future internet

MDPI

Article

Image of a City through Big Data Analytics: Colombo from the Lens of Geo-Coded Social Media Data

Sandulika Abesinghe [1], Nayomi Kankanamge [1], Tan Yigitcanlar [2,*] and Surabhi Pancholi [3]

1 Department of Town and Country Planning, University of Moratuwa, Katubedda, Moratuwa 10400, Sri Lanka
2 City 4.0 Lab, School of Architecture and Built Environment, Queensland University of Technology, Brisbane, QLD 4000, Australia
3 School of Architecture and Built Environment, Deakin University, Geelong, VIC 3220, Australia
* Correspondence: tan.yigitcanlar@qut.edu.au; Tel.: +61-7-31382418

Abstract: The image of a city represents the sum of beliefs, ideas, and impressions that people have of that city. Mostly, city images are assessed through direct or indirect interviews and cognitive mapping exercises. Such methods consume more time and effort and are limited to a small number of people. However, recently, people tend to use social media to express their thoughts and experiences of a place. Taking this into consideration, this paper attempts to explore city images through social media big data, considering Colombo, Sri Lanka, as the testbed. The aim of the study is to examine the image of a city through Lynchian elements—i.e., landmarks, paths, nodes, edges, and districts—by using community sentiments expressed and images posted on social media platforms. For that, this study conducted various analyses—i.e., descriptive, image processing, sentiment, popularity, and geo-coded social media analyses. The study findings revealed that: (a) the community sentiments toward the same landmarks, paths, nodes, edges, and districts change over time; (b) decisions related to locating landmarks, paths, nodes, edges, and districts have a significant impact on community cognition in perceiving cities; and (c) geo-coded social media data analytics is an invaluable approach to capture the image of a city. The study informs urban authorities in their placemaking efforts by introducing a novel methodological approach to capture an image of a city.

Keywords: city image; Lynchian elements; image processing; sentiment analysis; social media analytics; urban analytics; big data analytics; urban informatics; Colombo; Sri Lanka

Citation: Abesinghe, S.; Kankanamge, N.; Yigitcanlar, T.; Pancholi, S. Image of a City through Big Data Analytics: Colombo from the Lens of Geo-Coded Social Media Data. *Future Internet* **2023**, *15*, 32. https://doi.org/10.3390/fi15010032

Academic Editor: Manuel José Cabral dos Santos Reis

Received: 16 December 2022
Revised: 2 January 2023
Accepted: 5 January 2023
Published: 9 January 2023

1. Introduction

Cities are ever-changing environments with new urban elements being introduced into the built environment on a regular basis. In his seminal book 'Image of the City', Kevin Lynch [1] introduced how the city images can be conveniently understood through the five 'Lynchian' elements—i.e., landmarks, paths, nodes, edges, and districts. Moreover, people's experiences and perceptions about a city are also influenced by the image of the city. An image of a city provides the community with an orientation, direction, and emotional security about the city. Moreover, a poor city image, which is non-discernible by the above five elements and design, leads to psychologically unsatisfying urban environments for the people living and visiting a city [1]. A good city image has an influence on the shaping up of an overall city identity as well as people's place-based identities [2]. The image of the city is not only a critical factor having an impact socially on the local community, but it plays a significant role in boosting a country's economy by contributing to their branding, promoting tourism, and in staying competitive for attracting investors [3].

While a good city image positively impacts attractiveness, a poor city image, on the other hand, leads to many negative impacts, such as limited investment attractiveness, absence of prospects for the future, and so on [4]. In the age of globalization, a city's image is a mix of physical and social values, as well as a tool for branding where cities are competing to identify and establish their unique identities as their competitive edge [5–7].

Henceforth, in their attempts to create and maintain a good city image to achieve the highest expectations of the citizens and economy, contemporary cities are increasingly investing in better and more efficient ways to examine city images as an important tool to understand the changing perceptions of the citizens [8,9].

In recent years, a new dimension has been added to the attempts of discerning the idea of an image of the city with the breakneck speed of growth seen in the use of social media [10]. Social media can be identified as one of the main and largest data sources in the modern era and, more importantly, a potential platform to examine city images accurately within shorter time periods [11]. It holds millions of textures and graphical data related to every kind of topic. Most importantly, social media data is regarded as crowd-sourced, which is collected from the public [11]. Furthermore, social media data collection methods are timesaving, cost-effective, and a much more suitable method to avoid physical contact with the public in this COVID-19 pandemic situation [12].

A huge amount of data is available on social media to capture public opinion, and many big data analysis tools and algorithms are available to analyze them further. For instance, there are over two billion active social media users in the Asia–Pacific region, and it records the world's highest number of social network users. For example, in November 2022, as an Asian country, 76% of Sri Lankans used Facebook, 13% used YouTube, 5% used Pinterest, 2% used Instagram, and another 2% used Twitter [13]. People use aforesaid social media networks to share their thoughts, feelings, and observations within their network. Such information shared in social networks can be considered good reflections about landmarks (e.g., towers, museums), nodes (e.g., urban squares, train stations), edges (e.g., waterfronts, lakes), paths (e.g., nature trials, streets), districts (e.g., villages, neighborhoods), and their experiences attached to them. This opens a novel research direction and a tool for scholars to investigate the image of a city by analyzing social media content. The crowdsourced social media data can be regarded as one of the strongest potential platforms to examine city images accurately within shorter time periods.

The integration of data analytics with the Lynchian approach for exploring the image of the city has drawn interest from scholars belonging to diverse fields, including spatial cognition, urban studies, urban planning, information and communication technologies, and artificial intelligence [14–16]. Research studies have been investigating city images based on different techniques, such as using small-size data analytics—i.e., surveys and interviews—geographical information system analysis, sketch maps, and so on [16,17]. Now, with the help of the huge amount of existing social media data (i.e., social media big data) generated per minute, city images can be examined from a broader perspective and cover a much larger scale and scope [18].

However, despite its abundant and easy availability, the use of big data, specifically social media data and its analysis as an approach has found a limited application in the field of urban studies. Moreover, studies that have specifically used social media data to comprehensively test the image of the city using Kevin Lynch's theory base are even rarer [17]. For instance, references [19,20] have tried to understand one psychogeographical aspect of cities using crowdsourced data, which they are limited to one or two aspects such as place identity. Moreover, reference [21] have tried to understand the streets of London through Kevin Lynch's theory using Flickr and Open Street Map (OSM), which lacks discussions on how community perceptions on social media influence the development of the city image.

This paper, therefore, aims to contribute to this understudied area of research. This study, hence, attempts to address the question of 'How can the image of a city be examined by using geo-coded social media data?' To address the research question, the study adopted the Capture–Understand–Present (CUP) framework introduced by [22].

2. Background of the Literature

2.1. Image of a City and Its Elements

The public image of a city is designed by a series of physical and perceptible objects. There are other influencing factors on developing city images, such as the social meaning of an area, its related function and history, or even its name. The first descriptive introduction to the public's perception of the built environment is Kevin Lynch's study on city images [23]. Lynch explained that in cities, 'legibility,' or clarity in visuals, makes it easier for people to navigate. Based on his case studies in three cities in the USA, he explained that public image is built on the legibility of five urban elements—so-called Lynchian elements, which are landmarks, paths, nodes, edges, and districts—described in detail below.

Landmarks are a different type of point-of-reference that the observer does not enter. Instead, they are external. Additionally, they are usually a simple physical object, such as a building, a sign, a store, or a mountain [24]. Some landmarks are far away, seen from a variety of angles and distances, and used as radial references over the tops of smaller elements. Landmarks are often used as identity and even structure clues for the public, and they seem to be relied on more and more as a journey becomes more familiar. They may be located within the city or at a distance. Landmarks mostly deliver a constant direction for all practical purposes [1].

