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Public Perception of Tourism Cities before and during the COVID-19 Pandemic through the Lens of User-Generated Content

Yulin Chen

Department of Mass Communication, Tamkang University, Taipei 251, Taiwan; 143530@mail.tku.edu.tw

Abstract: The COVID-19 pandemic (coronavirus disease of 2019) sent the world into disarray and devastated the global tourism economy. In 2020 alone, the number of international tourists dropped by roughly 1.1 billion. This study examines user-generated content (UGC) on social media to elucidate the shift in people's perceptions of popular tourism cities from before the pandemic to during the pandemic. This paper analyzes the characteristics of the cues in tourism-city-related UGC (particularly those related to the pandemic) and identifies the cues that resonate most with the public. This paper collected the data using Instagram's application programing interface and then sorted the UGC based on content, type, time, likes, share, and comments. Between 1 January 2019 and 31 December 2019, it collected a total of 207,752 pre-pandemic posts and 173,131 peri-pandemic posts. The findings reveal that, during the pandemic, the interactivity of city-related UGC dropped, and only pandemic-related keywords gained public attention. By comparison, pre-pandemic positive posts mentioned local features and contained calls to action that were generally well-received. The findings also validate that UGC effectively reflects and enhances overall public perceptions, suggesting that, in a future which is forced to co-exist with SARS-CoV-2 in the long term, it is important to understand the positive and negative influences of UGC on tourism cities.

Keywords: COVID-19; tourism city; social media content; user-generated content (UGC)

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1. Introduction

City image (CI) represents the interaction and connection between people and city resources. It also reflects the experiences and memories of the city [1]. By analyzing the integration of societies and spaces and understanding cities' different meanings and purposes, it can better manage our cities. For people feeling estranged from a specific city, their impression of the city can be improved by the visual information they receive. Through visual content analysis and thematic analysis, this paper extracts people's imaginations and expectations from their primary perceptions and their historical, cultural, artistic, and life experiences [2]. A sustainable city image on social media can be seen as a type of soft power for building people's trust in the city [3]. As users on a social media platform increase, the platform's impact on CI increases concurrently, forming public trust that trumps the effects of official promotional content [4].

Key information and content should be specifically designed to improve content efficiency and enhance user interaction [5]. Another approach is to study the behaviors of social media users and to apply the results to make better decisions [6]. Although social media marketing is more affordable than other forms of marketing, the conversion rates of social media marketing are comparatively lower than other platforms. Therefore, utilizing user-generated content (UGC) on social media is a major challenge for city marketers. City planners can determine the effectiveness of social media interaction by examining the decisions made by users. Examining public engagement helps planners to determine accurately people's behaviors and demands and improve the community of cities [7].

The COVID-19 pandemic sent the world into disarray and devastated the global tourism economy. Based on statistics released by the World Tourism Organization of the United Nations (UNWTO), there were roughly 1.1 billion fewer international travelers in 2020 than in the previous year, a reduction of between 70% and 75%. The loss in international travel revenue was estimated to be USD 1.1 trillion, and the impact on the global economy was estimated to be USD 2 trillion. The World Tourism Cities Federation (WTCF) surveyed global travel trends in 2020. The findings indicated that international travel and revenue declined by over 60%; the international tourism industry lost 197.5 million jobs; GDP declined by USD 5.543 trillion; international travelers declined by 73%; and domestic travelers declined by 64% in 2020 compared to the previous year. Hong Kong's tourism industry was hit especially hard, starting from the mass protest event in 2019. That year, 55.91 million fewer travelers visited Hong Kong, a 14.2% decline compared to the previous year. Statistics released by the Office of National Statistics (ONS) of the United Kingdom, indicated that the number of travelers in 2020 was cut by three-quarters compared to the previous year. Thailand, whose economy relies heavily on the tourism industry, continues to be ravaged by COVID-19. Compared to pre-pandemic conditions, Thailand's tourism economy shrunk by 99%.

Therefore, the main purpose of this study is to analyze the UGC posted on social media to determine users' tourism city perceptions, with an emphasis on users' demand for and feelings towards city-related UGC during the pandemic. The secondary objective of this study is to extract city information [8] from UGC with the goal of obtaining a large amount of unstructured data. Pre-pandemic and post-pandemic city-related cues were extracted from the data and used to analyze post interactivity. This paper examines the shift in users' perceptions of sustainable tourism cities from before the pandemic to during the pandemic in the following two stages:

1. This paper first examines the evolution in the CI of major tourism cities from before the pandemic to during the pandemic;
2. It then surveys the cues in UGC about three tourism cities posted on social media to identify the cues that most resonated with the public before and during the pandemic.

In Section 2, this paper reviews relevant literature and introduces theories related to city-related features, urban communities, and city-related UGC. In Section 3, it outlines our hypotheses on the effects of the frequent use of constructive cues in city-related UGC before and during the pandemic on the interactivity of social media posts. These hypotheses allow us to evaluate the influence of information cues on post interactivity. In Section 4, it outlines our research process and methodologies. Section 5 details our analysis results. In Section 6, this paper provides a conclusion and suggestions on the management of city-related UGC.

2. Literature Review

2.1. City-Related Features and Urban Communities

Recent evidence shows that, with the rise of the Internet, users have become a vital part of image formation. They not only spread city image to their family and friends via word of mouth, but also use a variety of media platforms to interact with others, which is extremely helpful to spread positive city information. The advent of Web 2.0 and the rise of social media have further redefined the information distributors of digital media. Different from traditional offline media, a variety of travel information circulates over the Internet and on social media platforms. These platforms allow users to share their personal experiences and spread their perceived sustainable city image, as well as encourage users to interact with one another in many ways, such as through travel blogs, message boards, or in-app messengers. However, the rise of the Internet has weakened the influence of traditional media, while strengthening the influence of online social media.

CI reflects or captures the features of a city. These features can be regarded as the characteristics of the city. When people notice meaningful city features, they become invested in the city. This investment consequently translates to revisitation willingness. By analyzing city features, it can determine how these features impact visitation willingness and compare the tourism popularity of different cities. Cities can also promote their features to attract potential visitors and predict tourist preferences and recommendation willingness. Given that people's preferences greatly influence their recommendation willingness, key features become an important indicator of public behavior.

People use social media for entertainment and to enrich themselves. Some rely on the convenience of social media platforms to gain emotional support and recognition [9], while others are motivated by the desire to share content, connect with others, express themselves, or achieve personal goals [10]. Past studies on city promotion found that strong emotional cues [11], such as surprise or pleasure, were better at gaining public recognition. Other studies found that presenting the right information facilitated the development of common beliefs within social communities, mentioning that the mediating effects of information on behaviors and interactions increase concurrently with the functionality and emotional stimulus [12].

2.2. CI and UGC

With the prevalence of social media today, city planners are gradually shifting their promotional strategies. Planners now try to create a sustainable city image in line with people's experiences to express authenticity and personality. This shift has exposed the strategic value of UGC in forming CI and the benefits of using UGC to adjust or redesign CI. Statistics on social media show a spike in the growth of travel-related posts in recent years, turning researchers to social media for the collection of first-hand data. Social media posts have become evidence of people's travel decisions and their perceptions of the cities they visited. They have also been used to compare seasonal trends through time and space or to adjust existing plans to prevent over-promoting regional images. Social media posts have also been used in the meta-analyses of markets to design more accurate strategies to attract domestic and international travelers.

A previous study that analyzed the consistency between CI and city features found that the urban value conveyed by Mexico City was correlated to the information posted by the public. Marine-Roig (2017) compared official city images of Peru and those posted by the public and found significant differences between the two sets of images. People were more interested in the details of everyday life, while official images focused on promoting Peru's heritage. UGC reflects people's preferences and perceptions. Subsequently, people tend to prefer posting content on a universal platform, where they are able to convey their thoughts without having to learn new features.

The importance of social media manifests itself in its influence on people's emotions and experiences and in the ability to co-create city experiences [13,14]. In terms of CI design, Hjalager (2010) found an increased willingness among cities to strengthen their management of city-related UGC and formulate plans that support the promotion of city features and CI, including service development [15], experiential design [16], and event creation plans [17]. The development of UGC facilitates the formation of CI [18,19].

UGC has many advantages, including data diversity and public engagement [8]. Existing studies on UGC largely focus on content functionality or emotional exchange. The user-generated content (UGC) of urban knowledge represents a type of people-centered information exchange and a comprehensive presentation of people's extensive experiences in a collaborative environment. Originating from a people-oriented interactive environment of social media, UGC promotes multi-dimensional information interaction while adding value to the characteristics of cities through the activation of information technology. There are no known studies that focus on recent events and how positive cues serve as incentives for user involvement. Key features are an important indicator of public behavior. Existing studies on CI cannot fully explain the relationships between the key features of cities and public behaviors. More experiences and evidence are required to validate the effectiveness of city information to promp public perception and involvement. Therefore, this paper examines the UGC posted on social media to identify key information cues relating to sustainable tourism cities.

In terms of UGC research, researchers have used keyword analysis to explore the multidimensionality of political texts and public policies, or to understand extreme differences before and after the German political policy intervention. Other new applications of UGC analytics include crisis identification in cities or decision-making evidence of relevant governments. Additional applications are in-depth analyses of the intervening factors in citizens' welfare distribution, and the use of UGC to control research topics in public administration for policies that meet public needs. Additionally, to promote the rise and recovery of the urban economy and tourism, the disclosure of key elements of UGC, including symbolic elements that contain user-generated content, the online travel image of the destination, and the online image of the smart tourist destination, further benefits the refinement and alignment of urban elements.

The rapid development of social media and the Internet has promoted the rapid growth of UGC. This growth also affects a series of processes that take place before, during, and after a trip. In the tourism industry, the UGC of cities serves two main purposes: first, to offer information, and second, to provide a platform for people to make recommendations about cities, share ideas, and express travel intentions. In recent years, the online image of destinations has been mainly based on Twitter, Facebook, other social media travel booking platforms, online travel agencies (OTA), or information about attractions, hotels, or restaurants that represent the destination. Reviews and information published via online platforms are the foundation of UGC. When people actively, enthusiastically, and voluntarily express opinions, their comments represent the influence of the wisdom of the crowd. UGC is defined as community messages generated by non-experts. It can be regarded as a key indicator of successful interactive content, which is the main reason UGC is receiving more attention in communities.

