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Empirical Research Article

Role of Online Reviews in the Local Search Context

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Abstract

This research aims to understand the role of online reviews in the local search context by examining the effects of reviews on the representation of tourism businesses on local search platforms (LSPs). By simulating tourists' local searches for restaurants on three LSPs, namely Google, Bing, and Yelp, this study examines how different ranking results are generated across the platforms and how online reviews contribute to the differences. The findings suggest that online reviews are incorporated into LSPs as ranking factors and, thus, affect tourists' decision-making by influencing the information search results in the local search context. As one of the earliest studies on local search, this study discusses how the existing knowledge about the role of online reviews in tourists' decision-making needs to be reevaluated in mobile and more dynamic environments, and offers practical implications for tourism businesses' search engine marketing.

Keywords

local search; near me search; local search platforms; online reviews; ranking factors; online representation

1. Introduction

Online reviews play an instrumental role in shaping consumers' product choices by reducing their uncertainty regarding purchase decisions (Mudambi & Schuff, 2010). In particular, online reviews are considered crucial in the hospitality and tourism field because consumers perceive higher risks while purchasing an intangible product (Litvin et al., 2008). In hospitality and tourism literature, online reviews have been extensively studied in terms of their impact on consumer perception, decision making and business performance (Sparks & Browning, 2011; Ye et al., 2011).

An online review consists of different components such as review text, ratings, reviewer profiles, or managerial responses (Shin et al., 2021), and these components are incorporated into various platforms to serve a variety of business or marketing-related purposes (Xiang et al., 2017). Online travel agencies, such as Booking.com or Expedia, present ratings and volume on the search results (e.g., 4 out of 5-star rating based on certain number of reviews) and help tourists narrow down their choice set (Ghose et al., 2012). Community-based websites, such as TripAdvisor or Yelp, by incorporating reviewer profiles (e.g., profile photos) and readers' responses (e.g., peer evaluation votes), enable tourists to communicate with credible fellows and to recognize others' contributions (Korfiatis et al., 2012; Xu, 2014). Also, through managerial responses, these websites can facilitate interactions, and promote relationships between tourists and tourism businesses (Xie et al., 2016). On photo and video sharing platforms, such as Instagram or YouTube, when tourists click the hashtags embedded in the review text (e.g., #BurjAlArab), they can see a collection of relevant information (e.g., other reviews, photos, or videos about Burj Al Arab) (Shin et al., 2018). Particularly, the visual content garners tourists' affective responses to a product by delivering authentic and real-time representations (Lo et al., 2011; Ma et al., 2018). Depending on the functions they perform in the platforms, online reviews may exert different effects on tourists' perception or behavior and thus serve as rich, complex electronic word-of-mouth (eWOM) (Litvin et al., 2008; Ma et al., 2017).

Nowadays, local searches, also known as "near me" searches, constitute a major proportion of information search in hospitality and tourism (Yoon et al., 2018). Local search platforms (LSPs) accessed through smartphone applications such as Google or Bing Maps have become essential for tourists' on-site decision-making. According to a recent report, LSPs account for 54% of tourists' searches for activities and 48% of experience bookings (Delgado, 2019). When conducting local searches, tourists experience different contextual constraints due to the small screens of mobile

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devices, unstable internet connection, environmental distractions while walking or driving, and the limited time available for the search task (Liu et al., 2010). Within these contexts, it is important to provide easy-to-follow cues to tourists and, thus, LSPs exploit online reviews for such purposes. LSPs may use certain review components (e.g., ratings or volume) as ranking factors along with the distance of business to the user. For instance, when there are two restaurants of the same distance, the one with higher ratings or more volume could be ranked higher in the search results (Hunter, 2020). Considering that a business' ranking in search results is a primary cue for mobile users' choice (Pan, 2015), online reviews will likely affect tourists' decision-making by driving the search results of LSPs in the local search context.

While online reviews play an important role in the local search context, existing hospitality and tourism literature primarily focuses on explaining their impacts on tourists' decision-making in the pre-trip search context (Liu et al., 2010). As such, this study aims to document how online reviews are integrated into LSPs to understand the way they serve as decision cues within a unique information search context (Lamsfus et al., 2015; Wang et al., 2016). Specifically, we examined how online reviews were integrated into widely used LSPs as part of the search results and their role determining the rankings of search results. Given the significance of local search in the during-trip stage of travel (Google, 2014), this study helps us learn about the representation of hospitality and tourism products in today's technological environment and, particularly, how online reviews as a form of eWOM potentially impact tourists' on-site decision-making (Xiang et al., 2008).