Paths are how the observer travels on a regular, irregular, or potential basis. Streets, walkways, transit lines, canals, and railroads are examples of paths. People observe the city as they move through it, and perceive other environmental elements located and related along such paths [1].

Nodes are points in a city, strategic locations where an observer can enter and exit. They can be primarily junctions, points where transportation stops, paths cross or converge, or transition points from one structure to another. These nodes serve as the focal point and epicenter of a district, radiating their influence and serving as a symbol [25]. Nodes are typically the convergence of paths and events on the journey, and they are related to the concept of the path. Nodes can be found in almost every image and can even be the dominant feature in some cases [1].

Edges are the linear elements that the observer does not consider to be a path. They can be defined as the linear breaks in continuity between two phases: shores, railroad cuts, development edges, and walls. Such edges may act as permeable barriers that separate one region from another, or they may be seams, lines that connect two regions. Although not as prominent as paths, these edge elements are significant organizing features for many people, particularly in holding together generalized areas, i.e., the outline of a city by water or wall [1].

Districts can be defined as medium-to-large sections of the city. They are expected to have a two-dimensional extent, where the observer mentally gets the feeling of entering/ 'inside of'. Districts are recognizable as having a unique and common but identifying character. Such districts are considered exterior references if visible from the outside and always identifiable from the inside. Most people organize their city in this way to some extent, with individual differences in whether paths or districts are the most important elements. It appears to be dependent not only on the individual but also on the city in question [1].

The works done by Lynch emphasized the psychological need of people for contact with other people. Lynch's ideas about the thoughtful design of spaces to encourage social contact are acknowledged in the works of many key urban designers from his time and after [26,27]. Despite being criticized for more focus on the physicality of spaces, the underlying thought of the whole body of works that Lynch produced lies in the core idea of creating aesthetically appealing and psychologically satisfying spaces that satisfy human needs for social contact. His theory, therefore, stands contemporary and still finds its applicability in the age of social media—in other words, the contemporary digitized public space [15].

Moreover, the Lynchian approach makes itself distinguished from other urban analysis approaches as it is a creative qualitative approach based on the analysis of empirical data, i.e., 'mental maps', derived from people based on their perceptions. Rather than simply reporting surveys, this technique uses qualitative methods, such as observations, interviews, and conceptual map analyses, to generalize findings into the above higher-order conceptual categories. This makes Lynch's theory and approach a perfect base for this study as it assists in understanding the meaning that people attach with the help of data collected from social media.

2.2. Image of a City and Social Media Big Data

Meanings that people attach and their perceptions are key contributors to the development of an image as it converts an abstract space into place [28,29]. Lynch [1] argues that the legibility of the city influences the image of the city by shaping up the meaning, experience, and perceptions of the people. The advent of globalization and digital technologies has been a strong influencer on people's perceptions about the real world by shifting the meanings of time and distance and blurring the distinction between public and private [30–32]. With the prolific use of social media becoming common in the 21st Century, it has altered the working modes and has influenced many aspects of human lives and the meanings people attach to their surroundings [33].

Additionally, there is an increasing trend in using social media as a source of big data in urban research [34,35]. Platforms such as Instagram, Twitter, and Facebook generate considerably large amounts of geo-coded images, videos, and texts about users' daily lives, and much of this data is available in the public domain. The key attributes of social media data that make it an effective choice are that it is: (a) crowdsourced; (b) diverse in terms of data produced; (c) efficient in terms of capturing the perceptions of millions of users; (d) and accessible in the pandemic situation. As an emerging area of research, social media data has been applied in many disciplines, including: (a) marketing [36,37]; (b) disaster/crisis management [38,39]; (c) business analytics [40,41]; (d) political science [42,43]; (e) social science [44–46]; and so on. Especially, social media facilitates the inclusion of ordinary citizens in scientific decision making—i.e., citizen science [47,48].

Despite there being few scholars, such as [15], who questioned the relevance of Lynch's theory with the advent of digital technologies, arguing that Lynch's imminent fear of disorientation would have held no ground after the invention of Google Maps, number of other research studies have used online content as a tool to study the perceptions of urban environments. For instance, reference [49] mapped user behaviors and sentiments in New York using geo-coded Twitter data. Although the data sources and underlying algorithms were not disclosed, references [50–52] used the Instasights heat map, which is a web-based social media mapping tool, to monitor the impact of renewed waterfront areas in Spanish cities.

In their study of 26 cities, reference [41] used geo-tagged Panoramio photos to understand the perception of city images. Recently, reference [17] in their study, tested the use of 'big data' and 'small data' methods together in the Tri-City Region in Poland to explore the perception of city images. The study has proved the relevance of Lynch's theory in the digital age by deriving parallel social media-based indicators. Nonetheless, the use of social media to understand complex and subjective urban phenomena related to urban design [48,49] is an understudied but emerging area of research. Still, it demands more comprehensive studies to examine the image of a city through social media.

2.3. Social Media Analytics

This study adopted social media analytics as the major technique. Among many social media analytic framework studies, it is popular to use the Capture–Understand–Present (CUP) framework [22]. Capture is the process of gathering data from relevant social media sources, archiving the needed, and extracting the necessary [22]. Understand is the method of data processing to obtain meaningful results. It may involve statistical methods such as data mining, machine learning, and natural language processing. Present is the arranging of obtained results in a meaningful way and showing them as the final output.

3. Research Design

3.1. Case Study

The selected study area is the Colombo city of the western province of Sri Lanka. Colombo is the commercial capital of Sri Lanka, as well as the country's main economic hub. The study was conducted in Colombo not only because it is the commercial capital of the country but also because it is one of the best examples in the Sri Lankan context of a rapidly changing urban form influenced by globalization and triggered by economic changes. Additionally, it is the most densely populated area—over 52,000 per square miles.

This study used the Keywords–Hashtag (K–H) network mining method to identify popular keywords and hashtags tweeted or circulated together. K–H network mining acts as a content-based approach that was designed to enable related keywords and hashtags to discover from the links among keywords and hashtags. Such related K–H networks were explored algorithmically. Accordingly, this study identified 52 Lynchian elements. From them, 24 Lynchian elements were removed due to low occurrence (<10). This study considered the identified 28 Lynchian elements as the main keywords and their associated hashtags to mine tweets. After, a bounding box was demarcated, covering the location of the aforesaid 28 Lynchian elements. As in Figure 1, the case study is bounded by the bounding box coordinates of 6.88, 79.81 (Lower Left) and 6.98, 79.89 (Upper Right).