3. Research Hypotheses

The driving force behind CI is the reason for its influence on public behavior [20,21]. People's travel behavior is driven by internal motivation, such as desire and demand, combined the formation of city perceptions through external stimuli [22], or by internal factors, such as human desire, reputation, and social interaction, combined with tangible resources, such as beaches, entertainment facilities, or cultural attractions [23]. Therefore, it is necessary to understand city perceptions in order to effectively promote cities. Increasing people's knowledge about humanizing cities can help to enhance the perception of cities and improve travel intentions. Therefore, the exclusive value of the main impression of a city in network communities can be regarded as an indispensable element of a city. Market segregation, product development, and promotional plans are useful tools for promoting cities [24]. CI can be used to categorize public traits and open targeted dialogues with different groups of people. Previous empirical studies found that CI is a key factor influencing public involvement [25,26]. The types of city perceptions and rationale for selecting specific CIs can be determined by examining public behaviors [27–29].

3.1. City Perception and UGC Cues

Each CI is unique and contains distinct regional characteristics and imagery. They are often linked to people's attitudes [30], values [31], and beliefs [28,32]. CI influences pubic behavior [27], loyalty [33], satisfaction, and recommendation willingness [26,34], leading to different travel motivations [28]. Although UGC continues to provide essential clues about cities frequently, the disruption caused by the COVID-19 pandemic is bound to have an impact on the interactions of community posts. Therefore, this paper hypothesizes that the frequent use of city-related cues in UGC before the pandemic affected the interactivity of social media posts. The hypotheses formulated in this study are as follows:

Hypothesis 1. *Before the pandemic, user-generated posts that frequently and actively provided city-related cues affected the public's post interactivity.*

Hypothesis 1a. *Before the pandemic, user-generated posts that frequently and actively provided city-related cues affected post likes.*

Hypothesis 1b. *Before the pandemic, user-generated posts that frequently and actively provided city-related cues affected post comments.*

3.2. Negative Intervention and UGC Cues

In sociology, negative intervention is often used to describe disruptions in the decision-making process. Based on negative interventions, causality tools can be used to determine the adjustment conditions and carry out reform [35]. Subsequently, crisis management [36] and risk management [37–39] influence the relationship between CI and negative interventions [40]. For example, pandemic fear, terrorism, and protests negatively impact CI. Perceived risk and anxiety from lack of information and disease outbreak also impact CI. Negative interventions critically impact prevention conditions during a crisis. For example, negative interventions related to flu risk greatly influence prevention awareness among overseas travelers [20]. Moreover, the lack of information concerning disease or flu increases the public's perceived risk and anxiety and greatly influences travel behaviors [41,42]. According to the above studies, surveying the performance characteristics of personal messages helps to understand whether people's travel habits contain prevention measures and to reduce the effects of negative interventions on cities.

The COVID-19 pandemic greatly reduced the number of travelers in 2020, devastating the tourism industry. Therefore, this paper hypothesizes that the frequent use of city-related cues in UGC during the pandemic affected the interactivity of social media posts. The hypotheses formulated in this study are as follows:

Hypothesis 2. *During the pandemic, user-generated posts that frequently and actively provided city-related cues affected the public's post interactivity.*

Hypothesis 2a. *During the pandemic, user-generated posts that frequently and actively provided city-related cues affected post likes.*

Hypothesis 2b. *During the pandemic, user-generated posts that frequently and actively provided city-related cues affected post comments.*

4. Research Methodology

4.1. Selecting UGC on Instagram

To elucidate the interactivity of city-related UGC before and during the pandemic, this paper employed a content mining approach to collect UGC on social media for analysis and evaluation. It subsequently formulated effective inferences based on the data [43]. Past studies on CI largely analyzed data from Facebook and Twitter [18,44]. This study selected Instagram, which has a higher volume of visual content. Therefore, the platform is uniquely positioned to market cities and is the preferred social media platform for CI-related organizations to connect with the world [45]. The research framework comprised three steps. In Step 1, this paper collected UGC data from Instagram. In Step 2, it coded the unstructured text data and established code categories. In Step 3, this paper extracted and coded the key clues and assessed the reliability of these clues based on context, theme, and expert opinions.

This study extracted useful information from UGC to determine city-related clues and characteristics before and during the pandemic [46]. Instagram was chosen as the source of the research data. Since its launch in October 2010, Instagram has provided its users with instantaneous information. Users also share snippets of their lives on the platform, leading Instagram to become one of the most popular social media platforms in the world. Given that Instagram is generally recognized as an image-sharing platform, it has become a target platform for text-focused social media research. Instagram users typically attach images, videos, or hashtags to their posts. These attachments help to create and expand communities and prompt discussions.

4.2. Data Collection

This study first investigated city rankings in surveys conducted by different institutions in 2019. Due to the expansion of the study scope to include the comparison of cities in Eurasia, cities in France, Spain, and the United States, as compiled and ranked by the United Nations World Tourism Organization, were not selected. Instead, Hong Kong, Bangkok, and London were included in the study as they were the top city destinations published by Euromonitor International, an organization with more regional coverage. It is hoped that this study provides a direct comparison regarding various information, needs, or ideas about Eurasia cities with diverse cultures or urban characteristics. According to the Top 100 City Destinations: 2019 Edition published by British market survey company Euromonitor International, the three most popular tourism cities were Hong Kong, Bangkok, and London. Therefore, this paper performed a textual analysis of Instagram posts involving these cities to examine the message design and social interactivity of related posts [46]. This paper collected the data using Instagram's application programing interface and then sorted the UGC based on content, type, time, likes, share, and comments. Between 1 January 2019 and 31 December 2019, it collected a total of 207,752 pre-pandemic posts (114,549 on Bangkok, 28,202 on Hong Kong, and 65,001 on London) and 173,131 peri-pandemic posts (29,857 on Bangkok, 28,839 on Hong Kong, and 114,435 on London). This paper identified relevant cues from the data and analyzed post interactivity associated with the cues.

4.3. Keywords and Interactivity Analysis

Instagram posts are extremely casual, often containing punctuation errors, spelling errors, abbreviations, and emojis. This paper preprocessed the content by deleting links, people's names, and strange symbols to minimize the impact of these factors on the analysis results. It selected keywords concerning CI information or describing the features and types of CI. The purpose of this semantic analysis was to identify word characteristics, determine how often specific words were used by employing a standard natural language parser, and determine the semantic similarities between words and word categories [47]. The analysis results were then verified by an expert in the field without conflicts of interest. The preprocessed data enabled us to compare the thematic categories and words of the posts based on their similarities and evaluate whether the cities conveyed certain values and strategies [48]. This paper discarded irrelevant keywords before discussing and selecting the CIs and clues based on the semantic analysis results. Finally, it conducted a regression analysis on the one hundred most frequently used keywords to determine their influences of post interactivity.

5. Data Analysis and Results

5.1. Reliability and Validity

For reliability and validity analysis of the data, principal component factor analysis was performed to test the factor validity of the scale. The factor characteristic value of the pre-pandemic UGC cues had a total variance of 60.537% and a KMO value of 0.642. The factor characteristic value of the pre-pandemic UGC cues had a total variance of 69.561% and a KMO value of 0.63. The expected load factor for all items is >0.5, indicating good convergence and discriminant validity. In addition, the reliability test produced a Cronbach's alpha of 0.773 for the pre-pandemic UGC cues and 0.725 for the pre-pandemic UGC cues. Each of these results shows good reliability.

5.2. Hypothesis Testing and Data Verification

The results for Hypothesis 1 (before the pandemic, user-generated posts that frequently and actively provided city-related cues affected the public's post interactivity) achieved statistical significance (β = −0.031, $p < 0.000$). Therefore, H1 was supported. The results for Hypothesis 2 (during the pandemic, user-generated posts that frequently and actively provided city-related cues affected the public's post interactivity) achieved statistical significance (β = −0.031, $p < 0.000$) (Tables 1 and 2).

Table 1. Summary of hypotheses.

ID	Hypothesis	Hypothesis Verification
Hypothesis 1	Before the pandemic, user-generated posts that frequently and actively provided city-related cues affected the public's post interactivity.	Established
Hypothesis 1a	Before the pandemic, user-generated posts that frequently and actively provided city-related cues affected post likes.	Established
Hypothesis 1b	Before the pandemic, user-generated posts that frequently and actively provided city-related cues affected post comments.	Not established
Hypothesis 2	During the pandemic, user-generated posts that frequently and actively provided city-related cues affected the public's post interactivity.	Established
Hypothesis 2a	During the pandemic, user-generated posts that frequently and actively provided city-related cues affected post likes.	Established
Hypothesis 2b	During the pandemic, user-generated posts that frequently and actively provided city-related cues affected post comments.	Established

Table 2. Linear regression coefficient of determination and beta coefficient (before and during the pandemic).

	R	R^2	Adj. R^2	ΔF	F Change	Durbin Watson	Original Regression Coefficient	SE	Beta	T	p	R	R^2
						Before the pandemic							
Hypothesis 1	0.031	0.001	0.001	38403.838	0.001	118.445	0.000	0.711	−282.410	25.949	−0.031	−10.883	0.000
Hypothesis 1a	0.031	0.001	0.001	38124.226	0.001	120.689	0.000	0.714	−282.998	25.760	−0.031	−10.986	0.000
Hypothesis 1b	0.003	0.000	0.000	722.954	0.000	1.446	0.229	1.690	0.587	0.488	0.003	1.203	0.229
						During the pandemic							
Hypothesis 2	0.032	0.001	0.001	34050.859	0.001	180.580	0.000	0.777	−215.623	16.046	−0.032	−13.438	0.000
Hypothesis 2a	0.032	0.001	0.001	33729.102	0.001	181.600	0.000	0.781	−214.188	15.894	−0.032	−13.476	0.000
Hypothesis 2b	0.008	0.000	0.000	933.181	0.000	10.655	0.001	1.726	−1.435	0.440	−0.008	−3.264	0.001

The results for Hypothesis 1a (before the pandemic, user-generated posts that frequently and actively provided city-related cues affected post likes) achieved statistical significance (β = −0.031, $p < 0.000$). Therefore, Hypothesis 1a was supported. However, the results for Hypothesis 1b (before the pandemic, user-generated posts that frequently and actively provided city-related cues affected post comments) failed to achieve statistical significance (β = 0.003, $p < 0.229$). Therefore, Hypothesis 1b was rejected. The results for Hypothesis 2a (during the pandemic, user-generated posts that frequently and actively provided city-related cues affected post likes; β = −0.032, $p < 0.000$) and Hypothesis 2b (during the pandemic, user-generated posts that frequently and actively provided city-related cues affected post comments; β = −0.008, $p < 0.001$) achieved statistical significance. Therefore, both hypotheses were supported.

