walk	Birthday	Rooftop	Night		Atmosphere
Manager	Mask	Street	Coffee	Shower	Visit		
Care	Protocol	Block	Drink	Closed	Trip		
Wait	Social (distance)	Corner	Dinner	Open	Overall		
Reception	Restriction	Nearby	Dining	Amenity			

Upgrade		Area	Eat	Space			
Concierge			Anniversary	Parking			
Refund				Towel			
Request				Elevator			
				Size			
				TV			

A moderating variable, review recency, is defined as the degree to which online reviews are recent in terms of their posting date. This is measured by the number of months elapsed since the posting date of the review. It is reverse coded to make the results easier to understand: its positive correlation with helpfulness indicates that the more recent the reviews are, the more helpful votes they get. To examine the effect of review recency on helpfulness, many studies have examined the relationship between time elapsed since posting date and number of votes (Cao, Duan, & Gan, 2011; Tandon, Aakash, Aggarwal, & Kapur, 2020; Xie, Chen, & Wu, 2016). However, this approach reveals a critical problem in its capturing of the effect. For example, there may be a review posted in January 2020 that has five votes. While the five votes could have been accumulated over a long period, the review could also have got those votes while it was recent (e.g., during January 2020). If this is the case, its helpfulness needs to be explained in relation to its recency: it has many votes because, at some point in the past, it was up-to-date. However, it is hard to indicate this from the relationship between elapsed time and number of votes. This problem becomes serious if reviews tend to receive most of their votes while they are recent. According to the review data collected about the hotels in New York City (NYC), on average, 17.77 reviews were posted for each property, per month, from July to December 2019. TripAdvisor lists five reviews on each page in reverse chronological order (Figure 4.2), so most reviews on the front pages are likely to be recent ones posted in the current month. Considering that TripAdvisor users tend to check the first nine reviews before booking, they are likely to read only reviews that are recent at the time (TripAdvisor, 2019). It may

be difficult for them to see old reviews (e.g., those posted a few months previously). If they cast a vote on a certain review, it is likely to be a recent one. In other words, reviews will get most of their votes while they are recent. Figure 4.3 shows how many reviews were posted for the NYC hotels per month and how many votes the reviews posted in each month received. The graph for the number of votes shows a stable trend, inferring that most reviews get their votes within a limited period, very likely while they are still recent (i.e., listed on the front pages). Therefore, if the reviews communicated during this period are analyzed, the effect of review recency on helpfulness is more difficult to examine from the relationship between time elapsed and the number of votes.

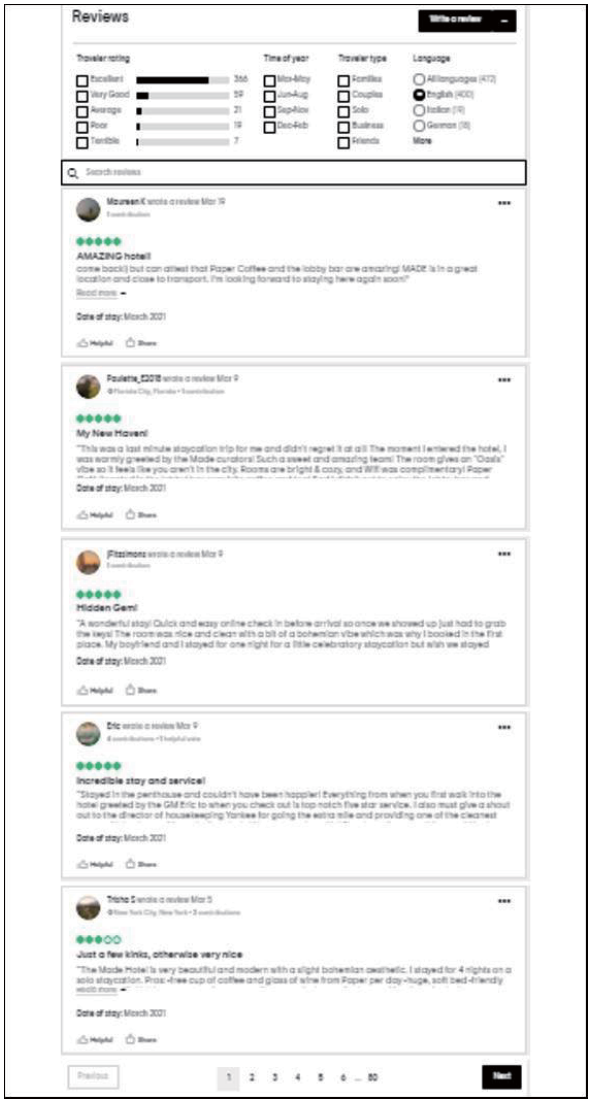

Figure 4.2. Screenshot image of TripAdvisor review page

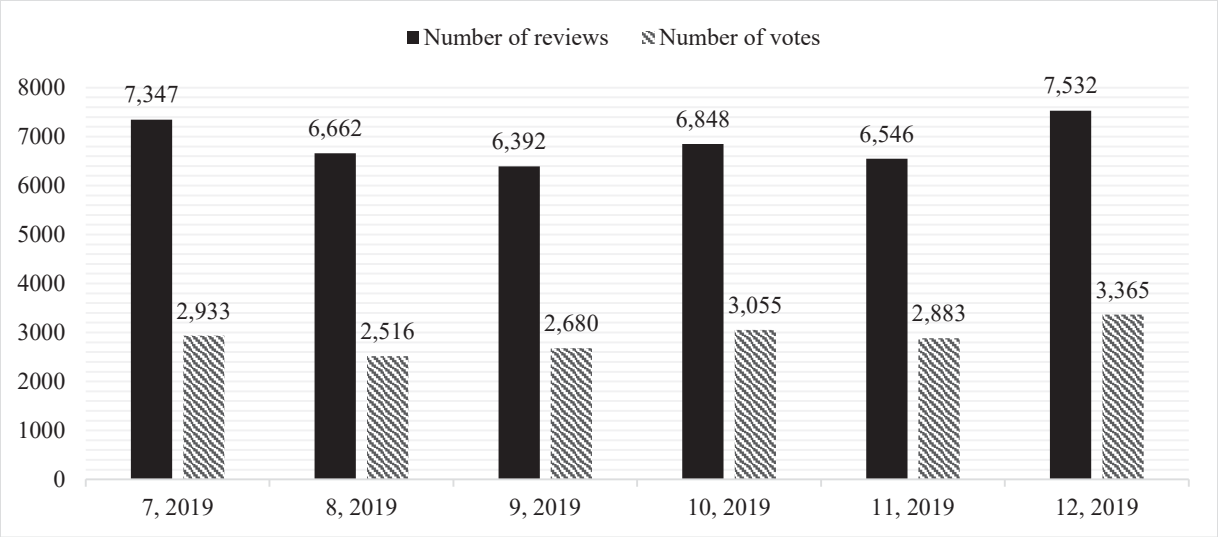

Figure 4.3. Total number of reviews posted for NYC hotels per month on TripAdvisor and number of votes the reviews posted in each month received (July – December 2019)

