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Analyzing the Impact of COVID-19 on Travel and Search Distances for Prominent Landmarks: Insights from Google Trends, X, and Tripadvisor

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Abstract: The COVID-19 pandemic profoundly affected people's travel behavior and travel desires, particularly regarding trips to prominent destinations. This study explores the pandemic's impact on travel behavior and online search patterns for 12 landmarks across six continents, utilizing data from three online platforms, i.e., Google Trends, X, and Tripadvisor. By comparing visitation and search behavior before (2019) and during (2020/2021) the pandemic, the study uncovers varying effects on the spatial separation between user location and landmarks. Google Trends data indicated a decline in online searches for nearby landmarks during the pandemic, while data from X showed an increased interest in more distant sites. Conversely, Tripadvisor reviews reflected a decrease in the distance between users' typical review areas and visited landmarks, underscoring the effects of international travel restrictions on long distance travel. Although the primary focus of this study concerns the years most affected by COVID-19, it will also analyze Tripadvisor data from 2022 to provide valuable insights into the travel recovery beyond the pandemic.

Keywords: pandemic; travel behavior; big data; social media; point of interest

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1. Introduction

The influence of COVID-19 on global travel has been profound and far-reaching since travel restrictions and border blockades in many countries led to a sharp decline in international travel [1]. Prominent landmarks are iconic symbols of a destination's cultural and historical significance that serve as tourist magnets and attract travelers from across the globe. This makes them crucial elements in studying global travel trends [2]. Visitation patterns of landmarks reflect disruptions to international travel caused by events such as pandemics, as well as shifts in travel interest. Big data from crowdsourcing and social media platforms offer valuable access to global spatio-temporal information related to landmarks, enabling a deeper analysis of the pandemic's effects on individuals' travel behavior and interest in visiting prominent sites. While some earlier studies investigated the effects of COVID-19 on user behavior within specific regions [3,4], a global analysis of the pandemic and its effects on travel and search behavior based on crowdsourced data is rare.

Crowdsourced contributions of spatial data can be active, e.g., when participating in citizen science projects, or passive, e.g., when sharing posts on social media apps [5]. Crowdsourced data are shared through a variety of online platforms. Each platform offers different primary functionalities, such as social networking, sharing ground-based or drone-based landscape imagery, provision of reviews for different types of points of interest

(POIs), or searching the internet for location information [5,6]. Since crowdsourced data are produced and shared by the user community, they are also commonly referred to as user-generated content (UGC) [7]. Prominent examples of platforms that publish UGC are X, a social media platform where users communicate primarily through posts (tweets), and Tripadvisor, a global travel website that allows individuals to review tourist sites, hotels, and other travel-related locations. Google Trends data is based on user-related online operations, i.e., web searches, and provides both spatial and temporal search statistics.

Previous studies explored the effect of COVID-19 on actual travel behavior [1,8], changes in travel plans, or interest in travel caused by the pandemic [9,10], but did not jointly analyze them or compare their outcomes.

One of the innovative aspects of this research is the examination of changes in both factual (Tripadvisor) and aspirational (X, Google Trends) travel behavior resulting from the pandemic. The study focuses on the spatial separation between users of various platforms and the landmark of interest, using UGC. It characterizes the spatiotemporal information provided by each data source regarding factual or aspirational travel, highlighting the specific aspects of travel behavior that each can help to illuminate. The study also advances the analyses of various UGC sources. For example, Google Trends data has primarily been used to monitor local search trends related to disease outbreaks, tourism demand, and local transportation use, such as ferries [11,12]. By utilizing this data to analyze aspirational travel toward specific landmarks while considering the spatial separation between those landmarks and the countries initiating searches, we can more closely examine the role of geography in changing travel aspirations during a pandemic. Additionally, while Tripadvisor reviews have been used to explore the trend towards more local travel to selected landmarks in the U.S. during COVID-19 [13], this study broadens the geographic scope to six continents, enhancing the generalizability of previous findings.

For this purpose, we selected two prominent landmarks from each continent, excluding Antarctica (Figure 1). These landmarks were identified based on web searches for notable sites across the continents, as well as the volume of Tripadvisor reviews they received. The analyzed landmarks may belong to multiple categories, including cultural, physical, natural, artificial, historical, and religious.

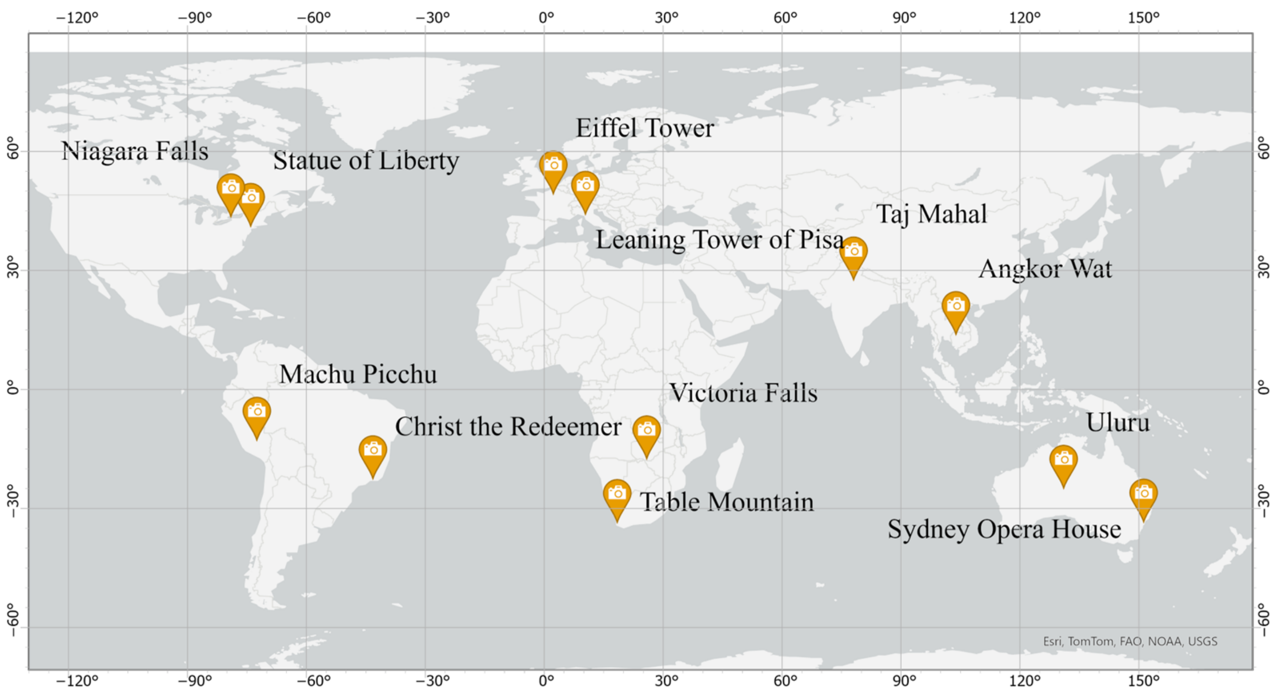

Figure 1. Landmarks analyzed.