5.3. Cue Characteristics of City-Related UGC

The results show that the organization of content on social media pages exerts a significant influence on the responses of users to the content and their behavioral participation. The results of the various verification tests are presented below.

5.3.1. Changes in Pre-Pandemic and Peri-Pandemic City-Related Cues

Hong Kong

In terms of Hong Kong, there was a frequent use of city-related cues in user-generated posts, which impacted post likes (β = −0.026, T = −4.380, $p < 0.000$) and comments (β = −0.019, T = −3.203, $p < 0.001$) before the pandemic (Tables 3 and 4 and Figure 1). The keywords that significantly and positively impacted post likes were "winner" (β = 0.020,

$p < 0.004$), "Indonesia" ($\beta = 0.060$, $p < 0.000$), "tour" ($\beta = 0.012$, $p < 0.043$), "protest" ($\beta = 0.039$, $p < 0.000$), "show" ($\beta = 0.018$, $p < 0.004$), and "people" ($\beta = 0.016$, $p < 0.012$). The keywords that significantly and negatively impacted post likes were "book" ($\beta = -0.019$, $p < 0.004$), "student" ($\beta = -0.013$, $p < 0.028$), "Japan" ($\beta = -0.015$, $p < 0.016$), "follow" ($\beta = -0.013$, $p < 0.039$), "Asia" ($\beta = -0.014$, $p < 0.027$), "food" ($\beta = -0.020$, $p < 0.002$), "event" ($\beta = -0.012$, $p < 0.046$), and "fashion" ($\beta = -0.018$, $p < 0.004$).

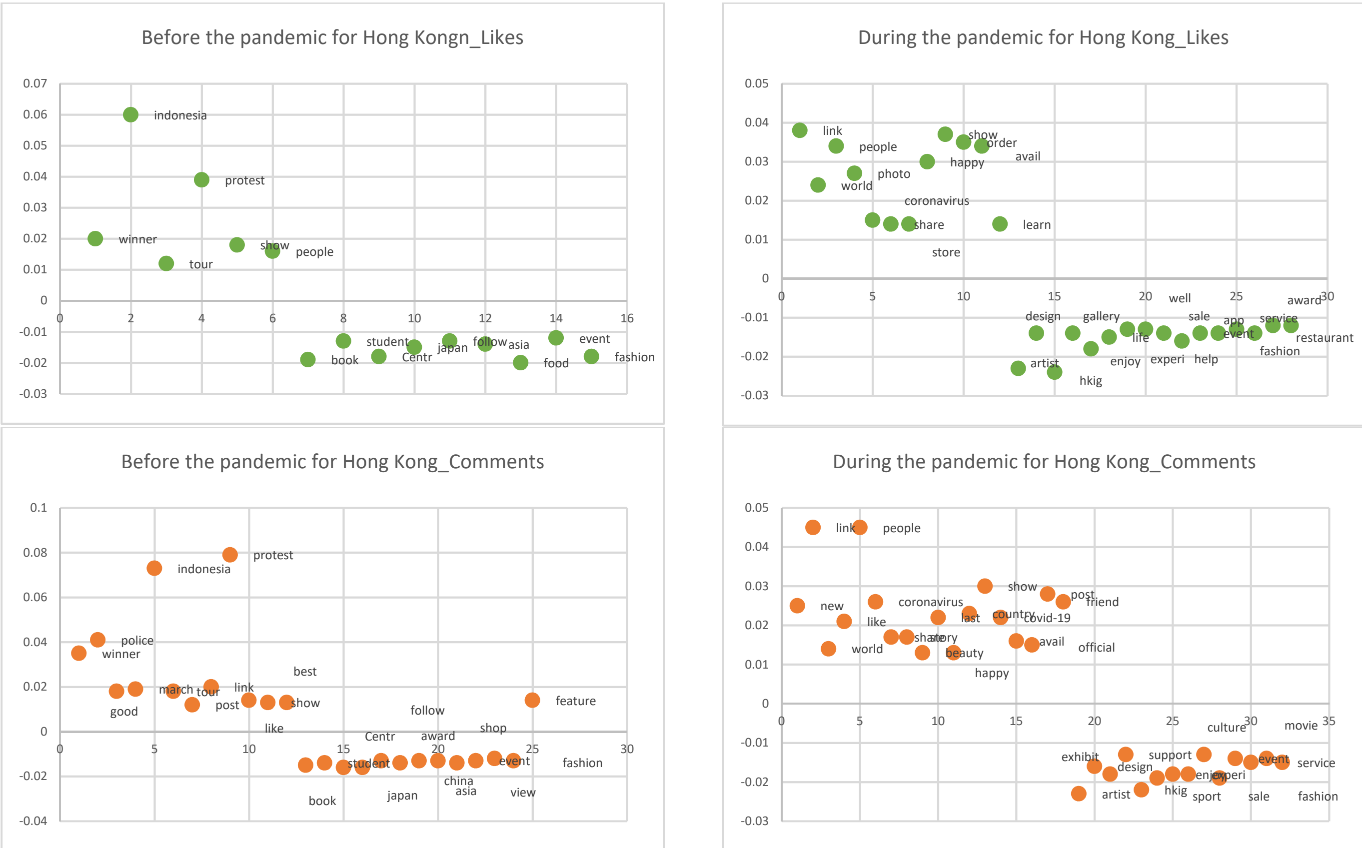

Figure 1. Changes in pre-pandemic and peri-pandemic city-related cues (Hong Kong).

Table 3. Linear regression coefficient of determination and beta coefficient (before the pandemic and during the pandemic in Hong Kong).

Hong Kong before the Pandemic								Hong Kong during the Pandemic							
Cues of Post Likes	β	T	*p*	Cues of Post Comments	β	T	*p*	Cues of Post Likes	β	T	*p*	Cues of Post Comments	β	T	*p*
winner	0.020	2.887	0.004	winner	0.035	5.122	0.000	link	0.038	6.127	0.000	new	0.025	3.917	0.000
Indonesia	0.060	9.194	0.000	police	0.041	5.777	0.000	world	0.024	3.74	0.000	link	0.045	7.243	0.000
tour	0.012	2.023	0.043	good	0.018	2.849	0.004	people	0.034	5.549	0.000	world	0.014	2.248	0.025
protest	0.039	4.988	0.000	march	0.019	2.992	0.003	photo	0.027	4.254	0.000	like	0.021	3.247	0.001
show	0.018	2.888	0.004	Indonesia	0.073	11.253	0.000	coronavirus	0.015	2.041	0.041	people	0.045	7.369	0.000
people	0.016	2.512	0.012	tour	0.018	2.958	0.003	share	0.014	2.365	0.018	coronavirus	0.026	3.401	0.001
book	−0.019	−2.899	0.004	post	0.012	2.016	0.044	store	0.014	2.213	0.027	share	0.017	2.87	0.004
student	−0.013	−2.191	0.028	link	0.020	3.234	0.001	happy	0.030	4.774	0.000	story	0.017	2.91	0.004
Central	−0.018	−2.777	0.005	protest	0.079	10.18	0.000	show	0.037	6.058	0.000	beauty	0.013	2.253	0.024
Japan	−0.015	−2.4	0.016	like	0.014	2.278	0.023	order	0.035	4.856	0.000	last	0.022	3.666	0.000
follow	−0.013	−2.059	0.039	show	0.013	2.007	0.045	avail	0.034	5.58	0.000	happy	0.013	2.077	0.038
Asia	−0.014	−2.21	0.027	best	0.013	2.203	0.028	learn	0.014	2.354	0.019	country	0.023	2.925	0.003
food	−0.020	−3.041	0.002	book	−0.015	−2.229	0.026	artist	−0.023	−2.922	0.003	show	0.030	5.029	0.000
event	−0.012	−1.992	0.046	student	−0.014	−2.277	0.023	design	−0.014	−1.996	0.046	COVID-19	0.022	3.78	0.000
fashion	−0.018	−2.896	0.004	Central	−0.016	−2.565	0.010	hkig	−0.024	−3.325	0.001	avail	0.016	2.66	0.008
				Japan	−0.016	−2.653	0.008	gallery	−0.014	−2.089	0.037	official	0.015	2.464	0.014
				award	−0.013	−2.087	0.037	enjoy	−0.018	−2.913	0.004	post	0.028	4.585	0.000
				follow	−0.014	−2.328	0.020	life	−0.015	−2.227	0.026	friend	0.026	4.275	0.000
				China	−0.013	−2.222	0.026	experi	−0.013	−2.112	0.035	artist	−0.023	−2.96	0.003
				Asia	−0.013	−2.147	0.032	well	−0.013	−2.13	0.033	design	−0.016	−2.33	0.020
				shop	−0.014	−2.1	0.036	sale	−0.014	−2.237	0.025	exhibit	−0.018	−2.626	0.009
				event	−0.013	−2.113	0.035	help	−0.016	−2.624	0.009	support	−0.013	−2.16	0.031
				view	−0.012	−2.054	0.040	event	−0.014	−2.214	0.027	hkig	−0.022	−3.065	0.002
				fashion	−0.013	−2.066	0.039	app	−0.014	−2.192	0.028	sport	−0.019	−2.688	0.007
				feature	0.014	2.25	0.024	service	−0.013	−2.074	0.038	enjoy	−0.018	−2.987	0.003
								fashion	−0.014	−2.376	0.018	experi	−0.018	−2.905	0.004
								restaurant	−0.012	−2	0.045	culture	−0.013	−2.201	0.028
								award	−0.012	−2.049	0.040	sale	−0.019	−3.078	0.002
												event	−0.014	−2.24	0.025
												service	−0.015	−2.44	0.015
												movie	−0.014	−2.107	0.035
												fashion	−0.015	−2.411	0.016

Table 4. Linear regression coefficient of determination and beta coefficient (before and during the pandemic for Hong Kong).