However, this problem can be alleviated if the opposite occurs: reviews get votes not only when they are recent but also when they become old. After the outbreak of COVID-19, the total number of reviews posted for NYC hotels per month decreased steeply: on average, 3.22 reviews were posted for each property per month. Nowadays, it is not unusual for TripAdvisor users to see reviews posted a few months ago on the front pages. Since the pandemic prevents people from traveling and posting reviews, old reviews tend to remain exposed to users on the front pages for longer. This means that old reviews will now have more opportunity to get votes relative to the pre-pandemic period. As shown in Figure 4.4 (the higher number of helpful votes for old reviews), the pandemic has enabled reviews to receive votes even when they become old. A similar trend was evident when analyzing the review data for all ten cities (Appendix 4.A). Therefore, if the reviews communicated during this period are analyzed, although it is not completely valid, the effect of review recency on helpfulness can be better captured by the relationship between the elapsed time and the number of votes. Thus, this study collected the reviews posted after the start of pandemic (i.e., July 2020 – February 2021) to mitigate the problem of using the elapsed time and number of votes to examine the effect of review recency on helpfulness.

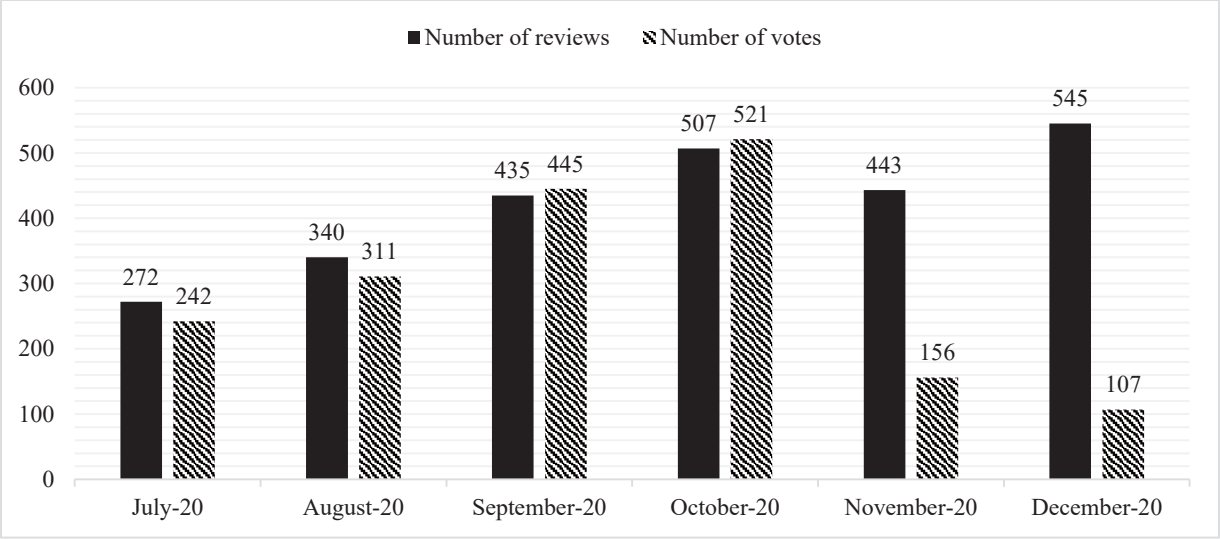

Figure 4.4. Total number of reviews posted for NYC hotels per month on TripAdvisor and number of votes the reviews posted in each month received (July – December 2020)

Regarding the control variables, two components of information about reviewers were adopted: the number of reviews a reviewer had written (reviewer's expertise) and votes their reviews had received (reviewer's contribution). In addition, review rating was included with its original value. Lastly, three textual characteristics (length, sentiment, and readability) were used. The length was measured by the number of words in the text. The sentiment was measured with a sentiment score calculated by using the Linguistic Inquiry and Word Count (LIWC) (Pennebaker, Chung, Frazee, Lavergne, & Beaver, 2014). The scores range from 0 to 100, with a higher value indicating positive sentiment. The readability was measured with the Flesch-Kincaid Grade Level, and ranged from 0 (easy to read) to 12 (hard to read) (Kincaid, Fishburne Jr, Rogers, & Chissom, 1975). Like review recency, readability was reversely coded to make the results easier to interpret: its positive correlation with helpfulness indicates that the more readable the text is, the more helpful it is.

4.4.3. Analysis

Using the results from these measures, statistical analyses were performed. To examine the moderating effect of review recency on the relationship between content and helpfulness, a hierarchical

regression analysis was used by taking review helpfulness as a dependent, content as an independent, and recency as a moderating variable.

The Negative Binomial (NB) model was used for the regression analysis. This model is used when a dependent variable shows the Poisson distribution: it is bounded in its range and its distribution is skewed in one direction (Greene, 2003). While the Poisson regression model can also be used, the assumption of mean-variance equality has to be met: the mean and the variance of a dependent variable must be equal. If this assumption is not satisfied, the NB model is often adopted as a quasi-Poisson regression model (Gurmu & Trivedi, 1996). The distribution of the data about review helpfulness appeared to be skewed: over 99% of the data were in the range between 0 and 6, where 13 was the maximum value. While this does show the Poisson distribution, the assumption of mean-variance equality was rejected (mean = 0.32, variance = 0.22). Therefore, the current study adopted the NB model for its analysis. To control for the unexpected impact of outliers, only reviews whose helpfulness was lower than seven were used for the analysis, resulting in 19,526 reviews being included in the analysis.