2. Research Background

While the first LSP was developed in the early 1990's (i.e., ActiveBadge), its market started to be recognized from the 2000's, when global positioning system (GPS) signals became publicly available (Huang et al., 2018). Driven by the advent of mobile computing, the enabling technologies have rapidly developed and several LSPs have appeared (Ahlers & Boll, 2007). As major tools of local search, LSPs have been increasingly used in a range of domains (e.g., restaurants, movies, hotels, gas stations, retail stores, etc.), and become important marketing opportunities for local businesses (Teevan et al., 2011). According to Google Trends, the average increase for the search interest in "near me" has been over 400% annually from 2011 (Pollak, 2018). In 2018, the market size of local search was valued at USD 23.74 billion and is estimated to reach USD 157.34 billion by 2026 (Gaul & Baul, 2019).

As context-aware applications, LSPs recognize user's location and conduct information search according to the context (Amin et al., 2009). They help users find nearby product or service providers by returning search results including a ranked list of local businesses and a range of information about each entity (e.g., name, address, distance, online reviews, etc.) (Tabarcea et al., 2017) (Figure 1). The search results are generated based on the following workflow: once users search for "restaurants near me," LSPs identify the businesses registered as restaurants through business data providers (e.g., Google My Business, Yahoo! My Business), and calculate the distance between users and restaurants by processing the geospatial information (e.g., address, zip code, geocode) (Middleton et al., 2018). Additionally, they assess the popularity and business quality of the restaurants by checking the number and mean rating of online reviews. Then, the restaurants are ranked in order of proximity, popularity, and business quality (Berberich et al., 2011).

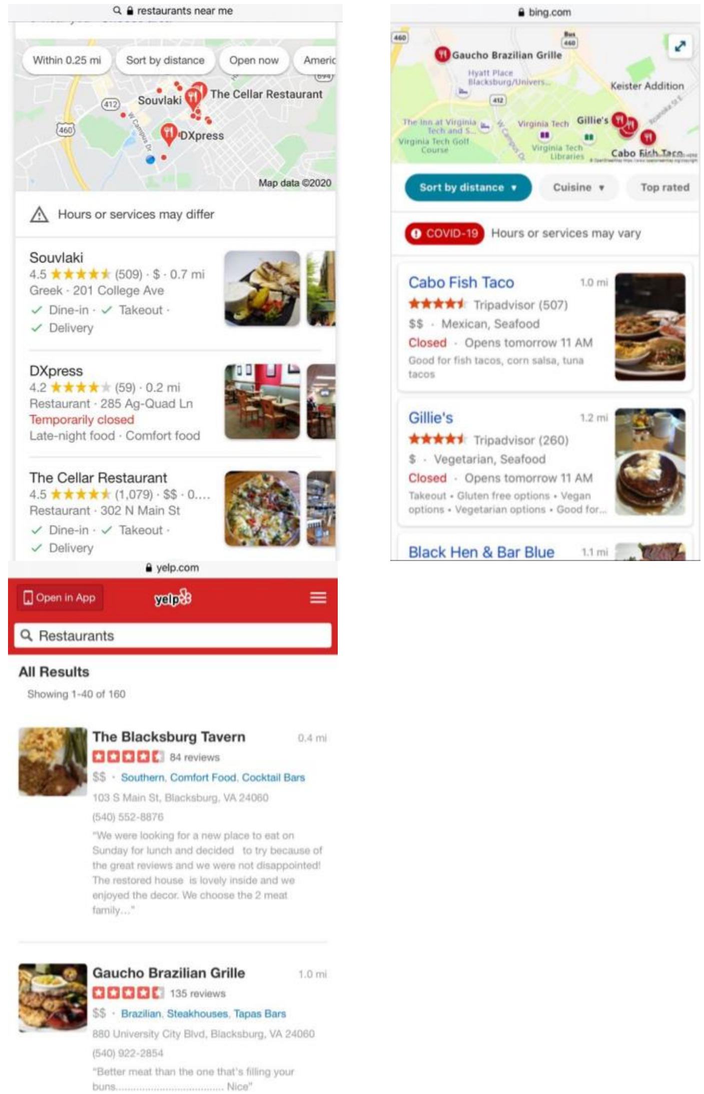

Fig. 1. Local search results of Google (left), Bing (center), and Yelp (right)