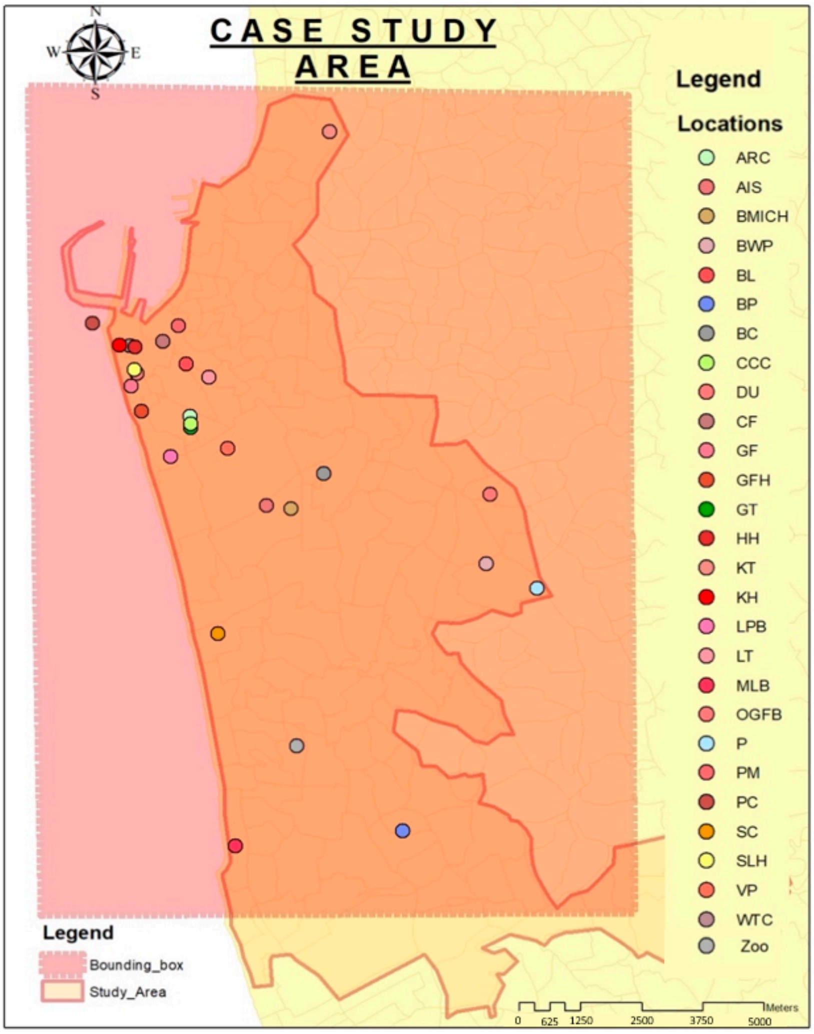


Figure 1. Case study area.

The identified 28 elements were: Altair Residential Condominium (ARC), Arcade Independence Square (AIS), Beddagana Wetland Park (BWP), Beira Lake (BL), Bellanvila Park (BP), Bandaranaike Memorial International Conference Hall (BMICH), Borella Cemetery (BC), Colombo City Center (CCC), Diyatha Uyana (DU), Colombo Fort (CF), Galle Face (GF), Galle Face Hotel (GFH), Gangaramaya Temple (GT), Hilton Hotel (HH), Kelaniya Temple (KT), Kingsbury Hotel (KH), Liberty Plaza Building (LPB), Lotus Tower (LT), Mount Lavinia Beach (MLB), One Galle Face Building (OGFB), Parliament (P), Pettah Market (PM), Port City (PC), Savoy Cinema (SC), Shangri La Hotel (SLH), Viharamahadevi Park (VP), World Trade Center (WTC), and Zoo (Zoo)

3.2. Social Media Analytics with the CUP Framework

As in Figure 2, this study adopted the Capture–Understand–Present (CUP) framework [22] to analyze and synthesize the data.

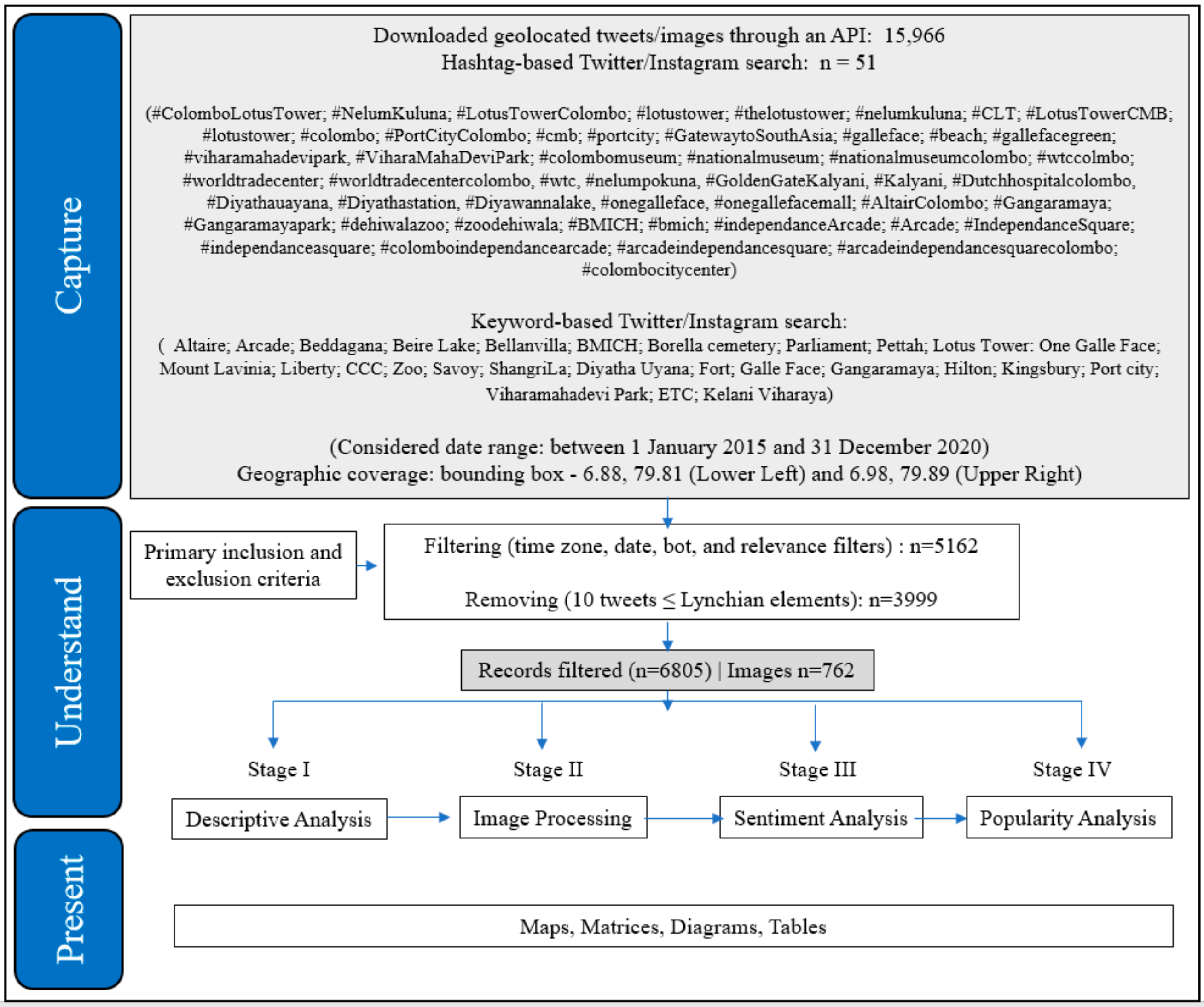


Figure 2. The CUP framework.

3.2.1. Capture: Twitter and Instagram Data

The first stage of the framework involves 'capturing' Twitter social media information. However, Twitter has certain merits and constraints. The main merits include: (a) Twitter is one of the most rapidly growing social media microblogging services; (b) Twitter allows researchers to use a free Twitter 'application programming interface' (API); (c) unlikely in Facebook and Instagram, Twitter data can be considered 'open data', which delivers succinct real-time data to the public [53]; (d) Twitter search and streaming APIs allow researchers to write queries based on certain keywords and/or hashtags to download information [54]; (e) and analyzing Twitter data is considered a novel approach of harvesting dispersed community knowledge [55].