	R	R^2	Adj. R^2	ΔF	F Change	Durbin Watson	Original Regression Coefficient	SE	Beta	T	*p*	R	R^2
Before the pandemic for Hong Kong													
Likes	0.026	0.001	0.001	18190.934	0.001	19.183	0.000	0.300	−118.288	270.007	−0.026	−4.380	0.000
Comments	0.006	0.000	0.000	258.992	0.000	0.947	0.330	0.937	−0.374	0.385	−0.006	−0.973	0.330
During the pandemic for Hong Kong													
Likes	0.019	0.000	0.000	12560.377	0.000	10.261	0.001	0.554	−52.482	16.384	−0.019	−3.203	0.001
Comments	0.009	0.000	0.000	171.925	0.000	2.460	0.117	10.040	0.352	0.224	0.009	1.568	0.117

The keywords that significantly and positively impacted post comments were "winner", "police" (β = 0.035, $p < 0.000$), "good" (β = 0.018, $p < 0.004$), "March" (β = 0.019, $p < 0.003$), "Indonesia" (β = 0.073, $p < 0.000$), "tour" (β = 0.018, $p < 0.003$), "post" (β = 0.012, $p < 0.044$), "link" (β = 0.020, $p < 0.001$), "protest" (β = 0.079, $p < 0.000$), "like" (β = 0.014, $p < 0.023$), "show" (β = 0.013, $p < 0.045$), and "best" (β = 0.013, $p < 0.028$). The keywords that significantly and negatively impacted post comments were "book" (β = −0.015, $p < 0.026$), "student" (β = −0.014, $p < 0.023$), "Japan" (β = −0.016, $p < 0.008$), "award" (β = −0.013, $p < 0.037$), "follow" (β = −0.014, $p < 0.020$), "China" (β = −0.013, $p < 0.026$), "Asia" (β = −0.013, $p < 0.032$), "shop" (β = −0.014, $p < 0.036$), "event" (β = −0.013, $p < 0.035$), "view" (β = −0.012, $p < 0.040$), "fashion" (β = −0.013, $p < 0.039$), and "feature" (β = −0.014, $p < 0.024$).

The presence of Hong Kong in user-generated posts impacted post likes (β = −0.006, T = −0.973, $p < 0.330$) and comments (β = 0.009, T = 1.568, $p < 0.117$) during the pandemic. The keywords that significantly and positively impacted post likes were "coronavirus" (β = 0.015, $p < 0.041$), "link" (β = 0.038, $p < 0.000$), "world" (β = 0.024, $p < 0.000$), "people" (β = 0.034, $p < 0.000$), "photo" (β = 0.027, $p < 0.000$), "share" (β = 0.014, $p < 0.018$), "store" (β = 0.014, $p < 0.027$), "happy" (β = 0.030, $p < 0.000$), "show" (β = 0.037, $p < 0.000$), "order" (β = 0.035, $p < 0.000$), "avail" (β = 0.034, $p < 0.000$), and "learn" (β = 0.014, $p < 0.019$). The keywords that significantly and negatively impacted post comments were "artist" (β = −0.023, $p < 0.003$), "design" (β = −0.014, $p < 0.046$), "hkig" (β = −0.024, $p < 0.001$), "gallery" (β = −0.014, $p < 0.037$), "enjoy" (β = −0.018, $p < 0.004$), "life" (β = −0.015, $p < 0.026$), "well" (β = −0.013, $p < 0.033$), "sale" (β = −0.014, $p < 0.025$), "help" (β = −0.016, $p < 0.009$), "event" (β = −0.014, $p < 0.027$), "app" (β = −0.014, $p < 0.028$), "service" (β = −0.013, $p < 0.038$), "fashion" (β = −0.014, $p < 0.018$), "restaurant" (β = −0.012, $p < 0.045$), and "award" (β = −0.012, $p < 0.040$).

The keywords that significantly and positively impacted post comments were "new" (β = 0.025, $p < 0.000$), "link" (β = 0.045, $p < 0.000$), "world" (β = 0.014, $p < 0.025$), "like" (β = 0.021, $p < 0.001$), "people" (β = 0.045, $p < 0.000$), "coronavirus" (β = 0.026, $p < 0.001$), "share" (β = 0.017, $p < 0.004$), "story" (β = 0.017, $p < 0.004$), "beauty (β = 0.013, $p < 0.024$), "last" (β = 0.022, $p < 0.000$), "happy" (β = 0.013, $p < 0.038$), "country" (β = 0.023, $p < 0.003$), "show" (β = 0.030, $p < 0.000$), "COVID-19" (β = 0.022, $p < 0.000$), "avail" (β = 0.016, $p < 0.008$), "official" (β = 0.015, $p < 0.014$), "post" (β = 0.028, $p < 0.000$), and "friend" (β = 0.026, $p < 0.000$). The keywords that significantly and negatively impacted post comments were "artist" (β = −0.023, $p < 0.003$), "design" (β = −0.016, $p < 0.020$), "exhibit" (β = −0.018, $p < 0.009$), "support" (β = −0.013, $p < 0.031$), "hkig" (β = −0.022, $p < 0.002$), "sport" (β = −0.019, $p < 0.007$), "enjoy" (β = −0.018, $p < 0.003$), "culture" (β = −0.013, $p < 0.028$), "sale" (β = −0.019, $p < 0.002$), "event" (β = −0.014, $p < 0.025$), "service" (β = −0.015, $p < 0.015$), "movie" (β = −0.014, $p < 0.035$), and "fashion" (β = −0.015, $p < 0.016$).

London

In terms of London, the use of city-related cues in user-generated posts impacted post likes (β = −0.047, $p < 0.000$) and comments (β = −0.037, $p < 0.000$) before the pandemic (Table 5, Table 6 and Figure 2). The keywords that significantly and positively impacted post likes were "world" (β = 0.015, $p < 0.000$), "story" (β = 0.010, $p < 0.015$), "night" (β = 0.020, $p < 0.000$), "share" (β = 0.009, $p < 0.033$), "every" (β = 0.012, $p < 0.005$), "thisislondon" (β = 0.011, $p < 0.014$), and "film" (β = 0.017, $p < 0.000$). The keywords that significantly and negatively impacted post likes were "link" (β = −0.009, $p < 0.024$), "U.K." (β = −0.011, $p < 0.009$), "design" (β = −0.013, $p < 0.003$), "fashion" (β = −0.012, $p < 0.011$), "travel" (β = −0.010, $p < 0.018$), "art" (β = −0.014, $p < 0.002$), "style" (β = −0.010, $p < 0.037$), "shop" (β = −0.013, $p < 0.001$), "Christmas" (β = −0.010, $p < 0.012$), "visit" (β = −0.009, $p < 0.027$), "ticket" (β = −0.008, $p < 0.049$), "music" (β = −0.012, $p < 0.005$), "food" (β = −0.013, $p < 0.002$), and "top" (β = −0.009, $p < 0.023$).

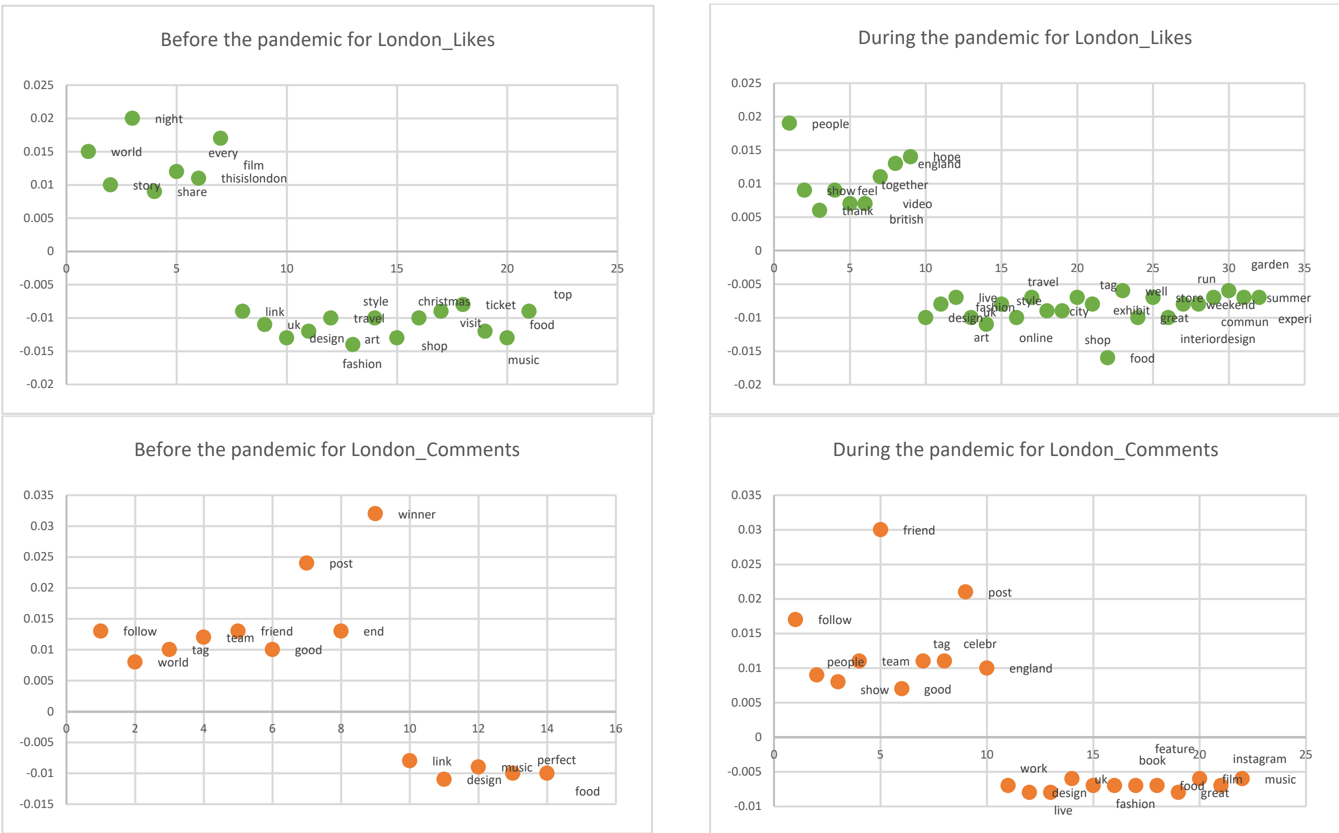

Figure 2. Changes in pre-pandemic and peri-pandemic city-related cues (London).

The keywords that significantly and positively impacted post comments were "follow" (β = 0.013, $p < 0.002$), "world" (β = 0.008, $p < 0.042$), "tag" (β = 0.010, $p < 0.032$), "team" (β = 0.012, $p < 0.003$), "friend" (β = 0.013, $p < 0.006$), "good" (β = 0.010, $p < 0.019$), "post" (β = 0.024, $p < 0.000$), "end" (β = 0.013, $p < 0.006$), and "winner" (β = 0.032, $p < 0.000$). The keywords that significantly and negatively impacted post comments were "link" (β = −0.008, $p < 0.047$), "design" (β = −0.011, $p < 0.007$), "music" (β = −0.009, $p < 0.038$), "perfect" (β = −0.010, $p < 0.013$), and "food" (β = −0.010, $p < 0.013$).

Table 5. Linear regression coefficient of determination and beta coefficient (before the pandemic and during the pandemic in London).