Prior to the regression analysis, all the variables were centralized to avoid multicollinearity issues. In the first model, only the control variables were included: reviewer's expertise, contribution, review rating, text length, sentiment, and readability. In the second model, the independent (review content) and moderating variable (recency) were added. In the final model, interaction terms were added. The R statistical package was used for the analysis. As a robust check, 2,000 times bootstrapping was conducted for each model, and the number of bootstrap sub-samples was 1,000.

4.5. Findings

The descriptive statistics are presented in Table 4.3. Looking at the independent variables, aspect 6 (General experience) shows the highest mean value, 0.28 (Std. = 0.18). Aspect 5 (Facilities: mean = 0.19, Std. = 0.17), aspect 1 (Staff service: mean = 0.18, Std. = 0.15), and aspect 4 (Food & Event: mean = 0.14, Std. = 0.14) appear to be mentioned more frequently than aspect 2 (Cleanliness & Safety: mean =

0.10, Std. = 0.11), aspect 3 (Location: mean = 0.08, Std. = 0.11), aspect 8 (Atmosphere: mean = 0.02, Std. = 0.05), or aspect 7 (Value: mean = 0.01, Std. = 0.04). With regard to the moderating and dependent variable, the average for review recency is 4.81 (Std. = 2.22) and for helpfulness is 0.32 (Std. = 0.47), indicating that most reviews had not received a vote. In terms of the control variables, the reviewer's expertise (mean = 486.62, Std. = 57,127.75) shows a large variance compared to contribution (mean = 24.42, Std. = 182.90). The average rating was 4.16 (Std. = 1.36), with an average length of 105.99 words (Std. = 105.24) and readability of 4.59 (Std. = 2.47).

Table 4.3. Descriptive statistics

Variables	N	Mean	Std.	Minimum	Maximum
Aspect 1: Staff service	19,526	0.18	0.15	0.00	1.00
Aspect 2: Cleanliness & Safety		0.10	0.11	0.00	1.00
Aspect 3: Location		0.08	0.11	0.00	1.00
Aspect 4: Food		0.14	0.14	0.00	1.00
Aspect 5: Facilities		0.19	0.17	0.00	1.00
Aspect 6: General experience		0.28	0.18	0.00	1.00
Aspect 7: Value		0.01	0.04	0.00	1.00
Aspect 8: Atmosphere		0.02	0.05	0.00	1.00
Recency		4.81	2.22	1	8
Helpfulness		0.32	0.47	0.00	6.00
Reviewer's expertise		486.62	57,127.75	0	7,983,398
Reviewer's contribution		24.42	182.90	0	12,906
Rating		4.16	1.36	1	5
Length		105.99	105.24	2	3,018
Sentiment		80.50	29.08	1.00	99.00

Readability		4.59	2.47	0.00	12.00

Table 4.4 shows the results of the regression analysis for the first, second, and third model. First, an overdispersion test was conducted to confirm the validity of using the NB model. If the dispersion of the model is significantly greater than 1, it indicates that the mean and variance of the dependent variable are not equal, called "over-dispersion", so a quasi-Poisson model needs to be adopted, such as the NB model (Gurmu & Trivedi, 1996). The results show that the assumption of mean-variance equality is rejected for all three models (Model 1: dispersion = 1.2745, $p < 0.001$; Model 2: dispersion = 1.2564, $p < 0.001$; Model 3: dispersion = 1.1888, $p < 0.001$). To estimate each model's explanatory power, the likelihood ratio index (LR Index) was applied, and all three models show values around 30%, indicating that their explanatory power is acceptable (Model 1 = 0.3369; Model 2 = 0.3621; Model 3 = 0.3626) (Park & Nicolau, 2015). By using several estimators of relative quality of statistical models (i.e., adjusted R squared, Akaike information criterion (AIC), and Bayesian information criterion (BIC)), the improvement from Models 1 to 2 ($\Delta R^2 = 0.0260$, $p < 0.001$) and from Models 2 to 3 ($\Delta R^2 = 0.0014$, $p < 0.001$) were examined: the models with a higher value for adjusted R squared and lower AIC and BIC are considered better (Ding, Tarokh, & Yang, 2017). As a robust check, the original and bootstrap results were compared in terms of significance and direction, and all the results were consistent.

Regarding the control variables, the effect of the reviewer's contribution ($\beta = 0.0005$, $p < 0.001$ in Model 3), rating ($\beta = 0.-0.0928$, $p < 0.001$ in Model 3), and length ($\beta = 0.0014$, $p < 0.001$ in Model 3) were consistently significant across all three models. While the impact of sentiment was not significant in Model 1 ($\beta = -0.0006$), it appeared to be significant in Model 2 and 3 ($\beta = -0.0008$, $p < 0.001$). These findings are similar to the findings of previous studies: a positive effect for reviewer's contribution (Huang, Chen, Yen, & Tran, 2015), negative for rating (Park & Nicolau, 2015), positive for length (Chua & Banerjee, 2015), and negative for sentiment (Zhou & Guo, 2015).

In terms of the independent variables, five aspects were shown to have significant effects on review helpfulness, either positively or negatively, in both Model 2 and 3: aspect 1 ($\beta = 0.0144$, $p < 0.001$ in Model 3), aspect 2 ($\beta = 0.0428$, $p < 0.001$ in Model 3), aspect 4 ($\beta = -0.1373$, $p < 0.001$ in Model 3), aspect 7 ($\beta = 0.0507$, $p < 0.001$ in Model 3), and aspect 8 ($\beta = -0.0699$, $p < 0.001$ in Model 3). These findings are in line with those of previous studies investigating the effects of the semantic features of online reviews: review helpfulness shows significant correlation with the extent to which specific topics about hotel products are mentioned in the text (Shin et al., 2020; Xiang, Du, Ma, & Fan, 2017).