Restricted API-based data accessibility can be considered the main limitation of Twitter, where APIs provide access to only 1% of publicly available Twitter data. Additionally, from a collected sample, only around 10% is either geo-located or geo-tagged [56]. Even the geo-coded tweets are becoming harder to collect due to not sharing personal mobile location information. As well, there are ethical barriers, as such information consists of the exact location (x,y coordinates of a location) information of the people.

For instance, only 22% of tweets consisted of geo-coded information from the total harvested data. Therefore, geo-tagged information is often collected through data providers—i.e., DataSift—with 100% access. This is a costly approach [38]. However, since this study related to location-specific keywords, such as Lotus Tower, Pettah, and so on, the aforesaid limitation did not affect the results of this study. As another limitation, reference [57] highlighted the bias of age groups of the Twitter data. Except for these limitations, an increasing number of studies use tweets as the main data source [58,59].

The obtained raw data consists of user ID, text body, available images and videos, time stamp, global positioning system (GPS) coordinates, and the language of the tweet. Then, this study adopted the five-step data-cleaning process presented by [60]. Those are time zone filter, date filter, bot filter, relevance filter, and text filter.

Time-zone filtering, date filtering, and bot Filtering are done through the Twitter APIs while collecting data. The UTC/GMT+5:30 time zone is used for the time-zone filter. These filter out the tweets tweeted within the given time zone. Date filtering is used to filter out tweets tweeted within a given time frame. This study contains tweets starting from 1 January 2015 to 31 December 2020. Bot filter is used to filter automated tweets. After these three filtering processes were completed, the extracted data was saved to '.CSV' formatted files.

Each file was then opened using Macro-enabled MS Excel for further cleaning. Relevance filtering was done to remove any irrelevant messages to the studying context or interests. All the conjunctions, Be-verbs, links, and special characters were removed using text filtering. After all these steps, the cleaned data was finally saved as a '.XLSX' formatted file for further processing.

Secondly, capturing Instagram social media information was done. Hashtag filtering and location filtering are functions offered by the Instagram app. Only the relevant images were downloaded at this stage. All the portraits, group photos, and advertisements were filtered out. Including Twitter images, altogether, 762 images were selected to create the final data set covering the 28 selected locations of Colombo city.

3.2.2. Understand and Present

Descriptive Analysis

Twitter/Instagram data consist of much information, such as 'created_date', 'username', 'user-screen name', 'text', 'photo/video', and 'user-location'. This study used a descriptive analysis (DA) to provide a larger view of the collected data. This study used three descriptive statistics, namely, Twitter statistics, user analysis, and web-link (URL) analysis. Identifying widely used hashtags is especially useful for urban planners as they reflect the emotive and evaluative reflections toward the places they visit [61]. Twitter statistics provide information about the number of users, number of retweets, and number of hashtags used. This study considered all 'retweets' as new tweets.

Image Processing

Image processing (IP) was conducted to understand the content of Instagram images and their importance to perceive Lynchian elements. With the computational limitations and the long process of training a large "Places" dataset, the study used a publicly available pre-trained model introduced by [62]. Zhou et al. [62] used wide residual networks in his process to train over 10 million image datasets. This model can predict each image with its content, whether it is a "Skyscraper", "Tower", "Park", "Beach", etc. It also provides its prediction probability. This probability was used as a weight to measure the final output. The formula used to calculate the probability is given in Equation (1) below.

$$\text{Probability Sum (class i)} = \sum_{k=1}^{k=n} \text{Probability (class i)} \tag{1}$$

where k is the index of the sum, n is the number of input images and i is the index of the class. Accordingly, the class with the highest probability sum value was selected as the predicted class for the relevant image. Each predicted class was then categorized into the suitable Lynchian component based on Kevin Lynch's definition of city image components.

Sentiment Analysis

Sentiment analysis (SA) can be identified as the most widely used text classification method to analyze a given textual phase and tell whether the selected phase is positive, negative, or neutral [63]. This study aims to classify how each tweet describes the respective place depending on the positive and negative factors/words of the tweet. Accordingly, a value ranging between (-4) and +4 was given to each tweet. To do so, it is required to make a Word Bag of positive and negative words. To make this Word Bag, this study extracted a portion of Positive and Negative words from the already downloaded filtered tweets. Using the obtained data, the positive sentiment values were measured as the ratio of the positive tweets to the total number of tweets, i.e., Positive sentiments = (Positively classified tweets/Total number of tweets) x 100. The study used Weka 2.0 open-source machine learning software and ArcGIS to perform and present the sentiment analysis [47,64].

Popularity Analysis

Popularity analysis (PA) was conducted by counting the number of tweets per year posted related to a place name. Popularity increases with the number of tweets tagged. Referring to this, the study analyzed the popularity of each Lynchian element among Twitter communities during the past six years. The results of these four analyses are presented in the next section.