Although most LSPs follow the workflow, two complexities are involved in identifying and ranking local businesses, which could introduce "biases" into the systems. On the one hand, when LSPs identify local businesses, each platform utilizes a different set of business data providers (Whitespark, n.d.). According to the local search ecosystem which visually explains the complexity of business data relationships (e.g., how business data flow across data providers and LSPs) (Figure 2), a number of data providers (written as "primary data aggregators" or "key sites in the ecosystem" in Figure 2) and LSPs (written as "core search engines" in Figure 2) exist, and all the platforms have complex relationships with each other (Zhekov, 2017). For example, one of the major data providers, Factual, is adopted by Bing but not Google. On the other hand, when LSPs rank local businesses, each platform utilizes its ranking algorithm that is developed based on its business model (Theuring, 2020). Although most LSPs employ the proximity of local businesses as a primary ranking factor, the proximity alone is not always sufficient to rank effectively: there could be a number of local businesses which are close to the users. Thus, LSPs have to set the second, third, or forth ranking factor and assign different weights to each (Long & Chang, 2014). All these issues (i.e., which factors need to be set as the second, third, or forth ranking factors; how much weights need to be assigned to each) are determined based on its business model, so each LSP develops an unique ranking algorithm (Mihm, 2010).

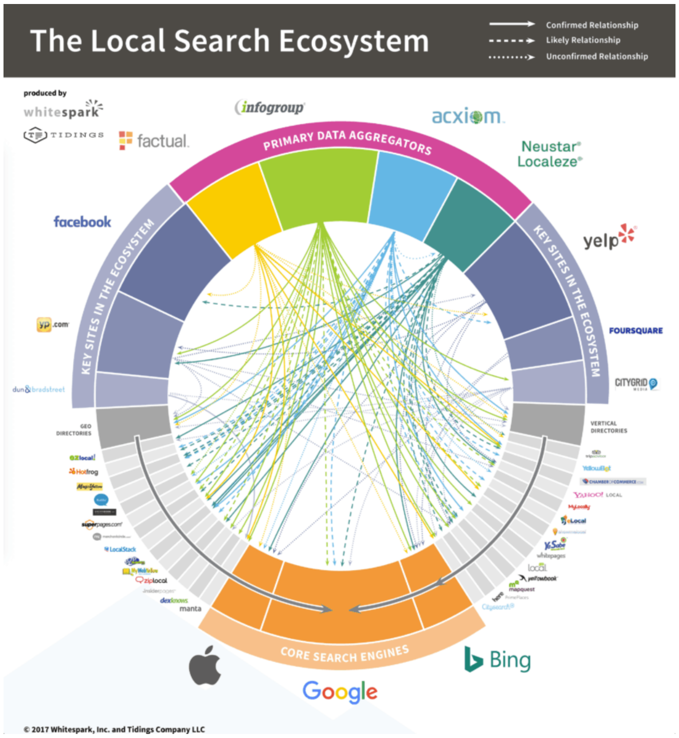

Fig. 2. Local search ecosystem

Although LSPs are context-driven systems with the common goal to support user's decision-making, they are complex socio-technical systems that represent the dynamic data relationships and different ranking algorithms (Lincoln, 2020). Therefore, local search research has to consider the potential differences in the search results across LSPs and, more importantly, be able to explain the possible causes of the "biases" in the results. These issues may be particularly important in the field where LSPs are recognized as an important trend, such as hospitality and tourism (Pedrana, 2014). From the early 2000s, travel-related services (e.g., tour guides, "you-are-here" maps, car or pedestrian navigation systems) have been the largest sectors of LSPs (Raper et al., 2007b). Google Trends showed that travel-related topics (e.g., restaurants, hotels, entertainment) are top-ranked "near me" search queries (Uberall, 2018). As the impacts of LSPs on tourist's decision-making have been recognized, the industry has adapted to the trends: local SEO has become an essential marketing practice together with general SEO (Morch, 2019). Given the dominance of LSPs and the associated broad changes in the field, hospitality and tourism may be one of the best fields to study how local businesses are represented through LSPs. Along with the understanding about the technology itself, the research on LSP's representation of tourism domain would develop our knowledge about tourist's decision-making, particularly within a mobile, on-site context.

3. Research Design

To document the way online reviews are integrated into LSPs as ranking factors, a series of analyses were conducted: 1) how different ranking results are obtained across three major LSPs, namely Google, Bing, and Yelp; 2) how the reviews contribute to the differences. For data collection, we simulated tourists' local searches for restaurants in Los Angeles (LA) (i.e., searching "restaurants near me" around popular attractions of LA) on Google, Bing, and Yelp. After collecting three LSPs' search results, we measured their rank similarity, which is the degree of similarity between two rankings. Then, we examined the impacts of online reviews on the rankings of search results in each LSP to explain how local search results vary depending on how the reviews are treated as ranking factors.