With regard to the moderating variable, the impact of review recency was positively significant ($\beta = 0.1955$, $p < 0.001$ in Model 3). This indicates that recent reviews tend to be perceived as more helpful than old ones, supporting the previous findings (Tandon et al., 2020; Zhu, Yin, & He, 2014). More importantly, the moderating effect of review recency was significant for the four independent variables: aspect 1 ($\beta = -0.0447$, $p < 0.001$), aspect 2 ($\beta = 0.0469$, $p < 0.001$), aspect 4 ($\beta = 0.0615$, $p < 0.001$), and aspect 7 ($\beta = 0.0621$, $p < 0.001$). Regarding aspect 2 and aspect 7, review helpfulness increased only when these aspects were more mentioned in the text. If the reviews were old, the positive impact disappeared (Figure 4.5). Interestingly, a stronger moderating effect of review recency was examined in relation to aspect 1 and aspect 3: while the reviews including more information about these aspects were perceived as more helpful if they were recent, the opposite happened if they were old reviews (Figure 4.6). Thus, Hypothesis 1 was accepted.

Table 4.4. Hierarchical regression analysis

Estimate	Model 1		Model 2		Model 3	
	Original	Bootstrap	Original	Bootstrap	Original	Bootstrap
Reviewer's expertise	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Reviewer's contribution	0.0005***	0.0005***	0.0005***	0.0004***	0.0005***	0.0005***

Rating	-0.0928***	-0.0927***	-0.0929***	-0.0929***	-0.0928***	-0.0928***
Length	0.0017***	0.0017***	0.0014***	0.0014***	0.0014***	0.0014***
Sentiment	-0.0006	-0.0006	-0.0008***	-0.0007***	-0.0008***	-0.0007***
Readability	-0.0012	-0.0012	-0.0015	-0.0015	-0.0015	-0.0015
Aspect 1			0.0127***	0.0126***	0.0144***	0.0142***
Aspect 2			0.0390***	0.0391***	0.0428***	0.0428***
Aspect 3			-0.0015	-0.0015	-0.0007	-0.0007
Aspect 4			-0.1373***	-0.1373***	-0.1373***	-0.1373***
Aspect 5			0.0003	0.0003	0.0004	0.0004
Aspect 6			-0.0047	-0.0045	-0.0041	-0.0042
Aspect 7			0.0446***	0.0446***	0.0507***	0.0508***
Aspect 8			-0.0667***	-0.0666***	-0.0699***	-0.0699***
Recency			0.2241***	0.2240***	0.1954***	0.1955***
Aspect 1*Recency					-0.0447***	-0.0447***
Aspect 2*Recency					0.0469***	0.0469***
Aspect 3*Recency					0.0022	0.0020
Aspect 4*Recency					0.0615***	0.0615***
Aspect 5*Recency					0.0001	0.0001

Aspect 6*Recency				0.0010	0.0009
Aspect 7*Recency				0.0621***	0.0622***
Aspect 8*Recency				-0.0087	-0.0087
Over-dispersion test	1.2745***		1.2564***	1.1888***	
LR	0.3369		0.3621	0.3626	
R^2	0.0327		0.0587	0.0601	
ΔR^2			0.0260***	0.0014***	
AIC	53726.00		52301.00	52296.00	
BIC	53788.99		52434.86	52393.45	

Dependent variable: Review helpfulness.

Aspect 1: Staff service; Aspect 2: Cleanliness & Safety; Aspect 3: Location; Aspect 4: Food & Event; Aspect 5: Facilities; Aspect 6: General experience; Aspect 7: Value; Aspect 8: Atmosphere

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

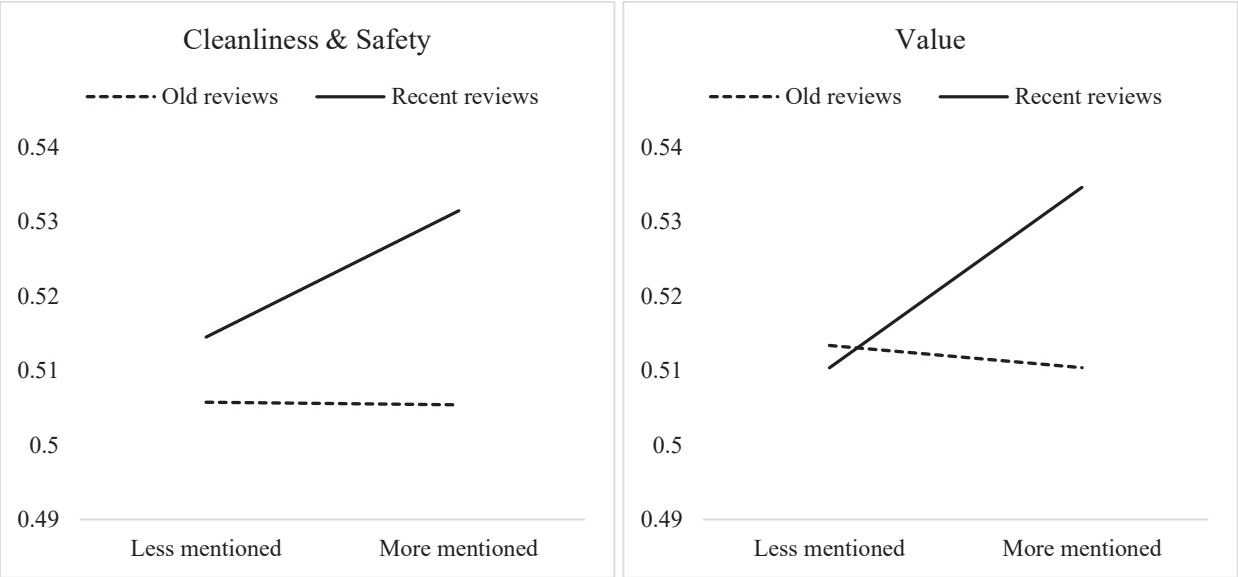

Figure 4.5. Interactions between recency and aspect 2 (Cleanliness & Safety) and aspect 7 (Value)

Figure 4.6. Interaction effects between recency and aspect 1 (Staff service) and aspect 3 (Food & Event)

4.6. Discussion

To understand the contextual effects of review recency on tourists' perceptions, this research investigates the interaction between review recency and content. By implementing social media analytics, the study examines how recent reviews are perceived differently, depending on their content. Given the variability of tourism products, the current study hypothesizes that recent reviews are appreciated more when information about specific aspects is included in the text.