4. Results

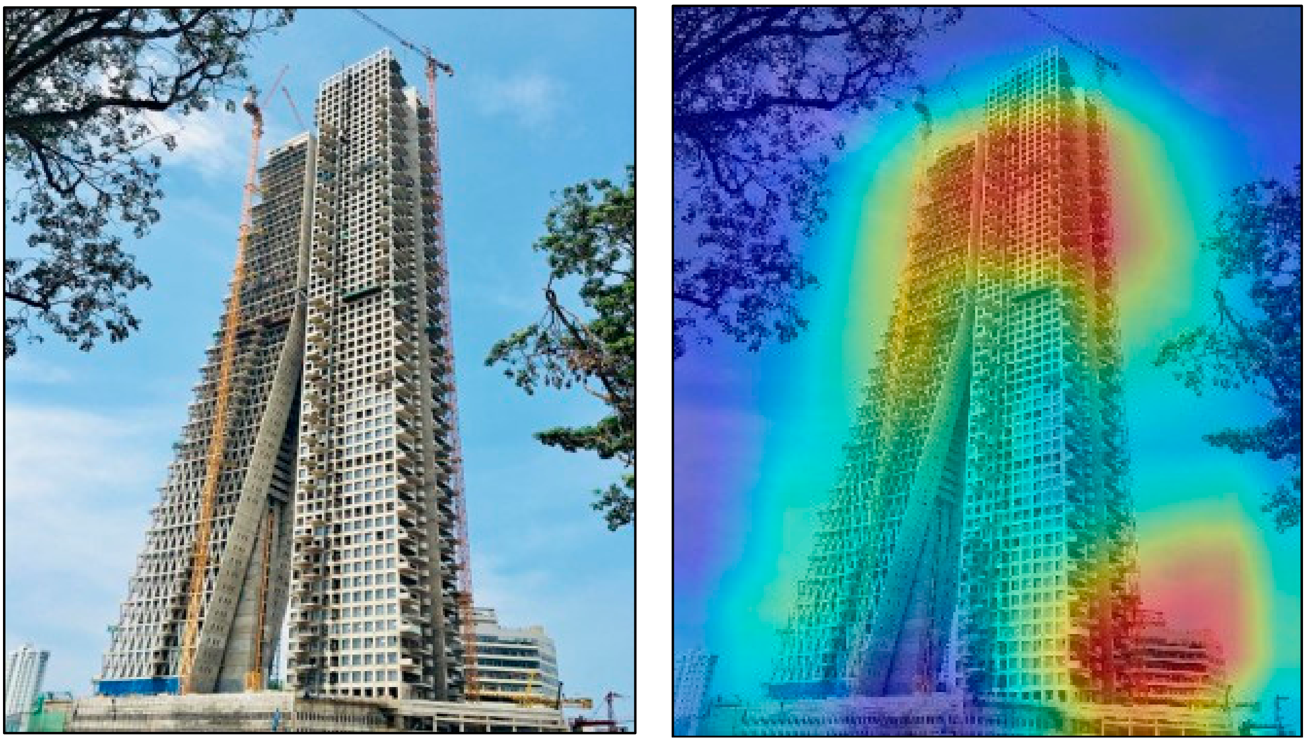
4.1. Descriptive Analysis

Of the 6805 tweets, 2586 (38%) were original and 4219 (62%) were retweeted with supportive content, reflecting the highly interactive nature of users. All Twitter discussions developed around 237 hashtags. The hashtag analysis identified (excluding 51 hashtags used for data mining) 86 key hashtags among them as the most strongly associated ones with the Lynchian elements. Among them, the most used 50 hashtags were: #selfie, #blue, #seaview, #skyporn, #Sky, #ocean, #sea, #coastline, #wonderofasia, #view, #train, #viewfromthetop, #cityview, #luxury, #luxuryhotel, #urbandesign, #greenbuilding, #economy, #green, #blue, #ScenicsNature, #Cloud, #Rooftop, #arialview, #discovercolombo, #development, #project, #waves, #randomshot, #roadride, #ship, #sand, #beach, #lankabeach, #naturalbeach, #Beauty, #weekend, #trave, #AwesomeMoments, #cappuccino #cappuccinoArt, #convocation, #sunset, #shopping, #fireworks, #restaurent, #foodlover, #foodie, #family, #dayout. Most of these hashtags were used in relation to the user experiences abiding with the Lynchian elements identified.

In total, 2190 users contributed to the creation of the dataset of 6805 tweets. About 79% of the tweets were circulated by individual users and 21% by institutions. However, 75% of the top 20 most active users were individuals. There were 576 tweets with informative URLs in the dataset. Within the period of 2015–2016, the total number of places identified for the analysis was 22. During the next two years of time (2017–2018), this number increased to 25. This number further increased to 28 from 2019–2020.

4.2. Image Processing

This study selected a unique number of random non-portrait Twitter and Instagram images from each place and tested them on Wide-resnet architecture [65–67]. The process of Image Processing can be divided into two main parts. They are the prediction of the class and the identification of the relevant Lynchian category. An exemplified demonstration of the image processing exercise is given in Figure 3. Accordingly, all 762 images were classified.



(a) (b)

Figure 3. Exemplified image processing. (**a**) Input image: inserted Image; (**b**) output image: heat map of the features used to make the correct predictions.

As given in Table 1, each prediction was saved with its relevant probability value. The obtained probabilities for each class were summed together to get the most probable prediction of the output class. Using the behavior of the predictions obtained for each place, this study sorted each Lynchian element into its right Lynchian category by referring to the Lynchian definition, i.e., Prediction Class—Skyscraper, Lynchian element—Landmark/Prediction Class: Ocean, Lynchian element: Edge.

Table 1. Identifying Lynchian categories.

Place Name and Code	Number of Photos	Prediction Class	Probability	Lynchian Category
Altair Residential Condominium (ARC)	25	Skyscraper	51.98%	Landmark
Arcade Independence Square (AIS)	30	Mosque/Outdoor	31.34%	Landmark
Beddagana Wetland Park (BWP)	28	Broadwalk	72.48%	District
Beira Lake (BL)	30	Canal	42.81%	Edge
Bellanvila Park (BP)	28	Park	32.46%	District
Bandaranaike Memorial International Conference Hall (BMICH)	30	Elevator lobby	22.94%	Landmark
Borella Cemetery (BC)	25	Cemetery	75.40%	Landmark
Colombo City Center (CCC)	30	Department Store	47.91%	Landmark
Diyatha Uyana (DU)	25	Park	25.36%	District
Colombo Fort (CF)	25	Library	21.52%	District
Galle Face (GF)	30	Ocean	22.62%	Edge
Galle Face Hotel (GFH)	30	Ballroom	30.78%	Landmark
Gangaramaya Temple (GT)	25	Temple	40.98%	Landmark
Hilton Hotel (HH)	28	Hotel	42.35%	Landmark
Kelaniya Temple (KT)	15	Temple	57.16%	Landmark
Kingsbury Hotel (KH)	30	Hotel/Outdoor	45.87	Landmark
Liberty Plaza Building (LPB)	30	Department Store	36.96%	Landmark
Lotus Tower (LT)	30	Tower	42.21%	Landmark
Mount Lavinia Beach (MLB)	30	Beach	27.41%	Edge
One Galle Face Building (OGFB)	30	Skyscraper	33.44%	Landmark
Parliament (P)	15	Legislative Chamber	59.2%	Landmark
Pettah Market (PM)	28	Bazaar	43.13%	District
Port City (PC)	30	Harbor	28.07%	District
Savoy Cinema (SC)	25	Movie Theatre	32.53%	Landmark
Shangri La Hotel (SLH)	30	Hotel	45.64%	Landmark
Viharamahadevi Park (VP)	30	Park	55.60%	District
World Trade Center (WTC)	25	Skyscraper	60.06%	Landmark
Zoo (Zoo)	25	Aquarium	31.99%	District
Total		762		

As of Table 1, from the identified Lynchian categories, 71% of places were identified as landmarks, 18% were Districts, and 11% were Edges. No Paths and Nodes were identified. The distribution of the aforesaid place names according to the Lynchian category is given in Figure 4.