3.1. Data Collection

In order to collect the data, LA tourist's local search for restaurant was simulated. First, local search queries were determined. With the 2020 official visitor map of LA, the places shown as touristic 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 found (e.g., Union Station, Universal Studios, Griffith Observatory, Venice Boardwalk) (see Table A1 in online Appendix). By 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, local search was conducted on each platform with the 67 queries. 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 search results collected through desktops might not be valid because the results could differ by devices. Thus, we randomly sampled some queries and checked whether the search results on desktops are different from those on smartphones. We confirmed that the search results are consistent between smartphones and desktops. Second, since the search results could be affected by personalization, the private browsing mode (i.e., incognito) was used. 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 search session, and the private browsing mode was used in each session, which is designed to prevent previous search history associated with 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 at the same day. If Google's search results collected a day before are compared with Bing's collected today and they are different, the differences could be attributed to time difference of data collection.

After conducting the local search on each platform, the restaurants data were collected from each session. Based on the statistics that local search users tend to see only the first page of search results (Uberall, 2018), we used the average number of restaurants appearing on the first result page on Google (20), Bing (18), and Yelp (30) for the collection, which is about 20 (all the numbers are on the basis of desktop search). From nine sessions, less than 20 restaurants were searched on either Google, Bing, or Yelp (i.e., Exchange LA (14), Row DTLA (8), The Getty Center (14), Manhattan Beach Pier (18), Porsche Experience Center (7), Van Nuys Airport (18), Westfield Topanga & The Village (10), NoHo Arts District (10), Descanso Gardens (18)), and 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 it is not a part of 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 (1–5), number of reviews, distance, price range ($–$$$$), and cuisine (see

Figure 1). While Google and Yelp used their own reviews, Bing utilized those from Yelp at the time of data collection (Now, Bing utilizes TripAdvisor reviews). As for the distance between the places used in the search queries and the searched restaurants, we calculated the point-to-point straight distance because the result page shows the straight line distance instead of walking or driving distance (when users click a certain restaurant for further search, the walking or driving distance is shown). 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 to make the results easy to interpret (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 (e.g., Du-Pars | Restaurant and Bakery, Du-Par's Restaurant & Bakery) and addresses (6333 W 3rd St, 6333 West 3rd Street) across the platforms. Thus, they were matched through manual inspection.

3.2. Data Analysis

To measure the rank similarity between the three LSPs, Webber's rank-biased overlap (RBO) was used (Webber et al., 2010). RBO ranges from zero (two search platforms' ranking results are opposites) to one (two search platforms' ranking results are exactly the same). As a rule of thumb, 0.5 has been used as a threshold that separates what is considered to be different and similar (Cardoso & Magalhães, 2011). Since RBO can compare only two ranking results at a time, three pairwise comparisons namely Google–Bing, Bing–Yelp, Yelp–Google were conducted. All the comparisons were performed through the R programming language.

To examine the impacts of online reviews on the rankings of search results, ordinal regression was performed using SPSS. Each restaurant was treated as one case with its ranking being the dependent variable and its mean rating and total reviews per restaurant as independent variables. For local search marketing the LSPs consider as an important ranking factors how many positive reviews a business has recently received (Richard, 2014). Thus, we included the mean rating and number of recent reviews per restaurant as additional independent variables. All the reviews timestamped within two months of the date of data collection were defined as recent reviews. This was done as both consumers and review platforms consider the reviews uploaded older than two months as not recent (Murphy, 2020). Distance, price range, and cuisine were used as control variables. Finally, the dependent variable, i.e., ranking, was reversely coded for the sake of interpretation: higher values of focal independent variables are correlated with higher rankings.

4. Findings

The descriptive statistics of restaurant information are presented in Table 1. Compared to Bing (3.81), the mean rating of reviews is higher in Google (4.41) and Yelp (4.12) (Figure 3). However, when the recent reviews are considered, the mean rating of Bing (4.12) increases values similar to that of Google (4.45) and Yelp (4.12) (Figure 4). Yelp shows a higher mean number of reviews (956.65) than Google (649.37) and Bing (558.81) (Figure 5), but Google (29.16) is higher than Bing (5.13) and Yelp (5.22) in terms of the number of recent reviews (Figure 6). As for the distance, Google (0.77) and Bing (0.76) tend to search the closer local restaurants than Yelp (1.41) (Figure 7). In all the three platforms, cheaper restaurants (price range: \$ ~ \$\$) are frequently ranked on the results (Google: 68.37%, Bing: 84.33%, Yelp: 89.27%) (Figure 8). Lastly, other than miscellaneous, while Asian, American, Latin, and European often appear on Google (60.84%), Bing (65.07%), and Yelp (72.99%), Bing and Yelp are more skewed toward Asian cuisine (Bing: 21.14%, Yelp: 31.40%). These statistics indicate that three LSPs represent tourism domain differently by presenting different sets of local restaurants