The objectives of this study are to analyze the changes in:

- Spatial patterns of online searches on Google for the chosen landmarks;
- The distance between the locations of tweets mentioning these landmarks and the landmarks;
- The distance between users' review activity areas on Tripadvisor and the location of the landmarks.

The study analyzes the annual changes in travel or searches based on UGC gathered for up to four years (depending on the type of analysis conducted), i.e., between March 2019 and February 2023. The annual time periods within that range were selected using the following rationale:

- Period 1 (March 2019–February 2020): "Business as usual". Few to no travel restrictions;
- Period 2 (March 2020–February 2021): "Pandemic onset". On 11 March 2020, COVID-19 was declared a global pandemic [14], followed by an increasing number of travel restrictions, both domestic and international;
- Period 3 (March 2021–February 2022): "Pandemic stabilization". Following the development of COVID-19 vaccines, a significant share of the population is vaccinated. For instance, in the US, 100 million people had been vaccinated by 12 March 2021. The travel restrictions are gradually lifted for eligible travelers e.g., those with "vaccine passports";
- Period 4 (March 2022–February 2023): "New normal". Travel restrictions are being removed for all travelers for the majority of destinations.

To accomplish the research objectives, the study uses tourists' digital footprints, including Google Trends data, tweets, and Tripadvisor reviews to explore user behavior changes during the COVID-19 pandemic. The datasets cover different aspects of user behavior information, allowing for the exploration of behaviors from various perspectives.

2. Literature Review

The COVID-19 pandemic has exerted a significant change on human mobility [15], resulting in a notable decrease in travel [16–19]. This is largely due to imposed travel restrictions in most regions around the world [20]. In addition, high infection rates diminished the travel appeal of affected countries, leading to a decline in international tourist arrivals [21]. As a result, many travelers delayed their holiday trips until after the pandemic while others changed their travel plans in favor of domestic destinations closer to their homes [22]. Analysis of tweets in London revealed a shift towards fewer but longer trips during the pandemic [23]. COVID-19 was also found to cause a drop in visitation to entertainment, food, medical, and shopping venues [24] and local parks [25]. The pandemic caused a shift in transportation modes and travel purposes towards reduced use of public transit, increased use of private cars, and a reduction in work trips [26]. Skyscanner data on air travel searches revealed a 30% drop in Europe and the Americas and a 50% drop in Asia, following the pandemic onset [27].

Tripadvisor is a widely used data source for analyzing user behavior, including destination choice [28]. One study utilized Tripadvisor data to capture travelers' reactions during the early stages of the COVID-19 pandemic, which often led to trip cancellations [29]. Similarly, another analysis of Tripadvisor data during the pandemic stabilization period examined travelers' concerns and travel behavior patterns [30].

Another valuable source of spatial footprint data on COVID-19 travel is the Google Communities Mobility Reports, available at https://www.google.com/covid19/mobility/ (accessed on 12 October 2024). Unlike traditional social media platforms, these reports do not contain publicly shared UGC. Instead, they are derived from the location history of Google Maps users who have opted into this service (Note that Google Maps users may opt out of sharing their locational history; we are not aware of their percentage and how it affects results generalizability). The dataset includes changes in visitation patterns across several categories of locations, including parks, at a spatial granularity of country level. Alongside other data sources, Google mobility data was utilized to assess the differential impact of COVID-19 on the tourism industry in Indonesia [31]. Other examples of (involuntarily) shared digital footprint data are credit card transactions and mobile phone data. A widely used source of mobile phone-based travel data is SafeGraph, available at www.safegraph.com (accessed on 12 October 2024), which provides visitation data at the POI level. One study analyzed shifts in visitations to attractions in Florida and New York using SafeGraph data and compared these changes to those observed in UGC platforms [13]. Another study employed SafeGraph data to investigate the impact of COVID-19 on visitation patterns in US national parks, revealing a shift towards locations closer to home [32].

Many researchers used personal search patterns from Google Trends, available at https://trends.google.com/trends/ (accessed on 12 October 2024) to explore temporal and spatial patterns of major topics of interest, e.g., to predict tourism demand [33–35]. Google Trends data were found to be highly responsive to social events, suggesting their usefulness for monitoring COVID-19 case dynamics [36]. For instance, a decline in search terms associated with overseas travel was reported during the onset of the pandemic [11], and a time series model forecasting tourism arrivals to Indonesia following the onset of COVID-19 was parametrized using Google Trends [37].

Overall, three categories of digital footprint data are commonly used in tourism publications: (1) locational information "involuntarily" shared by travelers using mobile devices such as mobile phones and credit card usage, (2) "involuntary" textual data generated by user online operations such as web search, and (3) voluntary UGC provided on social media, both generic (e.g., X, Instagram) and travel-specific [38]. The ever-increasing number of publications on travel demand and destination management utilizing these categories of Big Data [27] is driven by the advantages derived from the massive volume (including high temporal and/or spatial resolution) and velocity of data generation [39]. However, the digital footprint of big data has inherent unreliability, imprecision, uncertainty, and bias [40,41]. Because of privacy concerns, users often distort or omit self-identified profile location information in social media and crowdsourcing platforms [42,43]. The accuracy of self-declared home location is also influenced by gender and age [44]. Alternative methods to deduce a user's home location include using the city with the highest number of geotagged tweets, pinpointing the location of a user's main area of activities [27], or calculating the geometric median of geotags [45,46].

3. Data and Methods

The three analyzed data sources offer distinct types of spatio-temporal information on user travel and search behavior (Table 1), allowing them to complement one another in effectively describing and capturing user behavior.

Table 1. Data source illustration.

Data Source	Data Unit	Data Location	User Home Location	Temporal Information
Google Trends	Search rate over time by region	Country	Unknown	Date range
X	Tweet	Individual tweet	Unknown	Posted time
Tripadvisor	Review	POI location	User profile/history	Visit and posted time

Google Trends show the relative search interest (as a temporal search interest index) for a landmark in specific regions, such as countries, over a pre-defined time period. The data do not allow the inference of an individual user's location but provide aggregated information only. Since this study analyzes geotagged tweets, the tweet position, combined with the tweet text about the landmark in question, can be used to compute the distance between the tweet location and the mentioned landmark. However, the user's home location is unknown since the corresponding information in user profiles has been found to be unreliable or incomplete [43,47]. Alternative methods to infer a user's typical contribution area would require a user's history of tweets [48] which was, however, not collected in this study since the focus was on landmark-related tweets during the data download, and the use of currently available X APIs to download historical tweets is prohibitively expensive. The history of a user's reviews on Tripadvisor allows for the inference of their main activity area and thus to estimate their travel distance to a landmark in question. Since earlier studies demonstrated a significant mismatch between the home location provided on Tripadvisor user profiles and the history of user contributions [13], this study uses the latter to determine a user's main activity area. The timestamp of a Tripadvisor review submission may differ from the actual time the user visited the landmark and may thus be delayed. A major difference between the three data sources is that, in order to provide a review on Tripadvisor, the user needs to physically travel to the landmark prior to posting a review, whereas a site visit is not necessary to tweet about a landmark on X or conduct an online search for a landmark on Google. This, in turn, means that Tripadvisor data are more suitable for travel distance modeling whereas tweets and Google searches provide insights into people's interest in a landmark in combination with their whereabouts during tweeting or searching activities.