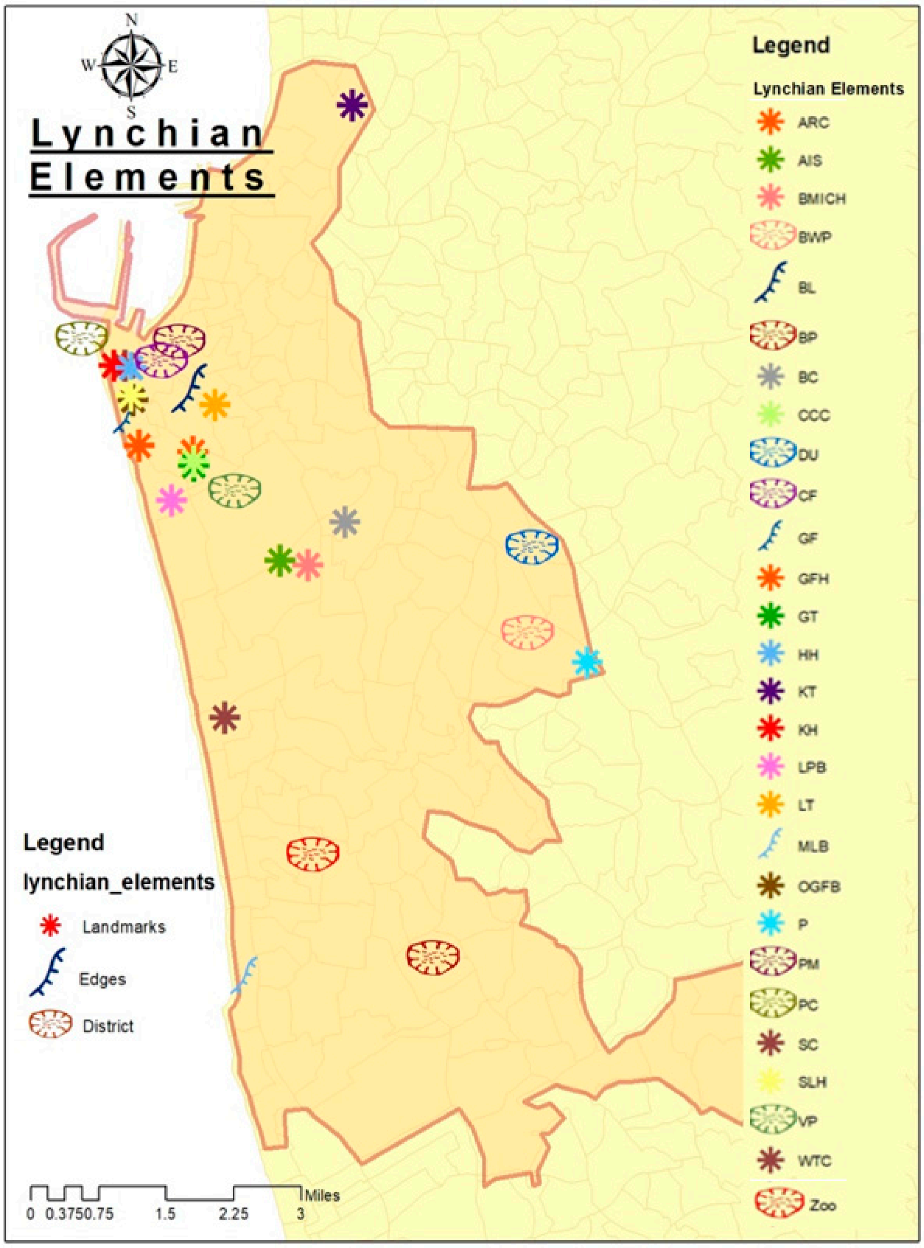


Figure 4. Distribution of place names according to the Lynchian category.

4.3. Sentiment Analysis

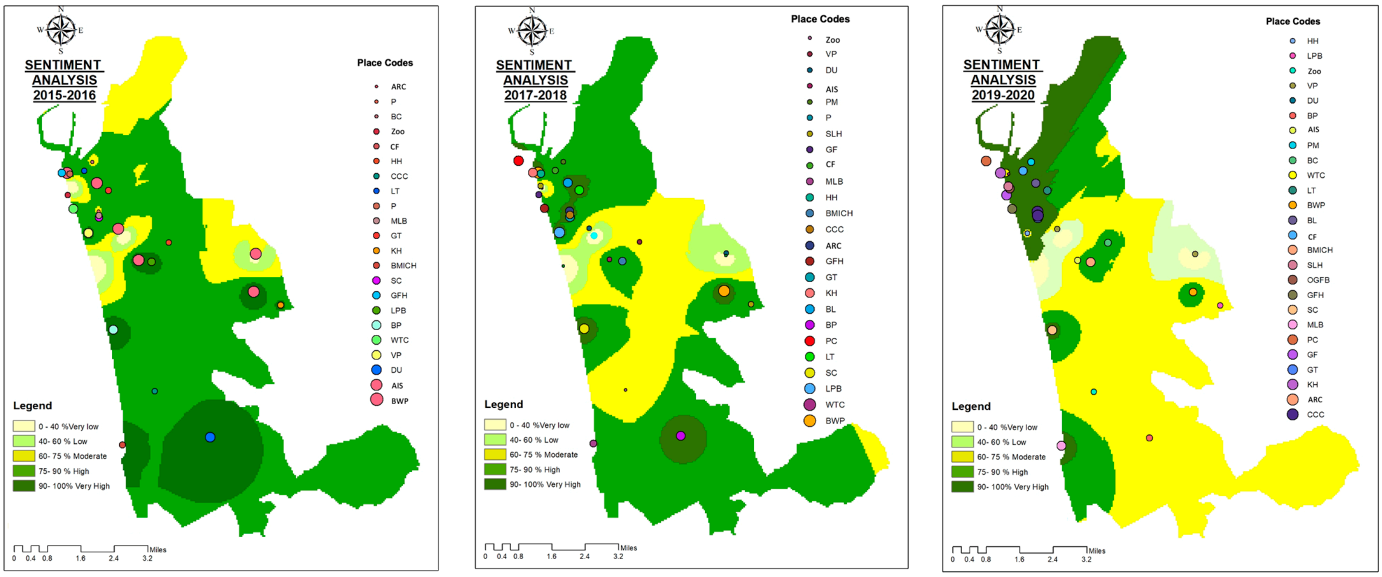
To proceed with the sentiment analysis, a bag of 720 words (482 words that give a positive meaning, i.e., good, happy; 238 words that give a negative meaning, i.e., unpleasant, dirty, garbage) were identified from the tweets. Table 2 represents the 'Place Names', 'Lynchian Category' derived from the image processing exercise, temporal distribution of the derived 'Sentiment Category–Positive/Negative'– per each place name and the positive sentiment percentages, and 'Composite Percentage values of Positive Sentiments' per each place name.

Table 2. Sentiment classification of tweets.

Place Name and Code	Lynchian Category	2015/16				2017/18				2019/20				C%P
		P	N	T	% P	P	N	T	% P	P	N	T	% P	
Altair Residential Condominium (ARC)	Landmark	2	1	3	66.67%	40	3	43	93.02%	7	0	7	100.00%	86.56%
Arcade Independence Square (AIS)	Landmark	16	0	16	100.00%	20	4	24	83.33%	21	7	28	75.00%	86.11%
Beddagana Wetland Park (BWP)	District	15	0	15	100.00%	22	0	22	100.00%	7	1	8	87.50%	95.83%
Beira Lake (BL)	Edge	12	7	19	63.15%	13	7	20	65%	11	6	17	64.75%	64.30%
Bellanvila Park (BP)	District	122	1	123	99.19%	47	2	49	95.92%	20	8	28	71.43%	88.85%
Bandaranaike Memorial International Conference Hall (BMICH)	Landmark	268	10	278	96.40%	80	7	87	91.95%	59	7	66	89.39%	92.58%
Borella Cemetery (BC)	Landmark	13	3	16	81.25%	2	1	3	66.67%	4	1	5	80.00%	75.97%
Colombo City Center (CCC)	Landmark	8	1	9	88.89%	13	1	14	92.86%	25	0	25	100.00%	93.92%
Colombo Fort (CF)	District	202	31	233	86.70%	183	21	204	89.71%	101	12	113	89.38%	88.60%
Diyatha Park (DP)	District	5	0	5	100.00%	6	2	8	75.00%	4	2	6	66.67%	80.56%
Galle Face (GF)	Edge	106	37	143	74.13%	128	15	143	89.51%	256	13	269	95.17%	86.27%
Galle Face Hotel (GFH)	Landmark	169	4	173	97.69%	257	19	276	93.12%	153	11	164	93.29%	94.70%
Gangaramaya Temple (GT)	Landmark	225	14	239	94.14%	168	11	179	93.85%	24	1	25	96.00%	94.66%
Hilton Hotel (HH)	Landmark	122	18	140	87.14%	164	16	180	91.11%	41	5	46	89.13%	89.13%
Kelaniya Temple (KT)	Landmark	34	7	41	82.93%	22	7	29	75.86%	39	8	47	82.98%	80.59%
Kingsbury Hotel (KH)	Landmark	322	19	341	94.43%	217	12	229	94.76%	314	11	325	96.62%	95.27%
Liberty Plaza Building (LPB)	Landmark	118	2	120	98.33%	298	3	301	99.00%	41	14	55	74.55%	90.63%
Lotus Tower (LT)	Landmark	102	25	135	75.55%	135	17	152	88.81%	100	16	116	86.2%	83.52%
Mount Lavinia Beach (MLB)	Edge	78	5	83	93.98%	65	7	72	90.28%	36	2	38	94.74%	93.00%
One Galle Face Building (OGFB)	Landmark	0	0	0	N/A	0	0	0	N/A	77	6	83	92.77%	30.92%
Parliament (P)	Landmark	14	7	21	66.66%	6	3	9	66.7%	3	2	5	60.00%	64.45%
Pettah Market (PM)	District	218	80	298	73.15%	130	23	153	84.97%	27	8	35	77.14%	78.42%
Port City (PC)	District	22	6	28	78.57%	47	12	59	79.66%	28	13	41	68.28%	75.50%
Savoy Cinema (SC)	Landmark	261	7	268	97.39%	108	3	111	97.30%	15	1	16	93.75%	96.15%
Shangri La Hotel (SLH)	Landmark	0	0	0	N/A	24	3	27	88.89%	38	3	41	92.68%	60.52%
Viharamahadevi Park (VP)	District	2	0	2	100.00%	3	1	4	75.00%	2	1	3	66.67%	80.56%
World Trade Center (WTC)	Landmark	3		3	100.00%	7	0	7	100.00%	9	2	11	81.82%	93.94%
Zoo (Zoo)	District	5	1	6	83.33%	3	2	5	60.00%	8	5	13	61.54%	68.29%
Total				2758				2410				1637		