This hypothesis is supported by the findings. The results show that while recent reviews tend to be perceived as more helpful than old ones, their recency is more appreciated more when particular aspects of a hotel product are mentioned in text: Staff service, Cleanliness & Safety, Food & Event, and Value. Compared to other aspects, such as Location or Facilities, these aspects are highly variable in terms of quality. While it is hard for a convenient location or the nice facilities of a hotel to become inconvenient or run down within a few months, the quality of the first four aspects mentioned above can change comparatively quickly. Tourists will want to know the up-to-date status of these variable aspects: even if a particular review provides a detailed evaluation of them, it will not be valid information if it was posted a few months ago. In other words, when tourists find recent reviews, they will want to get

information about the variable aspects. If those aspects are discussed much, the recency of the review is more likely to be recognized. Therefore, the findings show that the positive effect of review recency on considering the review as helpful becomes prominent when the variable aspects (Staff service, Cleanliness & Safety, Food & Event, Value) are more mentioned in the text. These findings are in line with those of previous studies on information recency: recently posted online information (e.g., social media posts) is perceived as fresher and more useful when its content is about current issues (Jatowt et al., 2011).

This can also explain the absence of an interaction effect between review recency and other aspects, such as Location and Facilities. Compared to the previously mentioned aspects, these two aspects are more stable in terms of quality. As their quality does not readily change, information about them would be useful for tourists even if the relevant reviews are not particularly recent. For this reason, the helpfulness of the information about these aspects is less likely to be affected by recency. In terms of General experience, it is hard to categorize it as either more or less variable in terms of quality because it reflects different aspects together. Thus, its interaction with review recency seems less likely. Finally, although Atmosphere can be considered a variable aspect, no interaction effect was found. Given the main words identified as being related to Atmosphere, this aspect primarily reflects interpersonal interactions (e.g., accommodating, welcoming) (see Table 4.2). The current study used reviews posted after the outbreak of the pandemic. During this period, people might have avoided unnecessary contact with staff and other guests. In this situation, the information about Atmosphere may be less relevant, regardless of the recency of the review.

4.6.1. Theoretical implications

First, this study provides empirical evidence that tourists' processing of online reviews is context-specific. Specifically, this study examines the interaction between review recency and content, and finds that reviews with similar content can be perceived differently, depending on how recent they are. Recognizing that online reviews comprise a variety of information components, it has been argued that

individuals consider different components together when processing the reviews. As the interactions between the different components are examined, it becomes important to investigate which and how specific components establish the context for others in order to understand the individual's processing of online reviews (Hlee et al., 2018). However, most tourism studies have explained tourists' perceptions of reviews by considering the impact of each component separately, overlooking possible interactions between components (Shin et al., 2020). While some studies have attempted to address this limitation, only a few components have been investigated to confirm their interactions: review ratings and text valence (Schlosser, 2011; Zhang et al., 2016; Zhou & Guo, 2015). By targeting other components (review recency and content), this study confirms the importance of considering the interactions between the components to understand the contextual effects of online reviews on tourists' perceptions.

Second, this study supports the importance of considering review recency when explaining how tourists process online reviews. In the hospitality and tourism field, review recency has been suggested as a key information dimension in understanding the impact of reviews on tourists' decision-making due to the variable nature of tourism products (i.e., their quality changes over time) (Filieri, Hofacker, & Alguezaui, 2018). While various components of online reviews have been investigated to explain their impact on tourists' cognitive and behavioral responses (e.g., reviewer's profile, review rating, text, or photos), review recency has received only limited attention (Otterbacher, 2009; Tandon et al., 2020). This study highlights the need to consider review recency to deepen our understanding of tourists' processing of online reviews. Furthermore, methodologically, this study highlights a problem in the previous approach for examining the effect of review recency on tourists' perceptions: namely, the relationship between time elapsed since the posting date and the number of helpful votes. Although this reveals a critical problem in its capturing of the effect, the approach has been adopted in many online review studies in the hospitality and tourism field (Cao et al., 2011; Tandon et al., 2020; Xie et al., 2016). Unlike previous research, which has not explicitly recognized the issue, this study draws attention to it and suggests an alternative approach for examining the effect of review recency.

Lastly, this study proposes a potential criterion for characterizing aspects of hotel products, which is variability: how variable a particular aspect is in terms of quality. In an attempt to understand hotel products, many tourism studies have investigated how various aspects of a hotel are perceived differently by tourists. The application of the two-factor theory in the hotel setting is one such example: which aspects are considered satisfiers and which dissatisfiers (Barsky & Labagh, 1992; Robinot & Giannelloni, 2010). By differentiating the aspects based on a specific criterion, the literature has developed a framework for conceptualizing a hotel product (Albayrak & Caber, 2015; Ramanathan & Ramanathan, 2011). By examining the interaction between review recency and content, this study indicates that tourists consider each aspect differently in terms of variability. This finding can contribute to improvement in the framework by proposing another potential criterion by which to characterize hotel aspects.

4.6.2. Practical implications

The findings show that the interaction between review recency and content in hotel reviews can reveal how each hotel aspect is perceived differently by customers: which aspects are regarded as those whose quality is more variable and thus, become the important topics of interest for customers when checking for up-to-date reviews. Although online reviews are used by a number of hotels for their management and marketing, they tend to be utilized in a limited way, such as for overhauling general performance by checking on overall ratings or by dealing with customers' complaints by leaving managerial responses to negative reviews (Sparks & Bradley, 2017). This study proposes additional ways of using hotel reviews. Hotels can adopt the approach this study used to understand better how customers perceive the various aspects in terms of quality variability. Considering that the variable nature of tourism products affects how tourists search and process information (e.g., with a preference for up-to-date information) (Filieri et al., 2018), the indications derived from the interaction between review recency and content can help hotel managers to manage different aspects of their products better.

Additionally, the findings underscore the importance of including an additional information component in an online review: which product aspects are evaluated in the review. What matters for the

users of an online review platform is how easy it is to filter out the helpful from the huge number of available reviews. To provide a more user-friendly experience, platform operators need to improve their interfaces to enable users to detect quality reviews more easily (Singh et al., 2017). This study shows that review recency is not the only component that makes a review useful: recent reviews are perceived as more helpful when the text includes an evaluation about aspects whose quality is changeable. If the aspects mentioned in the text are shown to the users, they can identify which aspects are evaluated in a review without reading the whole text (Tsur & Rappoport, 2012). By checking the aspect information together with the posting date, users can easily see whether a recent review actually talks about the issues that are more affected by time. It then becomes easier for them to find the reviews they want to read and also to assess their helpfulness. From the findings of the current study, the platform operators could get hints about improving their online review platforms.