London before the Pandemic								London during the Pandemic							
Cues of Post Likes	**β**	**T**	***p***	**Cues of Post Comments**	**β**	**T**	***p***	**Cues of Post Likes**	**β**	**T**	***p***	**Cues of Post Comments**	**β**	**T**	***p***
world	0.015	3.538	0.000	follow	0.013	3.080	0.002	people	0.019	5.915	0.000	follow	0.017	5.559	0.000
story	0.010	2.422	0.015	world	0.008	2.035	0.042	show	0.009	3.064	0.002	people	0.009	2.778	0.005
night	0.020	4.851	0.000	tag	0.010	2.151	0.032	thank	0.006	2.002	0.045	show	0.008	2.489	0.013
share	0.009	2.137	0.033	team	0.012	2.953	0.003	feel	0.009	2.876	0.004	team	0.011	3.638	0.000
every	0.012	2.821	0.005	friend	0.013	2.771	0.006	together	0.007	2.319	0.020	friend	0.030	9.515	0.000
thisislondon	0.011	2.450	0.014	good	0.010	2.342	0.019	British	0.007	2.489	0.013	good	0.007	2.392	0.017
film	0.017	4.183	0.000	post	0.024	5.951	0.000	video	0.011	3.616	0.000	tag	0.011	3.046	0.002
link	−0.009	−2.259	0.024	end	0.013	2.731	0.006	England	0.013	4.456	0.000	celebr	0.011	3.539	0.000
U.K.	−0.011	−2.604	0.009	winner	0.032	7.525	0.000	hope	0.014	4.538	0.000	post	0.021	6.950	0.000
design	−0.013	−2.993	0.003	link	−0.008	−1.982	0.047	design	−0.010	−2.763	0.006	England	0.010	3.446	0.001
fashion	−0.012	−2.540	0.011	design	−0.011	−2.676	0.007	art	−0.008	−2.385	0.017	work	−0.007	−2.209	0.027
travel	−0.010	−2.356	0.018	music	−0.009	−2.079	0.038	live	−0.007	−2.413	0.016	design	−0.008	−2.249	0.025
art	−0.014	−3.041	0.002	perfect	−0.010	−2.484	0.013	U.K.	−0.010	−3.347	0.001	live	−0.008	−2.573	0.010
style	−0.010	−2.090	0.037	food	−0.010	−2.471	0.013	fashion	−0.011	−3.399	0.001	U.K.	−0.006	−2.085	0.037
shop	−0.013	−3.287	0.001					travel	−0.008	−2.506	0.012	fashion	−0.007	−2.012	0.044
Christmas	−0.010	−2.508	0.012					style	−0.010	−3.022	0.003	book	−0.007	−2.168	0.030
visit	−0.009	−2.217	0.027					online	−0.007	−2.309	0.021	feature	−0.007	−2.254	0.024
ticket	−0.008	−1.973	0.049					city	−0.009	−2.770	0.006	food	−0.007	−2.096	0.036
music	−0.012	−2.838	0.005					shop	−0.009	−2.892	0.004	great	−0.008	−2.567	0.010
food	−0.013	−3.166	0.002					tag	−0.007	−2.011	0.044	film	−0.006	−1.987	0.047
top	−0.009	−2.275	0.023					exhibit	−0.008	−2.483	0.013	Instagram	−0.007	−1.969	0.049
								food	−0.016	−5.085	0.000	music	−0.006	−2.100	0.036
								well	−0.006	−2.078	0.038				
								great	−0.010	−3.185	0.001				
								store	−0.007	−2.225	0.026				
								interiordesign	−0.01	−2.768	0.006				
								weekend	−0.008	−2.671	0.008				
								commun	−0.008	−2.669	0.008				
								run	−0.007	−2.294	0.022				
								garden	−0.006	−2.036	0.042				
								summer	−0.007	−2.496	0.013				
								experi	−0.007	−2.229	0.026				

Table 6. Linear regression coefficient of determination and beta coefficient (before and during the pandemic for London).

	R	R^2	Adj. R^2	ΔF	F Change	Durbin Watson	Original Regression Coefficient	SE	Beta	T	*p*	R	R^2
Before the pandemic for London													
Likes	0.047	0.002	0.002	500570.076	0.002	141.872	0.000	0.542	−511.315	42.928	−0.047	−11.911	0.000
Comments	0.004	0.000	0.000	968.522	0.000	10.005	0.316	1.709	−0.833	0.831	−0.004	−10.003	0.316
During the pandemic for London													
Likes	0.037	0.001	0.001	39709.626	0.001	156.173	0.000	0.793	−308.512	24.687	−0.037	−12.497	0.000
Comments	0.009	0.000	0.000	10320.027	0.000	8.713	0.003	1.690	−1.894	0.642	−0.009	−2.952	0.003

The presence of London in user-generated posts impacted post likes (β = −0.004, $p < 0.316$) and comments (β = −0.009, $p < 0.003$) during the pandemic. The keywords that significantly and positively impacted post likes were "people" (β = 0.019, $p < 0.000$), "show" (β = 0.009, $p < 0.002$), "thank" (β = 0.006, $p < 0.045$), "feel" (β = 0.009, $p < 0.004$), "together" (β = 0.007, $p < 0.020$), "British" (β = 0.007, $p < 0.013$), "video" (β = 0.011, $p < 0.000$), "England" (β = 0.013, $p < 0.000$), and "hope" (β = 0.014, $p < 0.000$). The keywords that significantly and negatively impacted post likes were "design" (β = −0.010, $p < 0.006$), "art" (β = −0.008, $p < 0.017$), "live" (β = −0.007, $p < 0.016$), "U.K." (β = −0.010, $p < 0.001$), "fashion" (β = −0.011, $p < 0.001$), "travel" (β = −0.008, $p < 0.012$), "style" (β = −0.010, $p < 0.003$), "online" (β = −0.007, $p < 0.021$), "city" (β = −0.009, $p < 0.006$), "shop" (β = −0.009, $p < 0.004$), "tag" (β = −0.007, $p < 0.044$), "exhibit" (β = −0.008, $p < 0.013$), "food" (β = −0.016, $p < 0.000$), "well" (β = −0.006, $p < 0.038$), "great" (β = −0.010, $p < 0.001$), "store" (β = −0.007, $p < 0.026$), "interiordesign" (β = −0.010, $p < 0.006$), "weekend" (β = −0.008, $p < 0.008$), "run (β = −0.007, $p < 0.022$), "garden" (β = −0.006, $p < 0.042$), and "summer" (β = −0.007, $p < 0.013$).

The keywords that significantly and positively impacted post comments were "follow" (β = 0.017, $p < 0.000$), "people" (β = 0.009, $p < 0.005$), "show" (β = 0.008, $p < 0.013$), "team" (β = 0.011, $p < 0.000$), "friend" (β = 0.030, $p < 0.000$), "good" (β = 0.007, $p < 0.017$), "tag" (β = 0.011, $p < 0.002$), "post" (β = 0.021, $p < 0.000$), and "England" (β = 0.010, $p < 0.001$). The keywords that significantly and negatively impacted post comments were "work" (β = −0.007, $p < 0.027$), "design" (β = −0.008, $p < 0.025$), "live" (β = −0.008, $p < 0.010$), "U.K." (β = −0.006, $p < 0.037$), "fashion" (β = −0.007, $p < 0.044$), "book" (β = −0.007, $p < 0.030$), "feature (β = −0.007, $p < 0.024$), "food" (β = −0.007, $p < 0.036$), "great" (β = −0.008, $p < 0.010$), "film" (β = −0.006, $p < 0.047$), "Instagram" (β = −0.007, $p < 0.049$), and "music" (β = −0.006, $p < 0.036$).

Bangkok

In terms of Bangkok, the use of city−related cues in user−generated posts impacted post likes (β = −0.030, $p < 0.000$) and comments (β = −0.046, $p < 0.000$) before the pandemic (Tables 7 and 8 and Figure 3). The keywords that significantly and positively impacted post likes were "follow" (β = 0.043, $p < 0.000$), "photo" (β = 0.021, $p < 0.002$), "locate" (β = 0.012, $p < 0.032$), "thank" (β = 0.012, $p < 0.041$), "tour" (β = 0.035, $p < 0.000$), "zen" (β = 0.026, $p < 0.000$), "place" (β = 0.013, $p < 0.028$), "ticket" (β = 0.013, $p < 0.021$), "temple" (β = 0.026, $p < 0.000$), "Life" (β = 0.018, $p < 0.016$), "champion" (β = 0.047, $p < 0.000$), and "miss" (β = 0.029, $p < 0.000$). The keywords that significantly and negatively impacted post comments were "Thailand" (β = −0.023, $p < 0.001$), "Asia" (β = −0.020, $p < 0.001$), "hotel" (β = −0.018, $p < 0.004$), "center" (β = −0.012, $p < 0.044$), "style" (β = −0.033, $p < 0.000$), "night" (β = −0.013, $p < 0.028$), "sushi" (β = −0.014, $p < 0.027$), "avail" (β = −0.013, $p < 0.034$), "eatwithpanida" (β = −0.032, $p < 0.000$), "café" (β = −0.015, $p < 0.022$), and "amazingthailand" (β = −0.014, $p < 0.023$).

Table 7. Linear regression coefficient of determination and beta coefficient (before the pandemic and during the pandemic in Bangkok).