Note: P: Positive | N: Negative | T: Total | % P: Percentage of Positively classified Tweets | C%P: Composite Percentage values of Positive sentiments.

Using Table 2, Figure 5a–c was mapped based on the distribution of the percentages of positively classified tweets per place over the three-time lapse considered—2015/2016, 2017/2018/2019/2020.



(**a**) (**b**) (**c**)

Figure 5. Sentiment analysis with distribution of positively classified tweets: (**a**) sentiment analysis 2015–2016; (**b**) sentiment analysis 2017–2018; (**c**) sentiment analysis 2019–2020.

As of Figure 5a from 2015 to 2016, VP (District), AIS (Landmark), BWP (District), BL (Edge), DP (District), and WTC (Landmark) have received 100% positive comments from analyzed social media messages. BP (District; 99.19%), LPB (Landmark; 98.33%), GFH (Landmark; 97.69%), SC (Landmark; 97.39%), BMICH (Landmark; 94.4%), KH (Landmark; 94.43%), GT (Landmark; 94.14%), and MLB (Edge; 93.98%) were the other places which received over 90% of positive perceptions from the analyzed social media messages.

Nonetheless, apart from BWP and the WTC, the positive sentiments shared for other landmarks have significantly reduced from 2017 to 2018. For instance, AR, DP, and VP, which received totally positive (100%) tweets and Instagram posts between 2015 and 2016, received 83.33%, 75%, and 75% positive perceptions, respectively. Most significantly, all the other places which received over 90% of positive sentiments between the years 2015 and 2016 were either received lower, i.e., BP—95.92%, GFH—93.12%, BMICH—91.95%, GT—93.85%, and MLB—90.28%, or with a slight increment, i.e., LPB—99% and KH—94.76% from 2017 to 2018. Further, CCC and HH have moved up to the category with over 90% positive sentiments by 2017 and 2018.

When compared to the 2015–2016 and 2017–2018 categories, percentages of positively classified tweets have significantly declined in 2019–2020. For instance, BP has significantly lost the positive perceptions received around 2015 (99.19%) compared to 2019–2020 (71.43%). Similarly, LPB, ARC, DP, and VP experienced the same scenario. This is mainly due to the commencement of many city-beautification projects such as the AIS renovation project and DP construction projects around 2012. However, such projects lost community attractions due to low maintenance, the existence of expensive shops, and so on. In contrast, CCC, which received comparatively low positive perceptions around 2016 (88.89%) compared to other landmarks, has increased up to 100% around 2019 and 2020. CCC is a 47-story mixed-use development that opened in 2018. According to the analyzed social media data, CCC is so far perceived positively as a landmark due to its building architecture and facilities. Exemplary tweets posted sharing positive sentiments about ARC and DP are shown in Figure 6.

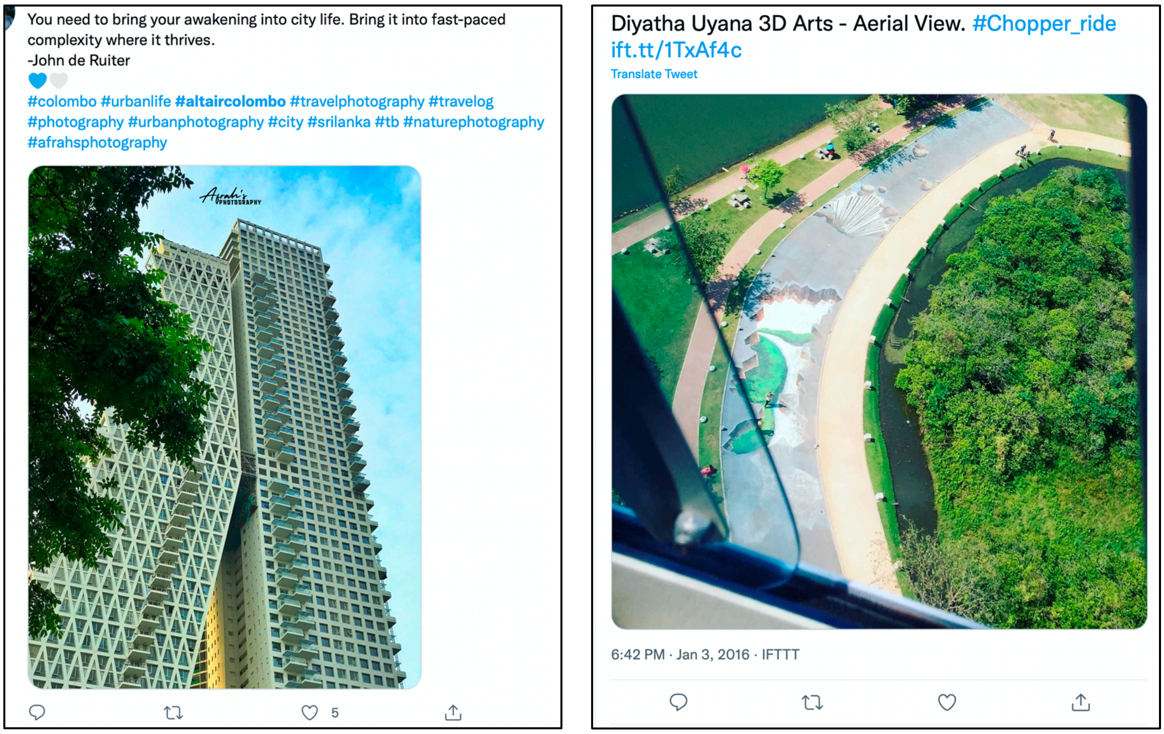


Figure 6. Exemplary tweets posted sharing positive sentiments about ARC and DP.

4.4. Popularity Analysis

Popularity analysis counted the number of tweets/Instagram messages distributed per each place name irrespective of the date tweeted. Figure 7 shows the color density matrix of the popularity analysis.