Lastly, although it is not its main focus, this study finds that old reviews are frequently presented to TripAdvisor users together with recent ones after the outbreak of the pandemic. Since TripAdvisor lists reviews in reverse chronological order, if only a few reviews have been posted recently, the ones posted a few weeks or months before will remain on the front pages. As the average number of reviews posted for a hotel per month has decreased since the outbreak of COVID-19, old reviews tend to stay longer on the front pages of TripAdvisor. This situation means that old reviews may receive a similar degree of attention as the recent ones. According to the data for the current study, the reviews posted in October 2020 got more votes (1.42 votes per review) than those posted in December 2020 (0.93 votes per review) on average. The pandemic has changed not only which hotel aspects tourists focus on when reading the reviews (e.g., cleanliness and safety) but also how many old reviews they read when making their decision. Given these findings, this study recommends that hotels adjust their online review management by extending the time range of their online review monitoring: if the reviews posted in the focal month were primarily monitored before the pandemic, those posted a few months ago also need to be monitored because they are likely to be read by many more customers.

4.7. Conclusion

This study seeks to explain the interaction effects of review recency and content on tourists' perceptions. By implementing social media analytics with hotel review data, this study finds that recent reviews can be perceived as being more (or less) helpful depending on their content. This study contributes to the literature on tourists' online review processing by confirming the importance of considering possible interactions between information components (i.e., the contextual effects of specific components on others).

However, there are some limitations that should be addressed in future research. First, the findings are based on limited sample data. Although the top ten US cities, in terms of their number of annual visitors, and all the searchable hotels on TripAdvisor were targeted, a relatively small number of reviews were collected and used for the analysis compared to other online review studies using social media analytics (Xiang et al., 2017). To make the findings more generalizable, future research needs to expand the data size by targeting more cities or other online review platforms (e.g., Google reviews or Yelp). Second, only a specific interaction effect was examined even though other components could be interacting with review recency. For example, the interaction between review recency and reviewer's expertise or review rating could develop our understanding of tourists' processing of online reviews further. Future research needs to test different interaction effects. Finally, although this study tried to address the problems of the existing method for examining the effect of review recency on helpfulness (i.e., examining the relationship between the time elapsed since the posting date and the number of votes), the current study's approach is still not free from this issue. Future research needs to devise more valid measures that can capture the relationship between review recency and helpfulness.

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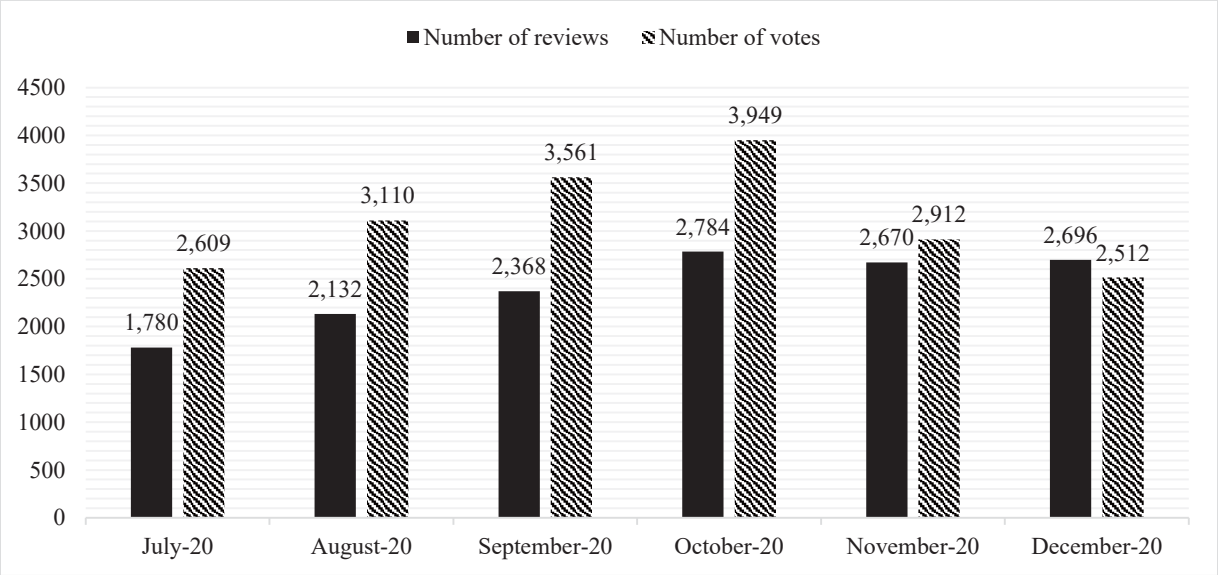
Appendix



Appendix 4.A. Total number of reviews posted for the hotels of ten US cities per month on TripAdvisor and number of votes the reviews posted in each month received (July – December 2020)

CHAPTER 5. CONCLUSIONS

The underlying argument of this dissertation is that understanding tourists' responses to online reviews depends on factors that transcend their information characteristics. Although a number of studies have attempted to explain the effects of online reviews on tourists' cognitive and behavioral responses, the majority of the literature has treated tourists' responses as static. While the effects of online reviews have been recognized in the hospitality and tourism field (Litvin, Goldsmith, & Pan, 2008), their context-dependent nature is understudied. By focusing on several contextual factors (i.e., the context of use and the nature of tourism products), a series of three essays were conducted to examine their effects on tourists' response to online reviews. Overall, the findings confirm the dynamic nature of online reviews by showing that the selected contextual factors affect the way tourists respond to reviews, as argued in the dissertation.

5.1. Study 1: Findings' Summary

The role of online reviews within the local search context is studied. To this end, the influence of online reviews on the representation of tourism businesses on local search platforms (LSPs) are examined with an analytical approach. After simulating Los Angeles (LA) tourists' local search for restaurants, the search results of the three LSPs—Google, Bing, and Yelp—were compared, and the effects of the reviews on the differences in the ranking results were examined.