3.1. Google Trends

Google Trends provides information about temporal and spatial online search patterns using a temporal and spatial search interest index. The data are based on the search penetration rate (percentage of search term requests normalized from 0 to 100) and come in two representations, namely (1) as a temporal plot with a daily to yearly temporal resolution for a selected geographic region, and (2) as a list of values with city to country spatial resolution, based on user settings. As an example, Figure 2 shows the worldwide temporal search interest index of Angkor Wat (Cambodia) between January 2018 and March 2023 with a weekly temporal resolution. The plot demonstrates a clear drop in search interest in the landmark at the onset of the pandemic around March 2020, with search interest rebounding in early 2022. The maximum number of requests per week at the beginning of 2019 corresponds to the maximum index value of 100.

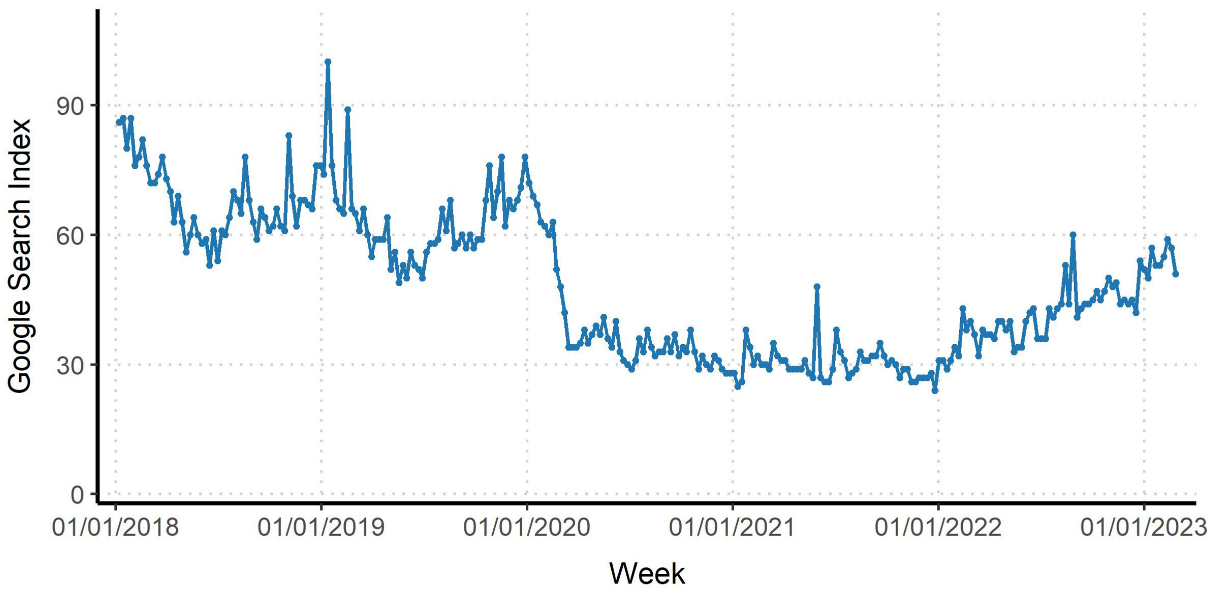

Figure 2. Angkor Wat Google Trends weekly search interest index.

The spatial search interest index represents spatial variability in search prompts within the sub-regions of the selected area, e.g., within countries for a worldwide search. Similar to the temporal search interest, the spatial index is normalized from 0 to 100, with the value of 100 representing the region with the highest penetration rate. For our study, search interest indices were collected for all 12 prominent landmarks originating from each country.

More specifically, the study considered only the countries that were among the top 50 in terms of the search interest index value (countries with ties on the lower index end were also retained which could lead to more than 50 countries for some landmarks) and whose search index value was greater than 1 (Table 2), thereby excluding the countries with a low interest in an attraction. Hence, the final dataset contained the temporal index reflecting the weekly number of internet searches for each of the study attraction points, with the searches originating from at most about 50 countries that were most interested in the attraction.

Table 2. Number of countries associated with 12 landmarks exhibiting a search interest index > 1.

Landmark	**Eiffel Tower**	**Leaning Tower of Pisa**	**Uluru**	**Sydney Opera House**	**Taj Mahal**	**Angkor Wat**
Countries	52	54	49	56	51	24
Landmark	Statue of Liberty	Niagara Falls	Machu Picchu	Christ the Redeemer	Victoria Falls	Table Mountain
Countries	52	51	52	59	50	24

For each country associated with a given landmark, the weekly search interest index values were extracted for the pre-pandemic period (1 March 2019 through 29 February 2020) and the pandemic period (1 March 2020 through 28 February 2021) from the 4-year dataset. By comparing these time series data between the two years, one can determine on a country-specific basis if there was a decline in search interest during the pandemic for a given landmark. Specifically, we calculated the mean weekly search index values for 2019 and 2020 for (1) the country where the landmark is located (local mean) and (2) all other countries (global mean). This allows us to measure the drop in search interest for both the local country and the remaining countries and compare these decreases. This comparison indicates whether the decline was more pronounced for the local country than for the global context.

3.2. X

Tweets were downloaded using two Twitter APIs: "standard v1.1" API and the "GET geo/reverse_geocode" API using the Request Python library. Only tweets related to the landmarks and falling within the period of interest were retained for further analysis, based on the following criteria:

1. Tweets mentioning landmark names, such as "Niagara Falls" or "Machu Picchu". This was achieved by incorporating the relevant search terms in the API scripts.
2. Tweets with geolocation information, which was implemented by including "has:geo" in the API search parameters.
3. Tweets posted between 1 March 2019 and 28 February 2023.

Tweets collected for the 12 landmarks were stored in a PostgreSQL database, including tweet ID, author ID, place ID, tweet content text, language, creation time, bounding box, coordinates, and position place type. The bounding box represents four coordinate points within which the tweet's position is located. It can enclose an exact location, a specific street, a POI, or an entire country. In the absence of exact coordinates, the centroid of the bounding box was used to determine the distance between the tweeting position and the landmark mentioned in the tweet.

The Twitter API used fuzzy search, which means that search results do not necessarily contain the exact search terms. For example, the "Table Mountain" POI search may return a tweet, "There is a table on the top of the mountain". Hence, retrieved tweets were filtered to remove those unrelated to the respective POI. The detailed filtering procedure is described in Appendix A. The number of tweets downloaded and retained for further analysis are listed in Table 3.

Table 3. Number of collected and retained tweets.