Table 1. 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 counts		
-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%)

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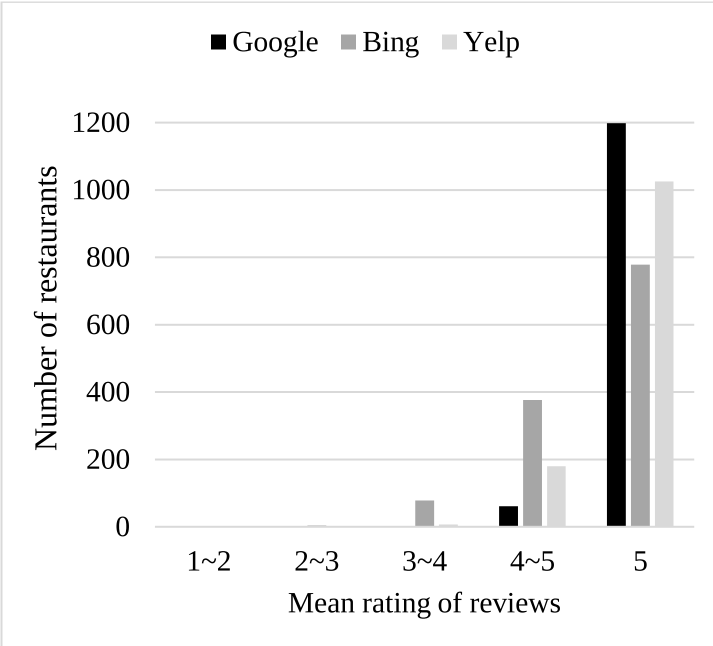