Bangkok before the Pandemic								Bangkok during the Pandemic							
Cues of Post Likes	**β**	**T**	***p***	**Cues of Post Comments**	**β**	**T**	***p***	**Cues of Post Likes**	**β**	**T**	***p***	**Cues of Post Comments**	**β**	**T**	***p***
follow	0.043	5.627	0.000	follow	0.076	9.866	0.000	color	0.013	1.976	0.048	follow	0.092	8.672	0.000
photo	0.021	3.165	0.002	love	0.021	3.353	0.001	like	0.017	2.228	0.026	die	0.081	8.877	0.000
locate	0.012	2.139	0.032	shop	0.018	2.880	0.004	Thailand	−0.019	−2.697	0.007	food	−0.030	−3.782	0.000
thank	0.012	2.042	0.041	best	0.012	2.021	0.043	line	−0.023	−2.557	0.011	delicious	−0.037	−3.945	0.000
tour	0.035	5.777	0.000	tour	0.050	8.161	0.000	EVEANDBOY	−0.043	−3.073	0.002				
zen	0.026	4.340	0.000	zen	0.028	4.803	0.000	food	−0.028	−3.465	0.001				
place	0.013	2.201	0.028	life	0.017	2.269	0.023	central	−0.027	−2.454	0.014				
ticket	0.013	2.303	0.021	menu	0.012	1.991	0.046	travel	−0.020	−2.374	0.018				
temple	0.026	4.341	0.000	champion	0.076	12.943	0.000	delivery	−0.019	−2.420	0.016				
life	0.018	2.406	0.016	house	0.013	2.245	0.025	hotel	−0.014	−2.316	0.021				
champion	0.047	7.970	0.000	Thailand	−0.015	−2.179	0.029	style	−0.024	−2.763	0.006				
miss	0.029	4.781	0.000	Asia	−0.017	−2.758	0.006	tea	−0.014	−2.384	0.017				
Thailand	−0.023	−3.325	0.001	style	−0.031	−3.386	0.001	cafe	−0.024	−2.715	0.007				
Asia	−0.020	−3.220	0.001	night	−0.012	−1.997	0.046								
hotel	−0.018	−2.893	0.004	delicious	−0.022	−2.815	0.005								
center	−0.012	−2.016	0.044	art	−0.013	−2.046	0.041								
style	−0.033	−3.665	0.000	eatwithpanida	−0.045	−5.292	0.000								
night	−0.013	−2.197	0.028	amazingthailand	−0.015	−2.322	0.020								
sushi	−0.014	−2.216	0.027												
avail	−0.013	−2.120	0.034												
eatwithpanida	−0.032	−3.764	0.000												
cafe	−0.015	−2.286	0.022												
amazingthailand	−0.014	−2.269	0.023												

Table 8. Linear regression coefficient of determination and beta coefficient (before and during the pandemic for Bangkok).

	R	**R^2**	**Adj. R^2**	**ΔF**	**F Change**	**Durbin Watson**	**Original Regression Coefficient**	**SE**	**Beta**	**T**	***p***	**R**	**R^2**
Before the pandemic for Bangkok													
Likes	0.030	0.001	0.001	13353.962	0.001	27.101	0.000	0.394	−122.145	23.463	−0.030	−5.206	0.000
Comments	0.004	0.000	0.000	201.920	0.000	0.472	0.492	1.240	−0.244	0.355	−0.004	−0.687	0.492
During the pandemic for Bangkok													
Likes	0.046	0.002	0.002	19709.181	0.002	64.127	0.000	0.585	−1390.001	17.358	−0.046	−80.008	0.000
Comments	0.014	0.000	0.000	966.943	0.000	60.018	0.014	1.912	−20.089	0.852	−0.014	−2.453	0.014

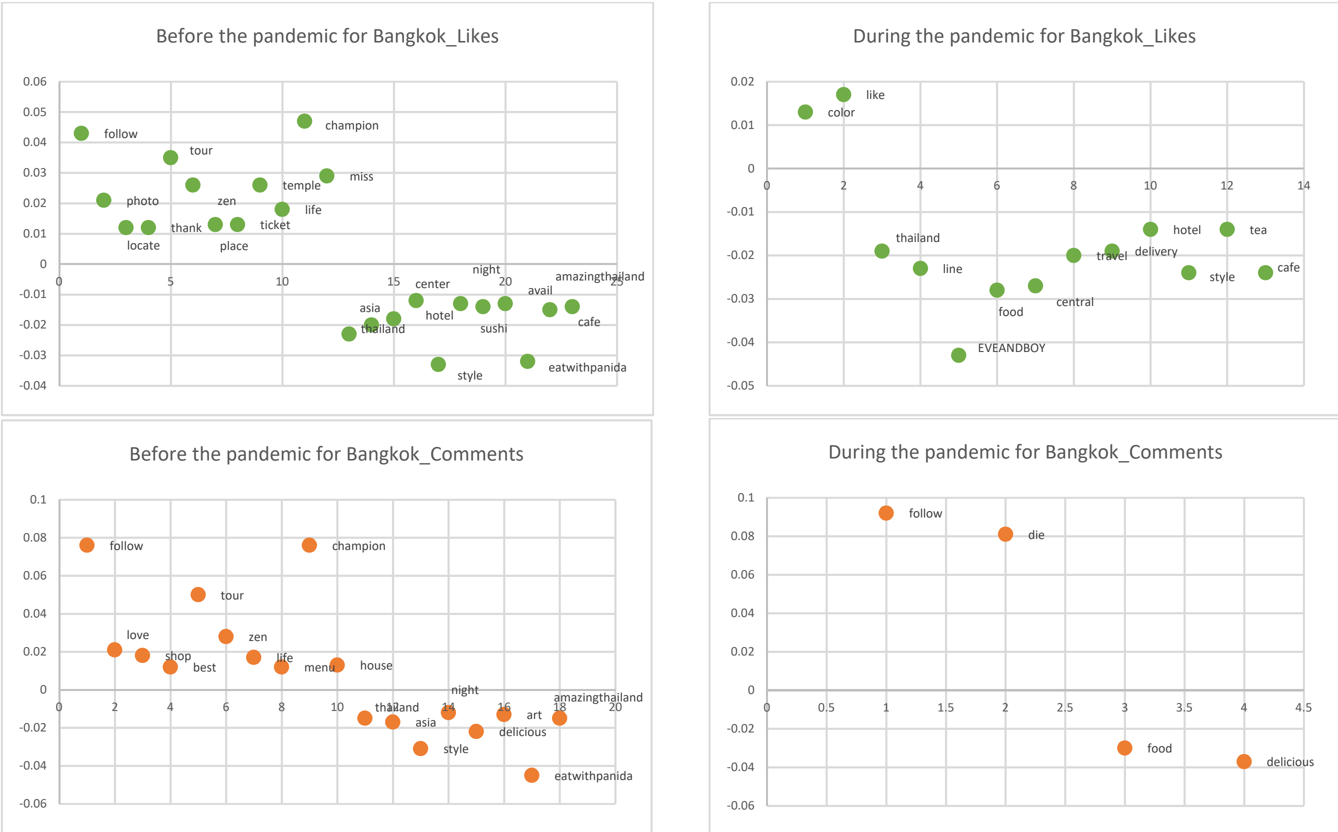

Figure 3. Changes in pre-pandemic and peri-pandemic city-related cues (Bangkok).

The keywords that significantly and positively impacted post comments were "follow" ($\beta = 0.076$, $p < 0.000$), "love" ($\beta = 0.021$, $p < 0.001$), "shop" ($\beta = 0.018$, $p < 0.004$), "best" ($\beta = 0.012$, $p < 0.043$), "tour" ($\beta = 0.050$, $p < 0.000$), "zen" ($\beta = 0.028$, $p < 0.000$), "life" ($\beta = 0.017$, $p < 0.023$), "menu" ($\beta = 0.012$, $p < 0.046$), "champion" ($\beta = 0.076$, $p < 0.000$), and "house" ($\beta = 0.013$, $p < 0.025$). The keywords that significantly and negatively impacted post comments were "Thailand" ($\beta = -0.015$, $p < 0.029$), "Asia" ($\beta = -0.017$, $p < 0.006$), "style" ($\beta = -0.031$, $p < 0.001$), "night" ($\beta = -0.012$, $p < 0.046$), "delicious" ($\beta = -0.022$, $p < 0.005$), "art" ($\beta = -0.013$, $p < 0.041$), "eatwithpanida" ($\beta = -0.045$, $p < 0.000$), and "amazingthailand" ($\beta = -0.015$, $p < 0.020$).

The presence of Bangkok in user-generated posts impacted post likes ($\beta = -0.004$, $p < 0.492$) and comments ($\beta = -0.014$, $p < 0.014$) during the pandemic. The keywords that significantly and positively impacted post likes were "color" ($\beta = 0.013$, $p < 0.048$) and "like" ($\beta = 0.017$, $p < 0.026$). The keywords that significantly and negatively impacted post likes were "Thailand" ($\beta = -0.019$, $p < 0.007$), "line" ($\beta = -0.023$, $p < 0.011$), "EVEANDBOY" ($\beta = -0.043$, $p < 0.002$), "food" ($\beta = -0.028$, $p < 0.001$), "central" ($\beta = -0.027$, $p < 0.014$), "travel" ($\beta = -0.020$, $p < 0.018$), "delivery" ($\beta = -0.019$, $p < 0.016$), and "hotel" ($\beta = -0.014$, $p < 0.021$).

The keywords that significantly and positively impacted post comments were "follow" ($\beta = 0.092$, $p < 0.000$) and "die" ($\beta = 0.081$, $p < 0.000$). The keywords that significantly and negatively impacted post comments were "food" ($\beta = -0.030$, $p < 0.000$) and "delicious" ($\beta = -0.037$, $p < 0.000$).

6. Conclusions

6.1. Results

6.1.1. Hong Kong

This paper analyzed the posts concerning Hong Kong and found that the UGC contained three distinct keyword groups, namely (1) politics-related keywords, (2) pandemic-related keywords, and (3) calls to action, which had higher interactivity. For the pre-pandemic posts, those with more likes contained travel-related keywords, such as “tour” and “show”, and politics-related keywords, such as “protest” and “people”, Posts containing politics-related keywords, such as “police” and “protest”, gained more comments. Posts containing calls to action, such as “post”, “link”, and “like”, gained more user interaction. By contrast, posts solely containing travel information or general passive information, such as “food”, “fashion”, “shop”, and “award”, were informative, but were less able to prompt user interaction.

For the peri-pandemic posts, those that gained more likes contained pandemic-related keywords, such as “coronavirus” and “avail”, or calls to action, such as “share” and “link”. Similarly, those that gained more comments contained pandemic-related keywords, such as “coronavirus” and “COVID-19”. Due to Hong Kong’s political situation, posts containing politics-related keywords, such as “people” and “country”, also gained higher user interaction, and those containing calls to action, such as “link”, “share”, “post”, and “friend”, gained more comments. By contrast, posts pandemic containing general information published during the pandemic and that contained keywords, such as “artist”, “design”, “hkig”, “gallery”, “fashion”, “restaurant”, and “culture”, were unable to attract users’ attention.

6.1.2. London

This paper analyzed the posts concerning London and found that the UGC contained three distinct keyword groups, namely (1) calls to action, (2) keywords prompting positive emotions or national image, and (3) purely informative travel-related keywords. For the pre-pandemic posts, posts with more likes and comments contained keywords that expressed the features of the city, such as “story”, “thisislondon”, and “film”, or calls to action, such as “follow”, “tag”, “friend”, and “post”. By comparison, posts that only contained travel-related or city-related keywords, such as “design”, “fashion”, “travel”, “art”, “music”, and “food”, were less able to resonate with the audience, gaining fewer likes and comments.