Landmark	Eiffel Tower	Leaning Tower of Pisa	Uluru	Sydney Opera House	Taj Mahal	Angkor Wat
Collected	30,186	4212	6313	10,792	25,975	10,096
Retained	27,576	3837	4225	9151	19,616	8478
Landmark	Statue of Liberty	Niagara Falls	Machu Picchu	Christ the Redeemer	Victoria Falls	Table Mountain
Collected	29,079	53,876	17,105	2907	7817	11,270
Retained	22,754	46,928	15,418	1877	6186	7946

For each landmark, the increase or decrease in mean distances between the pre-pandemic period (1 March 2019 through 29 February 2020) and during the pandemic (1 March 2020 through 28 February 2021) were computed. In addition, the rank-biserial correlation effect size was computed to further quantify the difference in distance between the two years.

Absolute correlation values below 0.05 are considered negligible, while correlations between 0.05 and 0.2 are classified as small. Correlations ranging from 0.2 to 0.3 indicate a medium effect, those between 0.3 and 0.4 represent a large effect, and values above 0.4 are deemed very large effects [49]. This framework provides a nuanced approach for evaluating the practical significance of the observed differences in our study.

3.3. Tripadvisor

Customized Python scripts were used to scrape reviews posted between March 2019 and February 2023 from Tripadvisor websites for the 12 landmarks using the Selenium and BeautifulSoup4 Python libraries. The following data was stored for each review: review text, reviewer's nickname, reviewer's self-provided home location, reviewer's Travel Map (visited cities), and visit and post time stamps. For each landmark, between 2000 and 10,000 reviews were extracted. Many reviewers provided abstract or non-specific home locations for their user profiles, such as "Earth" or "Somewhere in England". To check the validity of home location data in user profiles, the countries of the top three contributed places from each reviewer's Travel Map were identified using the Python Geopy library and subsequently compared with the country specified in the user profile.

Table 4 shows the percentage of Tripadvisor profiles whose user country matched and mismatched, respectively, contribution countries extracted from user Travel Maps between March 2019 and February 2023. We considered a match to be present if the self-provided home country matched any of the countries of the top three most frequently visited locations of a user. Table 4 also lists the percentage of Tripadvisor profiles that lack location information. Because of these low matching rates and the substantial number of missing location entries, we used reviewer contribution history, and not reviewer profile information to determine a reviewer's main activity area of contributions.

Table 4. Match, mismatch and missing proportion of Tripadvisor profile locations.

Landmark	Eiffel Tower	Leaning Tower of Pisa	Uluru	Sydney Opera House	Taj Mahal	Angkor Wat
Match (%)	56.0	62.5	73.1	61.5	53.7	45.0
Mismatch (%)	27.4	23.6	10.9	23.6	30.0	37.3
Missing (%)	16.6	13.9	16.0	14.9	16.3	17.7
N	5658	2664	499	2983	2857	3115

Table 4. *Cont.*

Landmark	Statue of Liberty	Niagara Falls	Machu Picchu	Christ the Redeemer	Victoria Falls	Table Mountain
Match (%)	64.2	63.2	56.8	60.5	52.2	56.4
Mismatch (%)	21.6	22.4	26.3	21.9	35.2	31.7
Missing (%)	14.2	14.4	16.9	17.6	12.6	11.9
N	4027	2498	1323	4073	673	2186

To improve location quality, Tripadvisor reviews from reviewers for whom the self-provided home country did not match the Travel Map history were removed from further analysis (Table 5).

Table 5. Number of collected and filtered Tripadvisor reviews.

Landmark	**Eiffel Tower**	**Leaning Tower of Pisa**	**Uluru**	**Sydney Opera House**	**Taj Mahal**	**Angkor Wat**
Collected	5658	2664	499	2983	2857	3115
Filtered	3169	1664	365	1836	1535	1403
Landmark	Statue of Liberty	Niagara Falls	Machu Picchu	Christ the Redeemer	Victoria Falls	Table Mountain
Collected	4027	2498	1323	4073	673	2186
Filtered	2584	1578	751	2463	351	1233

The great circle distance between the reviewer's main activity area (mostly specific at the city level, but occasionally also at the country or province level) and the landmark was computed using the Geopy Python library. To analyze the effect of the pandemic on travel distances, the reviews were separated into one-year periods and the review distances for the three years after the onset of the pandemic were compared to the baseline (pre-pandemic year of 2019). A significant percentage of Tripadvisor reviews include a timestamp indicating the month a landmark was visited, allowing us to estimate the delay between visitation and posting. Table 6 presents the mean delay, expressed in months, for filtered reviews posted in a given year, along with the number of reviews and the percentage that include a visitation timestamp. For most landmarks and years, mean delays are typically just a few months, with slightly longer delays observed for reviews posted in 2020 and 2021. This suggests that a considerable number of visits in 2019 were reviewed in 2020, potentially leading to an underestimation of reduced travel due to the pandemic in 2020. Likewise, some trips impacted by the pandemic may only be reflected in reviews posted in 2021. Therefore, to quantify changes in travel behavior, we compared the data from 2019 and 2021, rather than including 2020.

Table 6. Mean delay (in months) of posted Tripadvisor reviews.

		2019	**2020**	**2021**	**2022**			**2019**	**2020**	**2021**	**2022**
Eiffel Tower	Delay	1.2	4.4	1.7	1.2	Statue of Liberty	Delay	1.2	3.3	0.9	1.1
	Reviews	2592	147	82	348		Reviews	2150	141	90	203
	% Visit	98.2	98.0	100.0	98.9		% Visit	61.6	58.2	78.9	60.1
Leaning Tower of Pisa	Delay	1.1	2.6	2.5	1.0	Niagara Falls	Delay	1.0	2.1	0.4	0.9
	Reviews	1171	216	121	156		Reviews	1223	121	57	177
	% Visit	46.6	17.6	14.9	39.1		% Visit	75.6	71.9	78.9	74.0

Table 6. *Cont.*

		2019	2020	2021	2022			2019	2020	2021	2022
Uluru	Delay	0.7	1.8	1.5	0.9	Machu Picchu	Delay	1.4	5.1	1.5	1.3
	Reviews	235	48	35	47		Reviews	572	59	36	84
	% Visit	78.7	87.5	91.4	85.1		% Visit	35.1	20.3	47.2	39.3
Sydney Opera House	Delay	1.2	2.4	1.6	0.6	Christ the Redeemer	Delay	1.3	2.1	1.9	1.1
	Reviews	1479	182	40	135		Reviews	1818	319	142	184
	% Visit	79.9	83.0	85.0	73.3		% Visit	23.3	18.5	8.5	23.9
Taj Mahal	Delay	1.4	2.3	1.2	1.3	Table Mountain	Delay	1.8	0.7	3.6	2.2
	Reviews	1196	158	54	127		Reviews	375	50	9	799
	% Visit	76.3	71.5	92.6	80.3		% Visit	73.9	66.0	55.6	44.2
Angkor Wat	Delay	1.0	2.3	2.9	1.3	Victoria Falls	Delay	0.9	3.7	1.7	0.5
	Reviews	1104	163	14	122		Reviews	271	27	9	44
	% Visit	81.0	71.8	50.0	78.7		% Visit	73.8	85.2	77.8	81.8

4. Results

4.1. Google Trends Index Values

There was a decline in weekly search interest index values between 2019 and 2020 for all 12 landmarks (Table 7). That is, the pandemic led to a lower interest in all landmarks, both in the country of the landmark (local) and worldwide (global), but more so for the landmark country (local) than for other countries (global).