Fig. 3. Distribution of mean rating of reviews on three platforms

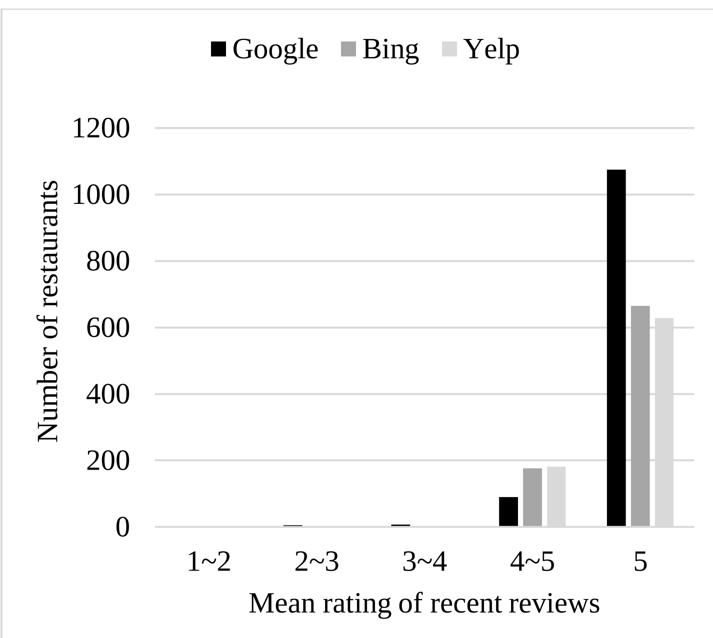

Fig. 4. Distribution of mean rating of recent reviews on three platforms

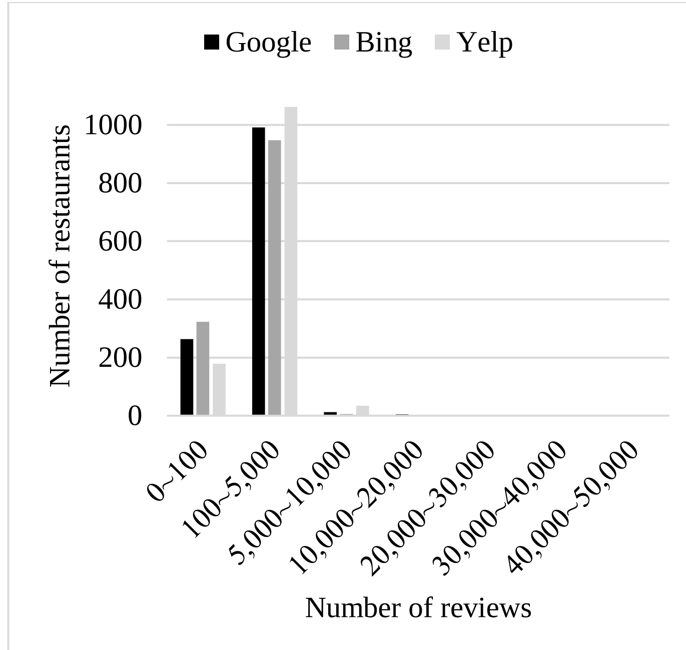

Fig. 5. Distribution of number of reviews on three platforms

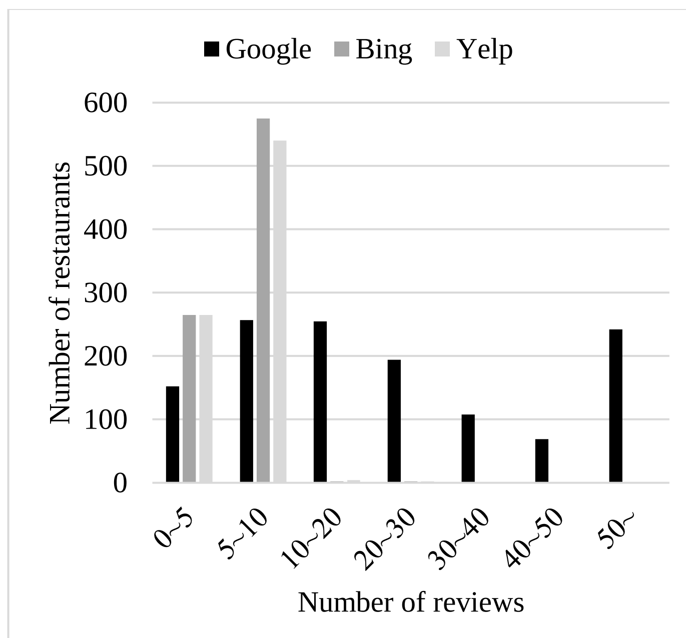

Fig. 6. Distribution of number of recent reviews on three platforms

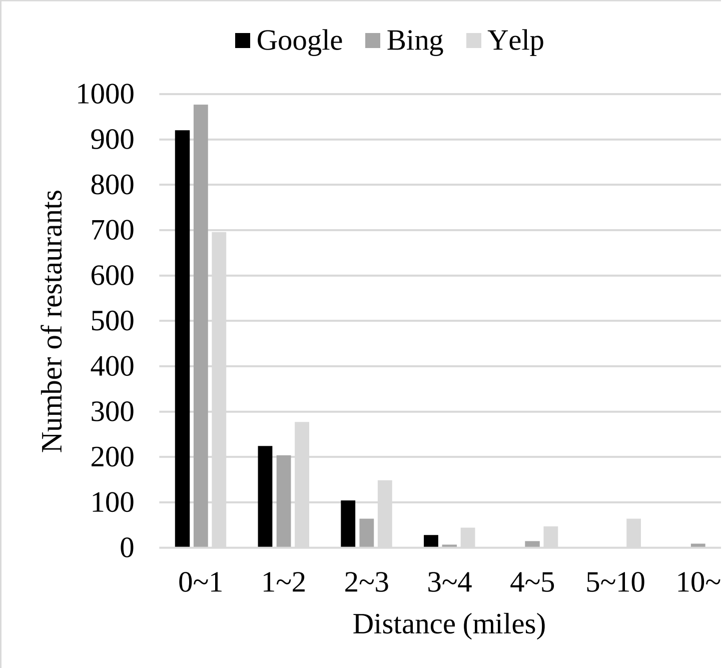

Fig. 7. Distribution of distance on three platforms

Table 2 shows the results of pairwise rank similarity comparison. The results indicate that three LSPs provide quite different rankings. In order 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, which is significantly lower than 0.5 according to one-sample t-test ($p < 0.001$). In Figure 9, the distribution of RBO scores is presented: among 67 RBO scores, how many cases fall into each interval. Although some comparisons appear quite similar (over than 0.5), most cases are examined as different (see Table A1 in online Appendix to check 67 RBO scores).