The findings showed that while all three LSPs provide a ranked list of the local restaurants according to tourists' location, the ranking results are significantly different in terms of composition (i.e., which restaurants are ranked in the list) and ranking (i.e., which restaurants are ranked as high or low) because of the difference in the way online reviews are treated in each LSP. Specifically, it was observed that the three LSPs use different components of online reviews for ranking (Google: the number of recent reviews; Bing: the number of reviews; and Yelp: the number of reviews and mean rating of recent reviews), which makes the platforms represent the local restaurant domain in a different manner.

With the examination of the effects of online reviews on the ranking results of LSPs, Study 1 confirms the context-dependent nature of online reviews. This study concludes that the manner in which online reviews affect tourists' decision-making is dependent on the context of their use; while online reviews facilitate tourists' choice of products by providing peer evaluations in general, they do this by influencing the products' online representation in the local search context.

5.2. Study 2: Findings' Summary

Building on Study 1, the effects of online reviews on tourists' responses were examined in the local search context. By focusing on the situational characteristics of the local search context (i.e., tourists tend to visit the place of interest soon after the search), Study 2 investigated how tourists process online reviews in a context different from its non-local counterpart (i.e., searching for a restaurant that can be visited in a month). Based on the construal level theory (CLT), Study 2 hypothesizes the higher effect of recent reviews on tourists' cognitive and behavioral responses in the local search context than in the non-local one.

To test this hypothesis, an experiment was conducted in a restaurant setting, and the findings showed that recent reviews have higher effects on tourists' responses in the local search context than non-local. While the rating of a recent review (recent rating) is considered more helpful than the aggregated ratings of all the reviews (overall rating) in both contexts, the positive effect of review recency on tourists' review perception became more prominent in the local search context. Similarly, even though the tourists' attitude toward and intention to visit a focal restaurant were more affected by the recent rating than the overall rating, the positive relationship between review recency and tourists' product perception became more pronounced in the local search context.

With the examination of the intensified effects of recent reviews in the local search context, Study 2 provides empirical support for the contextual effects of online reviews on tourists' decision-making.

Furthermore, this study discusses the importance of considering the temporal dimension (i.e., when tourists process online reviews) to further understand tourists' processing of online reviews.

5.3. Study 3: Findings' Summary

The contextual effects of review recency on tourists' review perception were further examined by building on Study 2. Since tourists consider different information components of online reviews simultaneously, Study 3 investigated how review recency becomes the context for processing its content. By focusing on the variability of tourism products, Study 3 hypothesized the interaction between review recency and content: recent reviews are perceived more helpful when they include information about aspects whose quality is more variable (e.g., service, cleanliness, and value) than stable ones (e.g., location and facilities).

This hypothesis was tested through social media analytics using the hotel review data collected from TripAdvisor. The findings revealed the significant moderating effects of review recency on the relationship between its content and helpfulness. Specifically, it was observed that while recent reviews are perceived as more helpful than old ones, their recency is appreciated more when their content includes further information about aspects whose quality easily changes (including Staff service; Cleanliness & Safety; Food & Event; and Value).

With the examination of tourists' different perceptions of recent reviews according to their content, Study 3 confirms tourists' contextual information processing in the online review setting. Moreover, this study proposes the need to consider various interactions between different information components to understand the contextual effects of online reviews.

5.4. Implications and Limitations

Theoretically, this dissertation contributes to the literature on tourists' information use by examining its context-dependence. The context-dependence of tourists' information use has been corroborated by previous research that examined the effects of different contextual factors on the way

tourists use information for decision-making (Fodness & Murray, 1997). Although tourists' information use comprises of various activities, the context-dependence has been usually studied in specific activities: which information sources tourists choose (Capella & Greco, 1987; Lehto, Kim, & Morrison, 2006), how much effort and time they invest (Fesenmaier & Johnson, 1989; Kim, Xiang, & Fesenmaier, 2015), and which goals they try to achieve (Vogt & Fesenmaier, 1998). Specifically, the context-dependence has been less discussed in the following activity even though it is a significant part of tourists' information use: how tourists process the content of information (e.g., how the content is perceived, how various information components are checked by tourists) (Darley & Smith, 1995). By providing empirical support through different approaches, the three essays reveal that tourists' information processing is influenced by the context of use (Study 1 and 2) and the nature of the tourism products (Study 3). Given its suggestion of the need to consider more activities of the tourists' information use to understand its dynamic nature, this dissertation can serve as a reference for future studies.

Second, this dissertation further explains the contextual effects of travel information by exploring the situational influences. Although the effects arising from the factors particular to a specific situation are claimed to be considered as important contextual factors, the existing literature has primarily focused on tourists' individual (Mayo & Jarvis, 1981; Woodside & Lysonski, 1989) or trip-related characteristics (Gitelson & Crompton, 1983; Snepenger, Meged, Snelling, & Worrall, 1990). This dissertation provides empirical evidence for the importance of situational factors in terms of understanding tourists' information use: in which search context tourists use the information (Study 1), how soon their visit will happen after their use of information (Study 2), and how recent is the information that they encounter (Study 3). These findings contribute to a better understanding of a broad range of contextual factors. This could form the empirical foundation for future studies to explore potential situational rather than conventional factors such as tourists' socio-demographics or their purpose for travel.

Third, this dissertation takes a further step toward identifying the factors beyond the information components of online reviews that affect tourists' perception and behavior. Several studies have explained

how online reviews affect tourists' decision-making by examining their effects on tourists' different responses such as the perceived helpfulness of online reviews, product attitude, or purchase intention (Racherla & Friske, 2012; Sparks & Browning, 2011; Vermeulen & Seegers, 2009). However, the existing literature has primarily investigated the information components of online reviews, including messengers' or messages' qualitative and quantitative characteristics (Filieri & McLeay, 2014; Liu & Park, 2015). This dissertation adds to the hospitality and tourism works that study the effects of online reviews on tourists' perception or behavior by examining how such effects vary depending on several contextual factors: the context of use in Study 1 and the timing of decision-making in Study 2. Furthermore, along with the elastic capacity model (ECM) (Kahneman, 1973) and the heuristic-systematic model (HSM) (Chaiken, 1980), the findings of Study 3 sheds light on the interactions between information components of online reviews, which examine their contextual effects on tourists' perception. These findings can be a framework for future research into the various contextual factors of review impact which have not been discussed in previous studies (Furner & Zinko, 2017; Huang, Tan, Ke, & Wei, 2018).