Table 7. Google Trends search index values for local and other countries (SD in parentheses) and their change between 2019 and 2020.

Landmark	Local Mean (SD) (2019)	Local Mean (SD) (2020)	Global Mean (SD) (2019)	Global Mean (SD) (2020)	Local Mean Decrease (%)	Global Mean Decrease (%)
Eiffel Tower	52.12 (13.48)	24.70 (7.84)	63.31 (8.02)	43.24 (4.02)	52.61	31.70
Leaning Tower of Pisa	45.90 (16.07)	19.64 (10.77)	50.31 (4.65)	40.55 (10.31)	57.21	19.40
Uluru	48.33 (16.09)	26.02 (6.53)	33.63 (11.43)	19.57 (3.63)	46.16	41.81
Sydney Opera House	35.00 (4.86)	11.51 (4.18)	30.60 (3.37)	19.64 (8.37)	67.11	35.82
Taj Mahal	62.21 (9.76)	39.30 (5.83)	64.46 (7.34)	43.15 (4.79)	36.83	33.06
Angkor Wat	54.69 (13.21)	16.02 (6.89)	62.98 (7.04)	34 (4.75)	70.71	46.01
Statue of Liberty	15.92 (3.77)	10.34 (3.17)	51.92 (7.69)	41.25 (7.87)	35.05	20.55
Niagara Falls	50.46 (20.60)	28.36 (12.51)	37.63 (7.86)	27.36 (5.51)	43.80	27.29
Machu Picchu	57.65 (10.31)	30.98 (16.11)	42.42 (4.73)	26.96 (3.98)	46.26	36.45
Christ the Redeemer	23.31 (6.75)	18.75 (5.94)	17.71 (2.60)	15.58 (3.35)	19.56	12.03
Table Mountain	29.21 (11.41)	14.49 (8.31)	26.35 (5.07)	15.94 (3.91)	50.39	39.51
Victoria Falls	51.81 (16.47)	22.25 (13.86)	29.69 (12.25)	18.66 (4.08)	57.05	37.15

To provide refined insight into the role of distance in Google search patterns, a drop rate was computed by subtracting the 2019 mean search rate from the 2020 mean search rate for each country. Using ordinary least squares regression, the relationship between the distance to the landmark for included countries and the drop rate was visualized (Figure 3). The regression lines clearly demonstrate that the search interest decreased more strongly with proximity to the landmark, whereas this effect fades for countries further away from a landmark of interest.

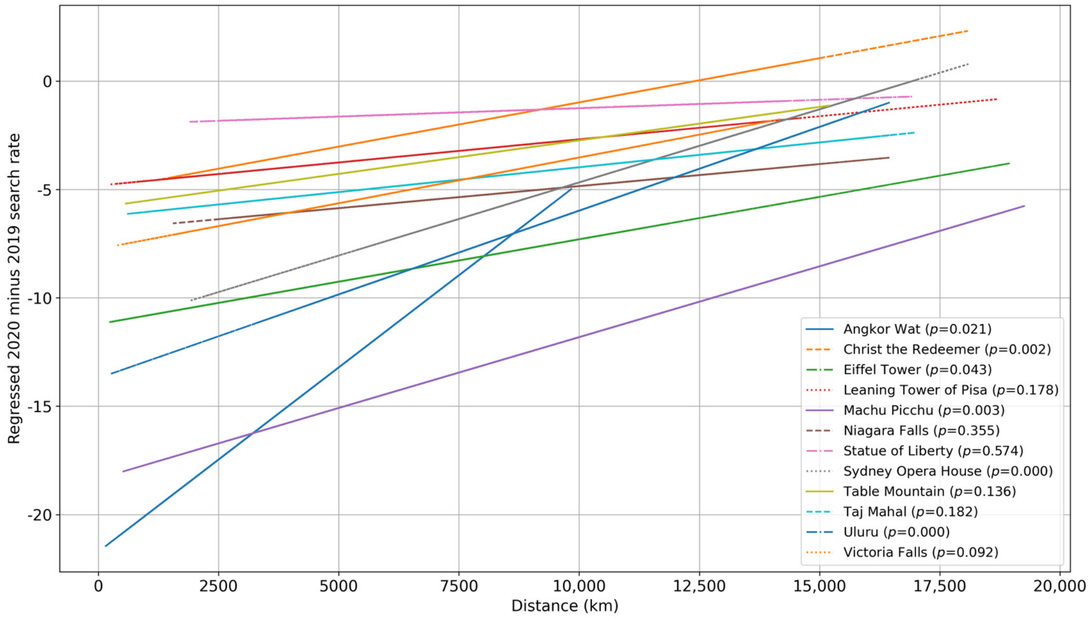

Figure 3. Regression between Google Tends drop rate and distance from country to landmark.

4.2. Tweeting Distances

Table 8 shows that distances between a tweeting location and the landmark mentioned in a tweet increased with the onset of the pandemic (last column). At the same time, the number of tweets mentioning a corresponding landmark decreased (second data column).

Table 8. Descriptive statistics of tweeting distances (in km) for 2019 and 2020 (SD in parentheses) and effect size.

Landmark	N (2019)	N (2020)	Mean (SD) (2019)	Mean (SD) (2020)	Effect Size	Relative Increase in Mean (%)
Eiffel Tower	9425	2596	1863 (3457)	4713 (3989)	0.47	153.0
Leaning Tower of Pisa	1231	444	1732 (3424)	3796 (4219)	0.33	119.2
Uluru	1551	525	2479 (4242)	4661 (5892)	0.18	88.0
Sydney Opera House	3306	1024	1347 (4165)	1570 (4396)	0.04	16.6
Taj Mahal	4758	3389	3548 (5070)	4491 (5251)	0.19	26.6
Angkor Wat	2828	727	661 (2207)	935 (2674)	0.02	41.5
Statue of Liberty	6190	3028	1830 (3393)	3037 (4009)	0.24	66.0
Niagara Falls	12,708	6835	495 (1847)	868 (2417)	0.16	75.4
Machu Picchu	4880	2089	1918 (3683)	3201 (4356)	0.27	66.9
Christ the Redeemer	574	530	4106 (5139)	7360 (4200)	0.40	79.3
Table Mountain	2529	1373	2220 (4647)	2559 (4937)	0.05	15.3
Victoria Falls	1463	1007	2231 (4193)	2360 (4074)	0.14	5.8

The Eiffel Tower exhibited the highest relative increase in distance, at 153.0%, while Victoria Falls recorded the lowest increase, at just 5.8%. Out of the twelve landmarks, nine had an effect size greater than 0.1, indicating notable changes in travel patterns. Figure 4 shows the probability density plot of tweet distances for each landmark before and during

COVID-19. Visual inspection clearly identifies a notable drop in short distances for 2020 compared to 2019, which led to the relative increase in distances for 2020.