For the peri-pandemic posts, posts with more likes contained keywords that prompted positive emotions or feelings, such as “thank”, “feel”, “together”, and “hope”, or those that highlighted national image, such as “British”, and “England”. Posts with more comments contained calls to action, such as “follow”, “tag”, and “post”. By comparison, posts containing only city-related or travel-related keywords, such as “fashion”, “travel”, “design”, “live”, “U.K.”, “food”, and “music”, were unable to prompt user demand, consequently gaining fewer likes and comments.

6.1.3. Bangkok

This paper analyzed the posts concerning Bangkok and found that the UGC contained three distinct keyword groups, namely (1) keywords highlighting regional images, (2) keywords prompting positive emotions, (3) and pandemic-related keywords. For the pre-pandemic posts, posts with more likes contained keywords that prompted positive emotion, such as “thank” and “champion”. In particular, those that contained keywords about city or regional images, such as “zen”, “place”, and “temple”, were able to attract user attention. By comparison, posts that contained only travel-related keywords, such as “Thailand”, “Asia”, “hotel”, “center”, “art”, and “amazingthailand”, were less able to gain user interest.

For the pre-pandemic posts, posts with more comments contained pandemic-related keywords, such as “follow” and “die”. By comparison, posts containing travel-related keywords, such as “food”, “central”, “travel”, “delivery”, and “hotel”, were less likely to prompt users to comment or like. These observations reiterate our hypothesis that travel-related cues are unable to gain public attention during a pandemic.

6.2. Hypothesis Verification

The findings of this study showed that UGC interactivity decreased in various countries during the pandemic. Only content containing pandemic-related keywords gained public attention. By comparison, pre-pandemic city-related UGC containing keywords that prompted positive emotions, those that highlighted local features, and calls to action gained more attention than other UGC [49]. These findings highlight the importance of social involvement in interactivity research [50]. Subsequently, the study of the key behaviors of public involvement can help researchers to understand underlying messages [51,52]. The findings of this study also indicated that, by using social media to promote cities, promoters are able to expand influence through participation [53]. Finally, based on our observations, it is confirmed that the public’s city demands are closely associated with community involvement [54].

Posts that contain positive and active keywords are more likely to gain emotional and interactive recognition. The narratives of UGC, which can include cultural, natural, recreational, entertainment, historical, and accommodation dimensions and themes, or attractive, emotional, and cognitive elements [55], significantly influence CI [56]. City researchers can review the attractive elements of UGC [19] to elucidate how UGC shapes and alters CI. Categorizing CI perceptions can also help researchers to uncover content cues [57] and images [58]. Past studies on UGC largely focused on functionality and emotional exchange. Few studies have centered on the relevance of UGC in current events or how positive content cues prompt user involvement [59,60]. To achieve successful CI communication and attract public affirmation and recognition, city promoters should strive to convey a consistent and active CI. Visual elements are an essential part of the clear projection of a sustainable city image, and they give meaning to symbolic signs and present the multifaceted characteristics of the city with the use of various informational symbols. They aim to guide people in tourism decision making, and they also positively impact the perception of the city.

6.3. Discussion

Sustainable city communication generally requires public involvement, such as liking, sharing, or commenting on social media posts [61]. Social media can serve as a communication tool between cities and the public. It can enhance city interaction and public trust [62,63] and change people’s impression of the city. Therefore, city promoters can take advantage of UGC on social media and the sharing economy to achieve their marketing goals [64]. Given that UGC serves a key function in expressing and enhancing overall public perception [17], it is more important to understand the positive and negative effects of UGC on CI [65,66].

Interactive platforms are built on sharing experiences and to provide users with resources that they need or desire. Social media is gradually replacing traditional media as more users are shifting to social media platforms for their authenticity and personalized features. Raising city awareness prompts travelers to stay in the city longer or participate in local events. It also creates opportunities for interaction and helps travelers to establish a deeper connection with and understanding of the city. Therefore, different backgrounds must be taken into account when planning and creating a presence on social media by combining image management and social media marketing.

According to the literature about information analysis, cities are often characterized by their diverse aspects of culture, food, and entertainment. Whether the information is an adjustment message of UGC or about improving the real-life experience in urban dialogue, it can be translated into the diverse value of UGC marketing. Many Internet users rely on social media to communicate and express their concerns, opinions, beliefs, and genuine perceptions about new things. For example, during the pandemic, the number of tweets with hashtags such as #coronavirus, #COVID-19, or #COVID on Twitter increased exponentially. This phenomenon led to social media platforms, such as Twitter, Facebook, YouTube, and TikTok, to handle misinformation about COVID-19 with a high degree of caution. A high volume of tweets containing panic and worrying information may cause public fear, which in turn affects trust in the government. If such issues persist without the implementation of necessary preventive measures, public distress and fear may increase. Therefore, it is particularly necessary to observe COVID-19-related social media messages to understand people's feelings and opinions during the pandemic.

Under the influence of the pandemic, urban organizations have tried to create new ways of interacting with the public through social media platforms, changing the reactive approach of traditional communication tools. For example, images and text resources on Instagram or recordings and content production using IGTV were adopted to enhance the public's active participation and sharing of their stories. In fact, as the pandemic wanes, it is not difficult to detect that managers, creators, or tourism industries have obtained a lot of interesting results through UGC research. This phenomenon indicates that making full use of UGC can effectively create sustainable value for cities.

6.4. Limitations of the Research and Suggestions

Sustainable cues in social media posts can be converted to heuristic information that highlights the characteristics of the commenters. Therefore, this paper recommends analyzing the cues in people's comments or reviews of UGC in the future to assess the credibility of information provided by new and experienced users, and commenters' professional knowledge would greatly affect their comments [67]. Many studies emphasized city personality and focused on city features [68,69]. Therefore, this paper recommends comparing users from different regions or cultures, such as the CI perceptions of people living in the West compared to those living in the East, to determine the differences in demand of information among different groups.

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References

1. Freire, J.R. Local People a Critical Dimension for Place Brands. *J. Brand Manag.* **2009**, *16*, 420–438. [CrossRef]
2. Ye, H.; Tussyadiah, I. Destination Visual Image and Expectation of Experiences. *J. Travel Tour. Mark.* **2011**, *28*, 129–144. [CrossRef]
3. Hunter, W.C. The social construction of tourism online destination image: A comparative semiotic analysis of the visual representation of Seoul. *Tour. Manag.* **2016**, *54*, 221–229. [CrossRef]
4. Katsoni, V. The Strategic Role of Virtual Communities and Social Network Sites on Tourism Destination Marketing. *e-J. Sci. Technol.* **2014**, *5*, 107–117.
5. Kavoura, A.; Sakas, D.P.; Tomaras, P.; Kiralova, A.; Pavlicek, A. Development of Social Media Strategies in Tourism Destination. *Procedia Soc. Behav. Sci.* **2015**, *175*, 358–366.
6. Bruhn, M.; Schoenmueller, V.; Schäfer, D.B. Are Social Media Replacing Traditional Media in Terms of Brand Equity Creation? *Manag. Res. Rev.* **2012**, *35*, 770–790. [CrossRef]
7. Boon-Long, S.; Wongsurawat, W. Social media marketing evaluation using social network comments as an indicator for identifying consumer purchasing decision effectiveness. *J. Direct Data Digit. Mark. Pr.* **2015**, *17*, 130–149. [CrossRef]
8. Lu, W.; Stepchenkova, S. User-Generated Content as a Research Mode in Tourism and Hospitality Applications: Topics, Methods, and Software. *J. Hosp. Mark. Manag.* **2015**, *24*, 119–154. [CrossRef]
9. Lin, P.M.; Fan, D.X.; Zhang, H.Q.; Lau, C. Spend less and experience more: Understanding tourists' social contact in the Airbnb context. *Int. J. Hosp. Manag.* **2019**, *83*, 65–73. [CrossRef]
10. Eginli, A.T.; Tas, N.O. Interpersonal Communication in Social Networking Sites: An Investigation in the Framework of Uses and Gratification Theory. *Online J. Commun. Media Technol.* **2018**, *8*, 81–104. [CrossRef]
11. Dafonte-Gómez, A.; Míguez-González, M.I.; Corbacho-Valencia, J.M. Viral Dissemination of Content in Advertising: Emotional Factors to Reach Consumers. *Commun. Soc.* **2020**, *33*, 107–120. [CrossRef]
12. Peters, B. The New Facebook Algorithm: Secrets Behind How It Works and What You Can Do to Succeed. The new Facebook algorithm: Secrets behind how it works and what you can do to succeed. *Buffer Soc. Blog* **2018**, *26*.