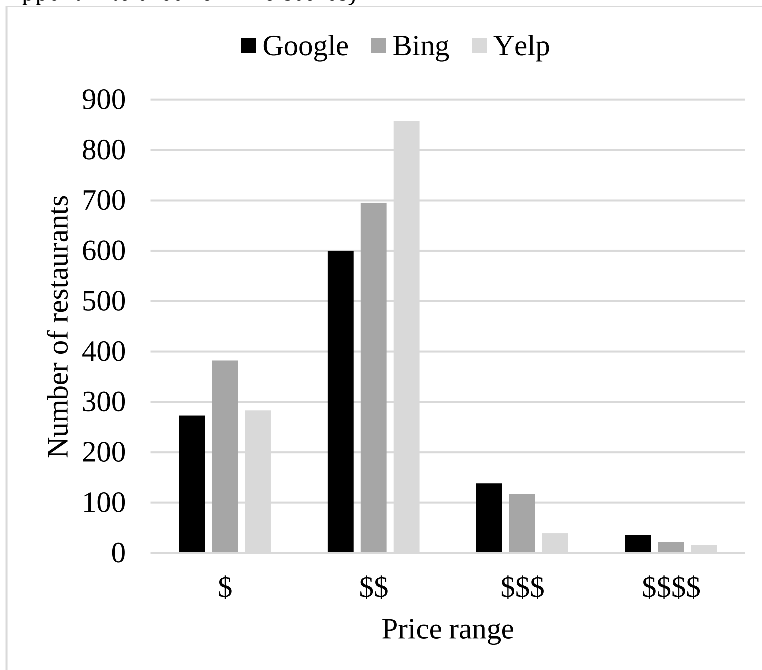

Fig. 8. Distribution of price range on three platforms

Table 2. Average of RBO score of three pairwise of 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***

*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$

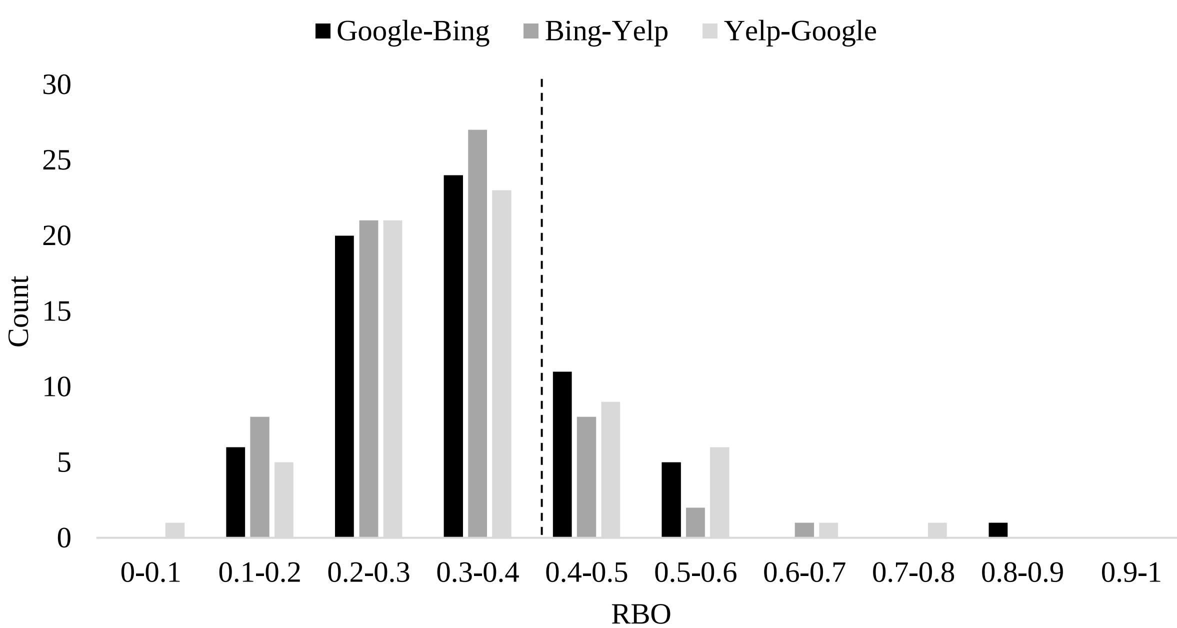

Fig. 9. Distribution of the RBO scores

Table 3 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 shows insignificant results, indicating the assumption is met (Chi-Square = 111.792, $p = 0.283$). Among the independent variables, distance is negatively significant (β = -0.208, $p < 0.005$), and the number of recent reviews is positively significant in a marginal way (β = 0.140, $p = 0.059$). Additionally, two cuisines, Breakfast, Bakery, Café & Dessert (β = -0.902, $p < 0.05$) and Fastfood (β = -1.521, $p < 0.001$) are negatively significant, indicating 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 3. 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	0.140	0.137 (-0.021~0.295)	0.074	1	0.059
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 4 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, $p = 0.548$). Similar to Google, distance is negatively significant (β = -0.537, $p < 0.001$). However, unlike Google, the number of reviews is positively significant (β = 0.170, $p < 0.05$), not recent reviews. Also, Asian (β = -0.511, $p < 0.05$) is negatively significant. All the original and bootstrap results are consistent.