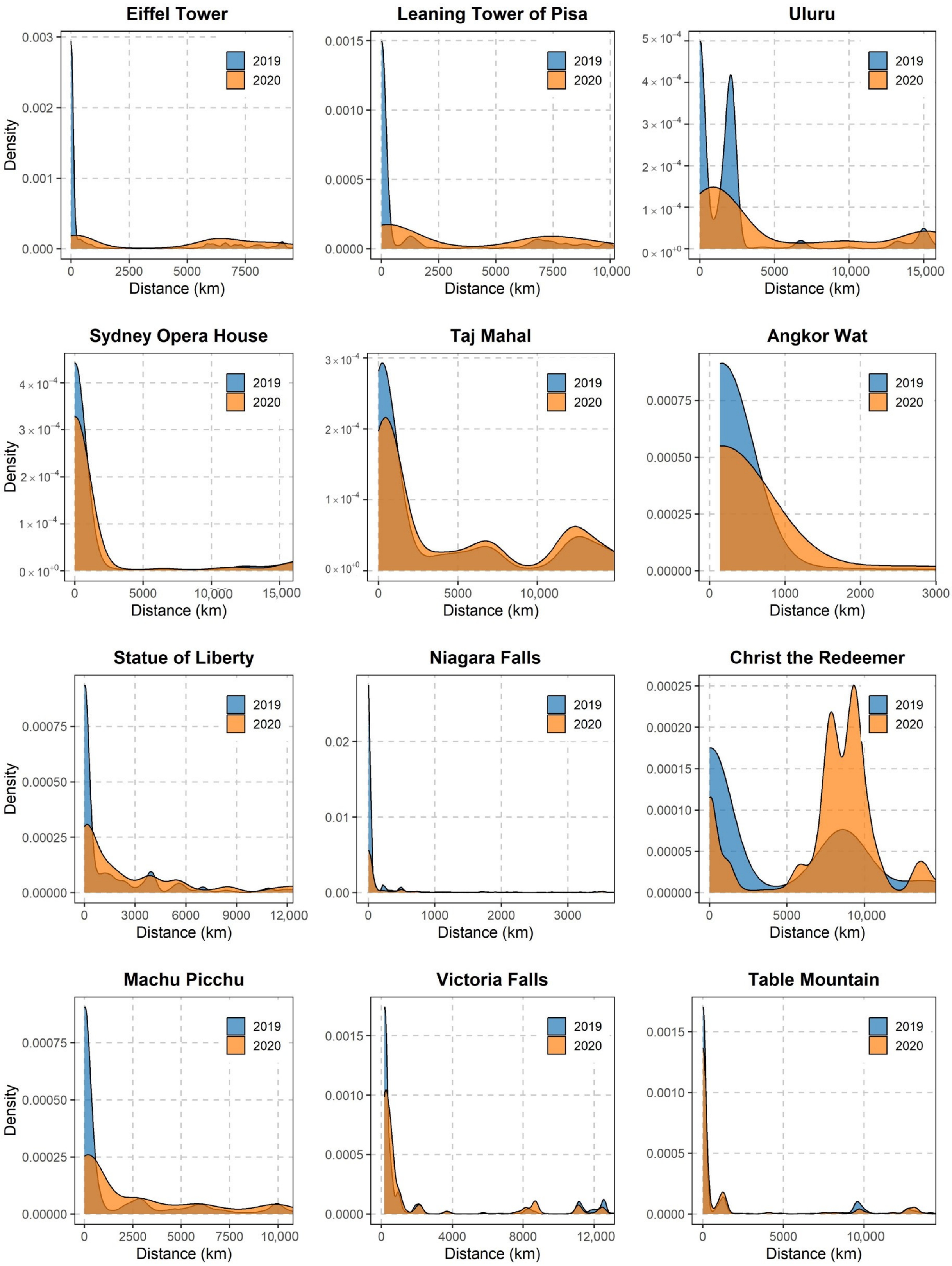

Figure 4. Probability density plot of tweeting distances for 12 landmarks.

4.3. Tripadvisor Travel Distance

Table 9 provides descriptive statistics of estimated distances between a user's main contribution area and a landmark location for 2019 and 2021. For 10 out of 12 landmarks, distances decreased between these two years, meaning that users tended to provide Tripadvisor reviews from locations closer to the landmarks during the pandemic than in 2019. The last column with more recent data from 2022 indicates that mean trip distances to the same 10 landmarks have increased compared to 2021. This suggests that travel behavior to these landmarks is normalizing and gradually returning to pre-pandemic patterns. Contrasting effects are evident for the two analyzed landmarks in Africa, i.e., Table Mountain and Victoria Falls. This discrepancy may be due to the limited number of reviews in 2021 (only nine) and the small number of neighboring countries from which travel reviews were submitted, resulting in unstable numerical results for distance changes.

Table 9. Descriptive statistics of Tripadvisor distances (in km) for 2019 and 2021 (SD in parentheses) and their change, and of distances (in km) for 2022 post-pandemic.

Landmark	N (2019)	N (2021)	Mean (SD) (2019)	Mean (SD) (2021)	Effect Size	Mean Decrease (%)	Mean (SD) (2022)
Eiffel Tower	2592	82	5719 (4444)	4303 (3562)	−0.171	24.76	4668 (3785)
Leaning Tower of Pisa	1171	121	3403 (4128)	1103 (2082)	−0.444	67.58	2538 (2082)
Uluru	235	35	6124 (5768)	3383 (3727)	−0.235	44.76	7627 (6516)
Sydney Opera House	1479	40	10282 (6525)	3863 (6126)	−0.493	62.43	9441 (6980)
Taj Mahal	1196	54	6203 (4306)	2222 (3450)	−0.550	64.17	4556 (4455)
Angkor Wat	1104	14	7987 (4697)	5433 (4704)	−0.308	31.98	7836 (4904)
Statue of Liberty	2150	90	5226 (3572)	3464 (3538)	−0.333	33.72	4854 (2854.)
Niagara Falls	1223	57	3727 (3945)	2093 (2769)	−0.318	43.83	3513 (3247)
Machu Picchu	572	36	6419 (4398)	4494 (3454)	−0.228	29.99	5521 (3346)
Christ the Redeemer	1818	142	4292 (4265)	1688 (2887)	−0.327	60.67	3677 (4026)
Table Mountain	375	9	7714 (4760)	8635 (3242)	0.136	-11.94	8146 (4523)
Victoria Falls	271	9	9262 (4226)	9823 (5509)	0.139	-6.06	7700 (4930)

5. Discussion

5.1. The Pandemic and Its Effect on Travel and Search Distances to Landmarks

All three platforms demonstrate a change in spatial separation between users and landmarks during the pandemic, albeit in different directions. With the onset of the pandemic, Google search interest for all 12 landmarks decreased (Table 7). This could be attributed to fewer planned trips due to travel bans, closed facilities, and the perceived risk of COVID-19 infections among tourists [50]. Within this general trend, the number of online searches for a landmark experienced a stronger drop in countries near the landmark in question (Figure 3), revealing a relative increase in search interest for more distant landmarks during COVID-19. Travel inspiration, i.e., dreaming about a destination [51], and motivational factors related to travelling to remote destinations, such as scenery and exotic experience [52], may contribute to this increased search interest. It may also reflect a strong desire to travel to remote tourism destinations during the pandemic [53].