13. Sigala, M. Social Networks and Customer Involvement in New Service Development (Nsd): The Case of Www.Mystarbucksidea.Com. *Int. J. Contemp. Hosp. Manag.* **2012**, *24*, 966–990. [CrossRef]
14. Sigala, M. Social Media and the Co-Creation of Tourism Experiences. *Manag. Mark. Tour. Exp. Issues Chall. Approaches* **2017**, 85–111.
15. Zehrer, A. Service experience and service design: Concepts and application in tourism SMEs. *Manag. Serv. Qual. Int. J.* **2009**, *19*, 332–349. [CrossRef]
16. Tussyadiah, I.P.; Park, S. When guests trust hosts for their words: Host description and trust in sharing economy. *Tour. Manag.* **2018**, *67*, 261–272. [CrossRef]
17. Fesenmaier, R.D.; Xiang, Z. Introduction to Tourism Design and Design Science in Tourism. In *Design Science in Tourism*; Springer: Cham, Switzerland, 2017; pp. 3–16.
18. Jabreel, M.; Moreno, A.; Huertas, A. Do Local Residents and Visitors Express the Same Sentiments on Destinations through Social Media? In *Information and Communication Technologies in Tourism*; Springer: Cham, Switzerland, 2017; Volume 2017, pp. 655–668.
19. Marine-Roig, E. Destination Image Analytics through Traveller-Generated Content. *Sustainability* **2019**, *11*, 3392. [CrossRef]
20. Lee, M.Y.; Hitchcock, M.; Lei, J.W. Mental mapping and heritage visitors' spatial perceptions. *J. Heritage Tour.* **2017**, *13*, 305–319. [CrossRef]
21. Park, H.; Seo, S.; Kandampully, J. Why post on social networking sites (SNS)? Examining motives for visiting and sharing pilgrimage experiences on SNS. *J. Vacat. Mark.* **2015**, *22*, 307–319. [CrossRef]
22. Uysal, M.; Jurowski, C. Testing the push and pull factors. *Ann. Tour. Res.* **1994**, *21*, 844–846. [CrossRef]
23. Kim, J.; Fesenmaier, D.R. Sharing Tourism Experiences: The Posttrip Experience. *J. Travel Res.* **2017**, *56*, 28–40. [CrossRef]
24. Baloglu, S.; Henthorne, T.L.; Sahin, S. Destination Image and Brand Personality of Jamaica: A Model of Tourist Behavior. *J. Travel Tour. Mark.* **2014**, *31*, 1057–1070. [CrossRef]
25. Chen, K.; He, Y.; Zhong, G. The Transformation of Information Literacy Connotation in Artificial Intelligence (Ai) Perspective and Target Positioning of Artificial Intelligence (Ai) Education: Also on the Implementation Path of Artificial Intelligence Course and Teaching in Basic Education. *J. Distance Educ.* **2018**, *36*, 61–71.
26. Prayag, G.; Hosany, S.; Muskat, B.; del Chiappa, G. Understanding the Relationships between Tourists' Emotional Experiences, Perceived Overall Image, Satisfaction, and Intention to Recommend. *J. Travel Res.* **2017**, *56*, 41–54. [CrossRef]
27. Chen, F.C.; Phou, S. A Closer Look at Destination: Image, Personality, Relationship and Loyalty. *Tour. Manag.* **2013**, *36*, 269–278. [CrossRef]
28. Huang, Y.; Wu, J.; Shi, W. The impact of font choice on web pages: Relationship with willingness to pay and tourism motivation. *Tour. Manag.* **2018**, *66*, 191–199. [CrossRef]
29. Reitsamer, B.F.; Brunner-Sperdin, A.; Stokburger-Sauer, N.E. Destination attractiveness and destination attachment: The mediating role of tourists' attitude. *Tour. Manag. Perspect.* **2016**, *19*, 93–101. [CrossRef]
30. Herrero-Prieto, C.L.; Gómez-Vega, M. Cultural Resources as a Factor in Cultural Tourism Attraction: Technical Efficiency Estimation of Regional Destinations in Spain. *Tour. Econ.* **2017**, *23*, 260–280. [CrossRef]
31. Zhang, H.; Fu, X.; Cai, L.A.; Lu, L. Destination image and tourist loyalty: A meta-analysis. *Tour. Manag.* **2014**, *40*, 213–223. [CrossRef]
32. Huang, B.X.; Peng, J.F. Research on the Evaluation of Undergraduate Information Literacy under the New Environment. *Res. Libr. Sci.* **2019**, *19*, 12–20.
33. Zhang, H.; Wu, Y.; Buhalis, D. A Model of Perceived Image, Memorable Tourism Experiences and Revisit Intention. *J. Destin. Mark. Manag.* **2018**, *8*, 326–336. [CrossRef]
34. Pantano, E.; Priporas, C.V.; Stylos, N. 'You Will Like It!' Using Open Data to Predict Tourists' Response to a Tourist Attraction. *Tour. Manag.* **2017**, *60*, 430–438. [CrossRef]
35. García, B.B.; Carreras, A.O.; Royo, E.R. User generated content in destination marketing organisations' websites. *Int. J. Web Based Communities* **2012**, *8*, 103. [CrossRef]
36. De Sausmarez, N. Crisis Management, Tourism and Sustainability: The Role of Indicators. *J. Sustain. Tour.* **2007**, *15*, 700–714. [CrossRef]
37. Gstaettner, M.A.; Rodger, K.; Lee, D. Visitor Perspectives of Risk Management in a Natural Tourism Setting: An Application of the Theory of Planned Behaviour. *J. Outdoor Recreat. Tour.* **2017**, *19*, 1–10. [CrossRef]
38. Pappas, N. Hotel decision-making during multiple crises: A chaordic perspective. *Tour. Manag.* **2018**, *68*, 450–464. [CrossRef]
39. Pappas, N. UK Outbound Travel and Brexit Complexity. *Tour. Manag.* **2019**, *72*, 12–22. [CrossRef]
40. Aliperti, G.; Rizzi, F.; Frey, M. Cause-Related Marketing for Disaster Risk Reduction in the Tourism Industry: A Comparative Analysis of Prevention- and Recovery-Related Campaigns. *J. Hosp. Tour. Manag.* **2018**, *37*, 1–10. [CrossRef]
41. Scott, K. *Measuring Wellbeing: Towards Sustainability?* Routledge: London, UK, 2012; pp. 1–212.
42. Scott, K. Happiness on Your Doorstep: Disputing the Boundaries of Wellbeing and Localism. *Geogr. J.* **2015**, *181*, 129–137. [CrossRef]
43. Weber, R. Constrained Agency in Corporate Social Media Policy. *J. Tech. Writ. Commun.* **2013**, *43*, 289–315. [CrossRef]
44. Mariani, M.M.; Mura, M.; di Felice, M. The Determinants of Facebook Social Engagement for National Tourism Organ-izations' Facebook Pages: A Quantitative Approach. *J. Destin. Mark. Manag.* **2018**, *8*, 312–325.

45. Hays, S.; Page, S.; Buhalis, D. Social media as a destination marketing tool: Its use by national tourism organisations. *Curr. Issues Tour.* **2013**, *16*, 211–239. [CrossRef]
46. Hochman, N.; Manovich, L. Zooming into an Instagram City: Reading the local through social media. *First Monday* **2013**, *18*. [CrossRef]
47. Sanchez, D.; Batet, M.; Isern, D.; Valls, A. Ontology-based semantic similarity: A new feature-based approach. *Expert Syst. Appl.* **2012**, *39*, 7718–7728. [CrossRef]
48. Slimani, T. Description and Evaluation of Semantic Similarity Measures Approaches. *Int. J. Comput. Appl.* **2013**, *80*, 25–33. [CrossRef]
49. Usakli, A.; Koç, B.; Sönmez, S. How 'social' are destinations? Examining European DMO social media usage. *J. Destin. Mark. Manag.* **2017**, *6*, 136–149. [CrossRef]
50. Dickinger, A.; Lalicic, L. Tourist-Driven Innovations in Social Media: An Opportunity for Tourism Organizations. In *Advances in Social Media for Travel, Tourism and Hospitality: New Perspectives, Practice and Cases*; Routledge: London, UK, 2017; pp. 41–53.
51. So, F.K.K.; King, C.; Sparks, B. Customer Engagement with Tourism Brands: Scale Development and Validation. *J. Hosp. Tour. Res.* **2014**, *38*, 304–329. [CrossRef]
52. So, K.K.F.; King, C.; Sparks, B.A.; Wang, Y. The Role of Customer Engagement in Building Consumer Loyalty to Tourism Brands. *J. Travel Res.* **2014**, *55*, 64–78. [CrossRef]
53. Mariani, M. Web 2.0 and Destination Marketing: Current Trends and Future Directions. *Sustainability* **2020**, *12*, 3771. [CrossRef]
54. Önder, I.; Gunter, U.; Gindl, S. Utilizing Facebook Statistics in Tourism Demand Modeling and Destination Marketing. *J. Travel Res.* **2019**, *59*, 195–208. [CrossRef]
55. Gartner, W.C. Image Formation Process. *J. Travel Tour. Mark.* **1994**, *2*, 191–216. [CrossRef]
56. Oliveira, E.; Panyik, E. Content, Context and Co-Creation: Digital Challenges in Destination Branding with References to Portugal as a Tourist Destination. *J. Vacat. Mark.* **2015**, *21*, 53–74. [CrossRef]
57. Költringer, C.; Dickinger, A. Analyzing destination branding and image from online sources: A web content mining approach. *J. Bus. Res.* **2015**, *68*, 1836–1843. [CrossRef]
58. Sanz, I.; Museros, L.; González-Abril, L. Exploring the Cognitive-Affective-Conative Image of a Rural Tourism Destination Using Social Data. In Proceedings of the Paper Presented at the JARCA Workshop on Qualitative Systems and Applications in Diagnosis, Robotics and Ambient Intelligence, Almería, Spain, 23–29 June 2016.
59. Michaelidou, N.; Siamagka, N.T.; Christodoulides, G. Usage, barriers and measurement of social media marketing: An exploratory investigation of small and medium B2B brands. *Ind. Mark. Manag.* **2011**, *40*, 1153–1159. [CrossRef]
60. Michaelidou, N.; Siamagka, N.T.; Moraes, C.; Micevski, M. Do Marketers Use Visual Representations of Destinations That Tourists Value? Comparing Visitors' Image of a Destination with Marketer-Controlled Images Online. *J. Travel Res.* **2013**, *52*, 789–804. [CrossRef]
61. Ángeles Oviedo-García, M.; Muñoz-Expósito, M.; Castellanos-Verdugo, M.; Sancho-Mejías, M. Metric Proposal for Cus-tomer Engagement in Facebook. *J. Res. Interact. Mark.* **2014**, *8*, 327–344. [CrossRef]
62. Kabadayi, S.; Price, K. Consumer–brand engagement on Facebook: Liking and commenting behaviors. *J. Res. Interact. Mark.* **2014**, *8*, 203–223. [CrossRef]
63. Den Eijnden, V.R.; Koning, I.; Doornwaard, S.; van Gurp, F.; Bogt, T.T. The Impact of Heavy and Disordered Use of Games and Social Media on Adolescents' Psychological, Social, and School Functioning. *J. Behav. Addict.* **2018**, *7*, 697–706. [CrossRef]
64. Dolnicar, S. A review of research into paid online peer-to-peer accommodation: Launching the Annals of Tourism Research Curated Collection on peer-to-peer accommodation. *Ann. Tour. Res.* **2019**, *75*, 248–264. [CrossRef]
65. Volgger, M. The End of Tourism through Localhood and Overtourism? An Exploration of Current Destination Governance Challenges. In *Overtourism: Tourism Management and Solutions*; Routledge: Oxfordshire, UK, 2019.
66. Volgger, M.; Taplin, R.; Pforr, C. The evolution of 'Airbnb-tourism': Demand-side dynamics around international use of peer-to-peer accommodation in Australia. *Ann. Tour. Res.* **2019**, *75*, 322–337. [CrossRef]
67. Hong, H.; Xu, D.; Wang, A.; Fan, W. Understanding the determinants of online review helpfulness: A meta-analytic investigation. *Decis. Support Syst.* **2017**, *102*, 1–11. [CrossRef]
68. Xiang, Z.; Fesenmaie, D.R. Big Data Analytics, Tourism Design and Smart Tourism. In *Analytics in Smart Tourism Design*; Springer: Cham, Switzerland, 2017; pp. 299–307.
69. Xiang, Z.; Gretzel, U. Role of social media in online travel information search. *Tour. Manag.* **2010**, *31*, 179–188. [CrossRef]