Table 4. 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 5 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, $p = 0.860$). It is similar Google and Bing in that distance is negatively significant (β = -0.196, $p < 0.005$). Also, the number of reviews is positively significant (β = 0.224, $p < 0.005$) like Bing's result. However, only Yelp results show positive significance of the mean rating of recent reviews in a marginal way (β = 0.357, p = 0.062). The bootstrap results show the same findings.

Table 5. 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	0.357	0.373 (-0.059~0.804)	0.191	1	0.062
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)				

5. Discussion

To understand the role of online reviews in the local search context, this research examines how reviews affect the rankings of search results on LSPs. The results show that different rankings are generated across three LSPs and online reviews significantly contribute to the differences. Although it is exploratory, this study documents the significant technological environment for tourists' on-site decision-making and how online reviews are being used to create the environment.

5.1. Theoretical Implications

This research suggests that, despite a number of hospitality and tourism studies on online reviews, the specific form of eWOM remains a fascinating research topic in the field because it plays different roles within various contexts. With a focus on the current situation in which tourists access online reviews in an increasingly mobile and dynamic environment, this research, on one hand, points out one of the major limitations of the existing literature, which a lack of discussion about the role of online reviews in the during-trip search context. Building on this, future research could examine the effects of online reviews on tourists' perception or choice of a place in the local search context and explain how the role of reviews as tourists' decision cues is affected by the mobile, spontaneous, and intuitive aspects of on-site decision-making (Liu et al., 2022). On the other hand, this research prompts future researchers to challenge the basic assumptions about tourists' usage of online reviews (e.g., using online reviews through desktop computers before the trip). For example, future research could re-evaluate the findings of desktop-based online reviews in mobile or another device context (Mariani et al., 2019) or consider tourists' usage of the reviews in the post-trip stage, such as confirming or modifying their pre-visit destination image during writing the reviews (González-Rodríguez et al., 2016).

Secondly, this research extends the literature on the online tourism domain by initiating the discussion about LSPs, which are becoming increasingly influential in travel-related information search. This research describes how LSPs incorporate online reviews as social knowledge to represent the hospitality and tourism domain. Although this research focuses on LSPs, it implies that many other systems (e.g., OTAs, social networking websites, media sharing platforms) would represent the domain in their own way, which was not discussed in previous literature on information technology that supports travel information search (Xiang et al., 2008). To remain relevant, future research needs to keep up with how these systems represent the domain by using different types of data (e.g., social networking sites using the visit history or current location of user's friends) (Yang et al., 2012). Furthermore, this research reveals the "biases" in LSPs' representation created by the integration of online reviews in the ranking system (Lincoln, 2020). Building on previous research arguing the impacts of online representation on tourists' perception (Xiang et al., 2009), future researchers could extend the current study by examining the effects of the "biases" on tourists' on-site behavior.

5.2. Practical Implications

The current research offers several practical implications for LSPs and local tourism businesses. The findings show that each LSP treat 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 with 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 our findings, each LSP can differentiate itself with other competitors with respect to the ranking algorithms, and help tourists to select the platform with a specific reason. In that way, LSPs could retain their users more effectively.

In addition, we 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 thoroughly 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 in a target platform: If Bing is the main target, tourism businesses need to focus on increasing the number of reviews, but they also has to consider maintaining the higher mean rating if Yelp is the main target.

5.3. Limitations and Future Research Directions

This research has several limitations. First, Google, Bing, and Yelp are considered representative LSPs. While they are the top-ranked platforms for local searches, there are other popular LSPs such as Apple Maps (Shaw, 2020). Further, this study considers a particular tourism domain around a specific area (i.e., restaurants in LA). By adopting various LSPs or targeting different domains, future research needs to improve the generalizability of the results. Additionally, some potential ranking factors are not considered in the analysis, such as mentions in social media, domain authority of website, or quantity of inbound links to websites (Shaw, 2020). By taking into account those ranking factors, future research would be able to provide a complete picture of the ranking algorithms of LSPs.

Declaration of competing interests

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Online Appendix

Table A1. RBO scores of 67 three pairwise of comparisons

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