Tweets revealed an increase in spatial separation between tweeting and landmark location between 2019 and 2020 which shows that X users kept posting about remote landmarks during the pandemic. This suggests that users retained interest in more exotic landmarks and probably had an interest in visiting them. Thus, conclusions are similar to those found from search pattern changes during COVID-19 in Google Trends data.

For Tripadvisor, a relative increase in visitations to nearby (local) landmarks during the pandemic, compared to pre-pandemic levels, is supported through earlier findings which demonstrated an increase in the proportion of local visitors to Florida state parks during COVID-19 based on Tripadvisor and Yelp review data [54]. Such a change in travel patterns can be attributed to the challenges faced by travelers from distant regions, such as travel restrictions and concerns of catching COVID-19 associated with long travel times [55].

5.2. UGC Data Quality

The unstructured text in tweets necessitated the use of algorithms, such as generating n-grams, to identify tweets referencing physical landmarks. The need for a manual validation process limits automated transferability to other landmarks and also reveals challenges associated with the analysis of unstructured data [56]. Certain UGC sources provide textual information that reflects travelers' sentiments and emotions about their experiences [57]. They can capture destination images and their resilience during crises, such as pandemics [58], and even influence the travel decisions of others, particularly spontaneous tourists [59]. In our study, we utilized locational data and timestamp information, which are objective and not influenced by emotions, to model changes in travel behavior and interest in landmarks. Future research could integrate semantic UGC insights into spatio-temporal travel analyses, potentially offering refined explanations for observed changes in user behavior during the pandemic. In terms of the timeliness of UGC, users often share their experiences immediately, allowing for faster detection of events like flu epidemics or earthquakes compared to official reports, as demonstrated by tweets [60]. Additionally, Google search results are generated in real-time. Given that our study focuses on timeframes spanning a year, we do not anticipate significant impacts from any delays in publishing for tweets or Google search results.

Data quality aspects within Tripadvisor relevant to our analysis encompass two key aspects, namely the accuracy of profile locations and delays of reviews. A review of Tripadvisor user profiles showed that a high percentage of user profiles either lack self-location information or provide an inaccurate location (Table 4). This led us to rely on the user's history of reviews, including Travel Map information, to determine a user's main activity area instead. Delays of up to several months between the visitation of a landmark and the posting of a review were observed on Tripadvisor, with average delays being greater for reviews posted in 2020 compared to other years. This delay was taken into account when analyzing changes in user visitation across different years, specifically when comparing data from 2019 and 2021. The significant impact of the pandemic on Tripadvisor review numbers in 2021 is evident in Table 10, which shows that each landmark received the lowest review count of the four-year period that year. Delays in user-shared information are also evident on other non-time-sensitive crowdsourcing platforms. For instance, on Flickr, delays can be calculated by comparing the EXIF data of images with their upload timestamps [61]. To ensure trustworthiness in its reviews, Tripadvisor uses an elaborate algorithm to detect and remove fake reviews, which were about 9% of submissions in 2020 [62]. The platform also employs review auditors to verify fake review detection performance.

Table 10. Sample size for Tripadvisor across four years.

Landmarks	2019	2020	2021	2022	Total
Eiffel Tower	4518	298	169	673	5658
Leaning Tower of Pisa	1837	337	200	290	2664
Uluru	352	56	40	51	499
Sydney Opera House	2404	277	51	251	2983
Taj Mahal	2236	273	81	267	2857
Angkor Wat	2432	348	35	300	3115
Statue of Liberty	3329	226	134	338	4027
Niagara Falls	1976	180	81	261	2498
Machu Picchu	983	93	77	170	1323
Christ the Redeemer	3053	473	214	333	4073
Victoria Falls	514	43	21	95	673
Table Mountain	665	79	18	1424	2186

A potential limitation of the study is that the selection of the 12 landmarks reflects only renowned international travel destinations and might therefore not adequately encompass visitation patterns to less prominent landmarks. Landmarks analyzed in this study were selected based on the volume of UGC available for analysis. Despite this criterion, limited data availability for certain regions and data sources, such as the Google Trends dataset for landmarks in Africa, could yield inaccurate results. Similarly, Tripadvisor data suffers from data scarcity for some regions, as indicated by just nine reviews for Table Mountain and Victoria Falls in 2021.

Finally, social platform penetration rates vary across countries, cultures, and demographics, leading to potential user selection or sample bias [63]. Consequently, conclusions drawn from UGC analysis may not accurately represent the entire population and may overlook the perspectives of less privileged groups, posing challenges for interpreting the results [40]. Similar inconsistencies in result interpretations may originate from differences in the socio-demographic profiles of travelers. Future studies may explore the possibilities of weighing social media data by social media percolation rate for specific population strata.

5.3. Contribution Recovery

While a substantial body of research has analyzed the immediate effects of the pandemic on travel behavior, recent studies have begun to explore the recovery process in the post-pandemic context, offering a broader perspective [64]. One study, for example, revealed that the recovery process for rural tourist destinations in China differs for different types of rural tourist destinations, yet overall the rural tourism market has yet to fully recover [65].

Using annual review numbers on Tripadvisor over the course of four years, Table 10 shows a strong decline in review activities for all 12 landmarks from 2019 to 2020, and from 2020 to 2021. This is followed by a moderate increase in 2022, suggesting a partial, but not complete, recovery in travel activity to desired locations after the pandemic, supporting findings from previous research [65,66]. As previously noted in connection with Table 9, the 2022 data indicates that not only are Tripadvisor review numbers recovering post-pandemic, but travel characteristics, including trip distances, are also showing signs of normalization.

The pandemic not only affected visitation patterns to prominent landmarks, but also tweeting and search activities related to these landmarks. To illustrate the similarities of user activities among the three datasets, Figure 5 presents a plot of normalized monthly Google Trends search data, tweet counts, and Tripadvisor review numbers from 1 March 2019 to 1 March 2023, for three selected landmarks.

The figure demonstrates that COVID-19 had a significant impact on all three data sources, indicating that users tweeted, reviewed, and searched for landmarks considerably less during the pandemic than before. However, as recovery from the pandemic progressed, users began to search for landmarks more frequently, resulting in a rapid recovery of the Google Trends search index (blue line). Although the volume of tweets and reviews remained significantly lower than pre-COVID-19 levels, both metrics demonstrated gradual recovery over time.