Finally, this dissertation proposes both theoretical and practical settings which provide a basis for studying the contextual use of online reviews in the hospitality and tourism field. On the one hand, by explaining the varying effects of online reviews with CLT, prospect theory, ECM, and HSM, this dissertation shows that those theoretical frameworks can provide a useful model for discussing the contextual effects of reviews on tourists' perception: how the same online review can be differently perceived depending on the associated temporal distance (i.e., how soon the actual visit happens after processing the reviews) (Study 2) and the interaction between review recency and content (Study 3). On the other hand, this dissertation indicates that local search is a prospective setting for examining the dynamic effects of online reviews on tourists' decision-making by arguing that online reviews affect tourists' decision-making as ranking factors in the local search context (Study 1). Given the broad range

of contextual factors whose effects can be explained by the different theories, this dissertation offers clearer directions to future research in this field.

Other than theoretical implications, this dissertation makes contributions to managerial insights. The understanding of tourists' processing of online reviews in different situations can serve as a guideline for tourism businesses to hone their marketing strategies. Today, there is greater availability of information about tourists' contexts, including their location (accessed from the geospatial data of smartphones users), party members (accessed through the tagging feature on social media platforms), physiological condition (accessed through smartwatches), and the progress of their travel itineraries (accessed through data from calendar applications) (Jannach & Zanker, 2020). This provides tourism businesses opportunities to target potential customers based on more precise contextual cues; therefore, the manner in which the situational factors affect tourists' behaviors becomes an increasingly important question to help them leverage the cues to improve their marketing strategies (Lamsfus, Wang, Alzua-Sorzabal, & Xiang, 2015).

This dissertation offers several implications for tourism businesses, particularly in terms of online marketing. By showing the different representations of tourism businesses across LSPs, Study 1 suggests the need to review multiple platforms to fully assess businesses' online popularity. Furthermore, some guidelines are proposed on improving their popularity on each platform. In Study 2, the findings demonstrating the higher effects of recent reviews on tourists' decision-making imply that tourism businesses need to prioritize LSPs for managing online reviews (e.g., checking and leaving responses to newly-posted reviews) to make the efforts in improving their online reputation more effective. Lastly, Study 3 finds that tourists have different perceptions of each aspect of tourism products in terms of the variability of quality and that such perceptions can be explained by examining the interaction between information components of online reviews. Based on the findings, a prospective approach is proposed for utilizing online reviews for the purpose of improving product management.

Along with the implication for tourism businesses, this dissertation provides implications for online platforms in the field of hospitality and tourism. The first two studies present guidelines that can be applied to improve LSPs' promotion strategy and usability. By examining how LSPs are different in terms of their ranking algorithms (e.g., which information of online reviews is used as a major ranking factor), Study 1 suggests that LSPs can improve their promotional strategies by differentiating themselves from competitors by disclosing their ranking mechanism. As for usability, Study 2 recommends that LSPs include information about recent reviews (e.g., the rating or number of recent reviews) in their main result pages. This is suggested based on the finding that tourists highly rely on recent reviews for their product choices in the local search context. Similarly, Study 3 identifies the information that needs to be added in the interface design to provide better experiences to users in the online review platform setting: major keywords written in a review indicating which product aspects are evaluated in its text.

Despite the theoretical and practical contributions, this dissertation has several limitations. As mentioned previously, there are a variety of potential contextual factors that affect tourists' responses to online reviews: when consumers read online reviews (Huang et al., 2018; Jin, Hu, & He, 2014), whether they are under time pressure when processing them (Gottschalk & Mafael, 2017), which types of platforms consumers use to process online reviews (Floyd, Freling, Alhoqail, Cho, & Freling, 2014; Gu, Park, & Konana, 2012), which devices they use (Furner & Zinko, 2017), etc. Although this dissertation aimed to understand how the surrounding context affects the impacts of online reviews on tourists' responses, only a limited part of the context was studied. By using the findings of this dissertation as a starting point, future research should explore more varied contextual factors in the hospitality and tourism field and thereby develop the knowledge on the dynamic nature of online reviews.

Second, an online review is composed of different information components, and they generate a holistic effect on tourists' perception and behavior (Shin, Du, Ma, Fan, & Xiang, 2020). To fully understand the dynamic effects of online reviews, the manner in which those various components interact with contextual factors needs to be studied. Similar to review recency, other components (e.g., the

readability of text or the number of photos) could have varying impacts depending on whether the reviews are used in the local or non-local search context; for instance, reviews with more readable text or fewer photos might be perceived as more helpful in the local search context because they are more convenient to be read even on the small screens of mobile devices (Furner & Zinko, 2017). While review content interacts with how recent it is, its helpfulness can be either more or less appreciated depending on the reliability of the reviewer (Yang, Shin, Joun, & Koo, 2017). Although this dissertation emphasizes the multiple information components of online reviews, only two components—review recency and content—were investigated to explain the contextual effects of online reviews. To further understand these effects, future research should study the various components of online reviews in terms of their interaction with different contextual factors.

Lastly, the findings of each study are difficult to generalize because they are derived from a limited sample data. As for the studies using the crawled data (i.e., ranking result or online reviews), the sample data are limited in terms of the geographic scope (i.e., New York, Miami, Los Angeles, Orlando, San Francisco, Las Vegas, Honolulu, Washington D.C, Boston, and Chicago) and observation period (i.e., after the outbreak of COVID-19). Also, specific platforms are assumed to be representative of LSPs (i.e., Google, Bing, and Yelp) and online review platforms (i.e., TripAdvisor). With regard to the study using the survey data, all the participants are residents of the United States. Furthermore, as each study targets a specific hospitality sector (i.e., restaurants or hotels), its findings might be domain-specific, and they might have to be interpreted with caution. To make the findings more generalizable, future research could target other hospitality sectors (e.g., airlines, attractions) and expand the data collection geographically or longitudinally.

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