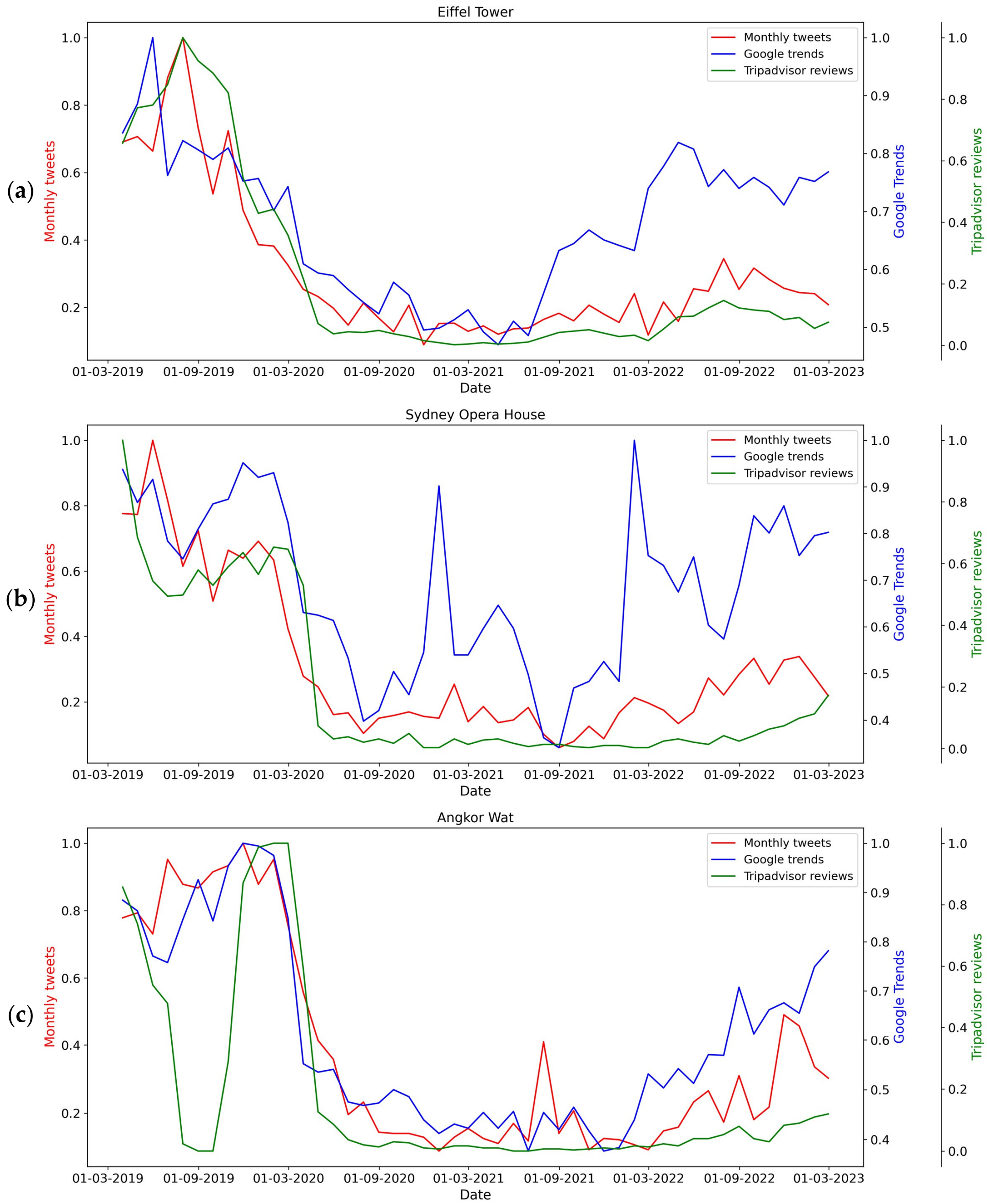

Figure 5. Normalized monthly tweets, Tripadvisor reviews number and Google Trends search index for Eiffel Tower (**a**), Sydney Opera House (**b**), and Angkor Wat (**c**).

6. Conclusions

This research contributes to the field of travel and search behavioral changes associated with the COVID-19 pandemic using UGC. It is unique in that it compares this effect based on data from three distinct platforms, i.e., Google Trends, X, and Tripadvisor, jointly analyzing changes in factual and aspirational travel. Online engagement patterns related to remote landmarks increased during the pandemic relative to nearby landmarks, indicating a heightened desire to visit those landmarks. Despite this desire, due to travel restrictions, management and promotion of landmarks need to adapt their strategies to also cater to a local market during times of limited travel opportunities, such as pandemics. Tourism boards and marketers can strategically promote lesser-known destinations to local travelers by emphasizing their safety, uniqueness, and appeal, especially in a landscape where international travel may face disruptions. Understanding these evolving dynamics will enable local governments to enhance infrastructure and services to accommodate anticipated shifts in tourist traffic. Such initiatives would also support ongoing efforts by city and regional administrations to mitigate overtourism in popular hotspots. This could involve collaborating with local governments to develop new attractions, as exemplified by the "Visit Amsterdam, See Holland" project [67]. Given the increased online engagement with remote landmarks during the pandemic, tourism marketers can effectively target their campaigns, such as by offering virtual tours as a temporary solution to keep attractions prominent in the minds of potential visitors [68]. While our study acknowledges signs of tourism recovery, it is crucial to recognize that the sector has not fully rebounded to pre-pandemic levels. This underscores the ongoing challenges and uncertainties faced by the tourism industry, emphasizing the need for adaptable strategies and informed decision-making.

In future endeavors, post-pandemic travel recovery trajectories will be more comprehensively examined through an extension of the study period. Furthermore, the effect of other events, such as hurricanes, on travel behavioral change, will be explored using various UGC platforms.

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Appendix A Tweet Filter Process

To remove tweets which contain the landmark terms but are unrelated to the actual landmark, the 'findall()' function of the Python "RegEX" library was applied to downloaded tweets. This function returns only strings which match a given set of substrings. For example, the Python code "(?i)\bEiffel\sTower\b | \bEiffelTower\b | \bEiffeltower\b" ensures that only tweets including "Eiffel Tower" and its common variations are retained in the filtered dataset.

After this step, a tweet may include the landmark name of interest but still be unrelated to the landmark location itself. For example, "Uluru" also appears in tweets within the phrase "Uluru Statement" which is a petition. To remove such tweets the tweet texts for each landmark were combined into a lowercase text and stop words were removed. Then, the "ngram" function from the nltk library in Python was applied to calculate the frequency of individual words, bigrams (two-word combinations), and trigrams (three-word combinations) of tweet posts containing the landmark name. The top 60 combinations for each frequency category were selected and examined manually regarding their relationship to the actual landmark. As an example, Figure A1 illustrates the top 20 results of that function for "Eiffel Tower". Figure A1b,c contain "bahria", which is a town near Karachi in Pakistan with a famous replica of Eiffel Tower. Since these tweets refer to a different location and not the original Eiffel Tower landmark, they were removed from further analysis. Relating to the removal of bots (i.e., automated tweets), it is known that bot-generated tweets often exhibit recurring patterns in their content [69], such as in advertisements and services (like weather or traffic news). Consequently, in the next step, we removed bot-generated tweets with frequently repeated word pairs for 12 landmarks. The numbers of tweets filtered using this approach range from 262 for the Leaning Tower of Pisa to 4517 for the Taj Mahal.

Figure A1. Twitter word frequency of tweets containing "Eiffel Tower" for individual words (**a**), bigrams (**b**), and trigrams (**c**).

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