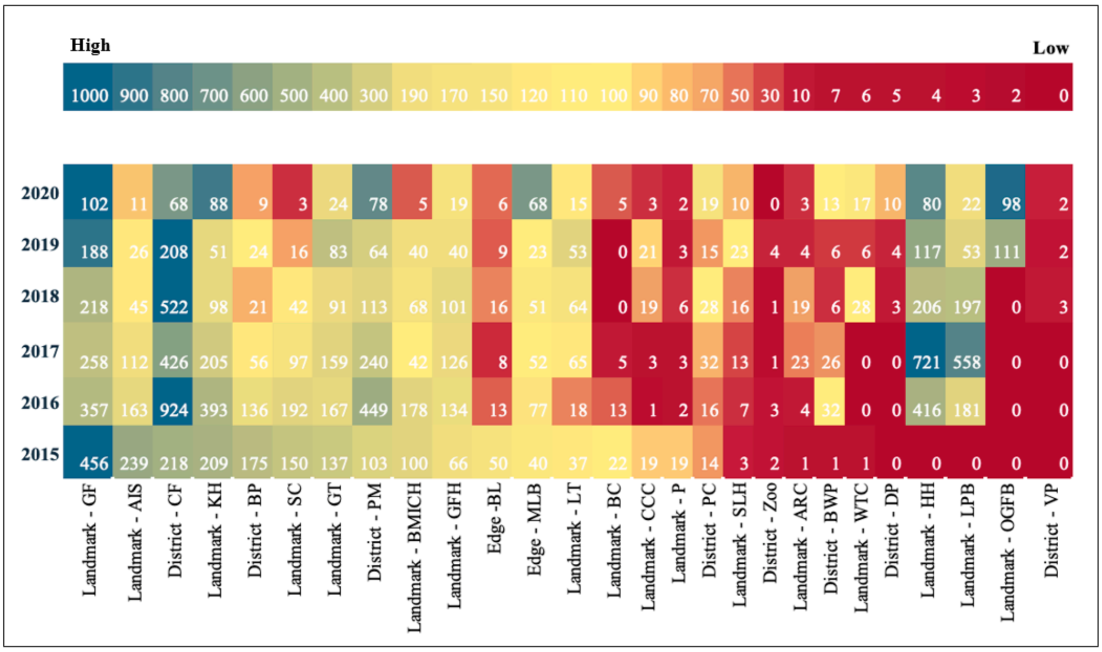


Figure 7. Color density matrix: Twitter popularity analysis.

The frequency of the posts shared on Twitter and Instagram shows the community perceptions toward making memories with the places. According to Figure 7, GF, AIS, CF, KH, HH, LPB, PM, and BMICH can be considered the places which have received high attention on Twitter and Instagram. Table 3 shows the exemplary positively and negatively classified tweets, where Table 4 lists the frequently used word in the Twitter and Instagram posts shared per selected locations with increasing popularity.

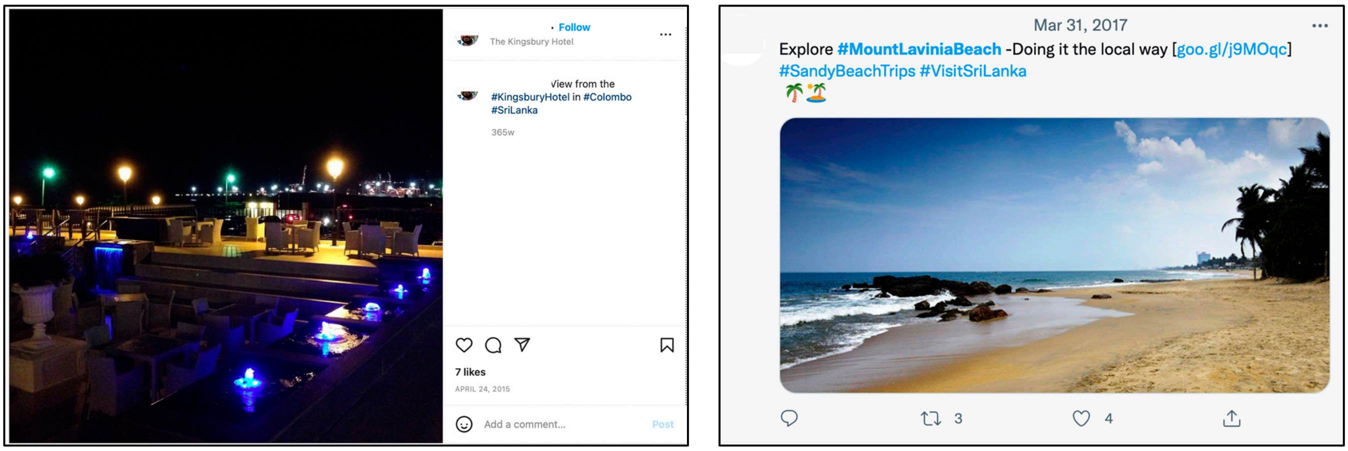
Table 3. Exemplary positively and negatively classified tweets.

Place Code	Lynchian Category	Date	Text	Geo-coordinate	Sentiment
ARC	Landmark	13 March 06:18:32 +0000 2021	Altair Colombo #cmb Sri Lanka next best thing architecture #Altair	6.91862, 79.8541	Positive
CCC	Landmark	23 November 16:13:07 +0000 2021	We do not remember days, we remember moments 🎏🎎 friends happy Sunday movies Scope Cinema Gold Class at CCC 😊👩👌🎹🎧🥛	6.9176001, 79.85552449	Positive
BWP	District	12 January 11:30:35 +0000 2017	Beautiful greenish naturephotography Beddagana Wetland Park	6.89136398, 79.90899324	Positive
DP	District	9 August 14:54:01 +0000 2020	Diyatha Uyana then and now low maintenance, fading 3D arts	6.9045, 79.9098	Negative
BL	Edge	18 May 03:23:00 +0000 2017	The remote and picturesque view of Colombo from the historic beiralake	6.93333333, 79.85	Positive
Zoo	District	1 February 03:56 00 +0000 2022	Reality of Sri Lanka's National Zoological Gardens at Dehiwala. Elephants being trained for any performance is cruel. This is slavery. #DehiwalaZooCruelty #SayNoToCaptivity #CaptivityIsCruel #SayNoToElephantSlavery #DehiwalaZoo #ShermilaOut #ElephantAbuse	6.85680556, 79.87288889	Negative

Table 4. Frequently used words attached to selected Lynchian elements.

Place Code	Frequently Used Words
GF (Landmark)	Photo (39), sunset (35), beautiful (14), time (14), night (11), view (11), evening (11)
AIS (Landmark)	Time (24), night (23), evening (17), love (15), selfie (15), life (14), friends (13), good (12), architecture (11), lounge (11), tea (10)
CF (District)	Station (278), railway (272), café (34), train (18), Dutch (13)
KH (Landmark)	Sky (32), night (30), love (21), view (21), time (19), good (18), dinner (16), life (14), party (14), sunset (14), family (13), happy (13), harbor (13), good times (12), evening (11), travel (10)
HH (Landmark)	Photo (125), night (57), dinner (51), ballroom (41), good (29), Christmas (24), life (21), party (21), happy (19), poolside (17), love (15), #beautiful (14), beautiful (14), graze (14), thank (14), #love (13), #oktoberfest (13), #weddings (13), best (13), grand (13), view (13), #family (12), #life (12), #travel (12), tower (11), video (11),
MLB (Edge)	Beach (53), hotel (27), sunset (21), family (15), #mountleviniabeach (15), #mountlaviniahotel (15), sea (10)

Landmarks such as GF and AIS attract people due to their location and building architecture. KH and HH are two prestigious hotels located facing the main road of Colombo 01. Especially, OGFB (Landmark), DP (District), and MLB (Edge) have gained more popularity in recent years compared to 2015. Nonetheless, places such as BL (Edge), LT (Landmark), and P (Landmark) have gradually lost popularity. Figure 8 demonstrate the sceneries created by the KH and the MLB, and Figure 9 shows temporal changes of the sentiment values by zones.



(**a**) (**b**)

Figure 8. Sceneries of: (**a**) KH shared on Instagram; (**b**) MLB shared on Twitter.

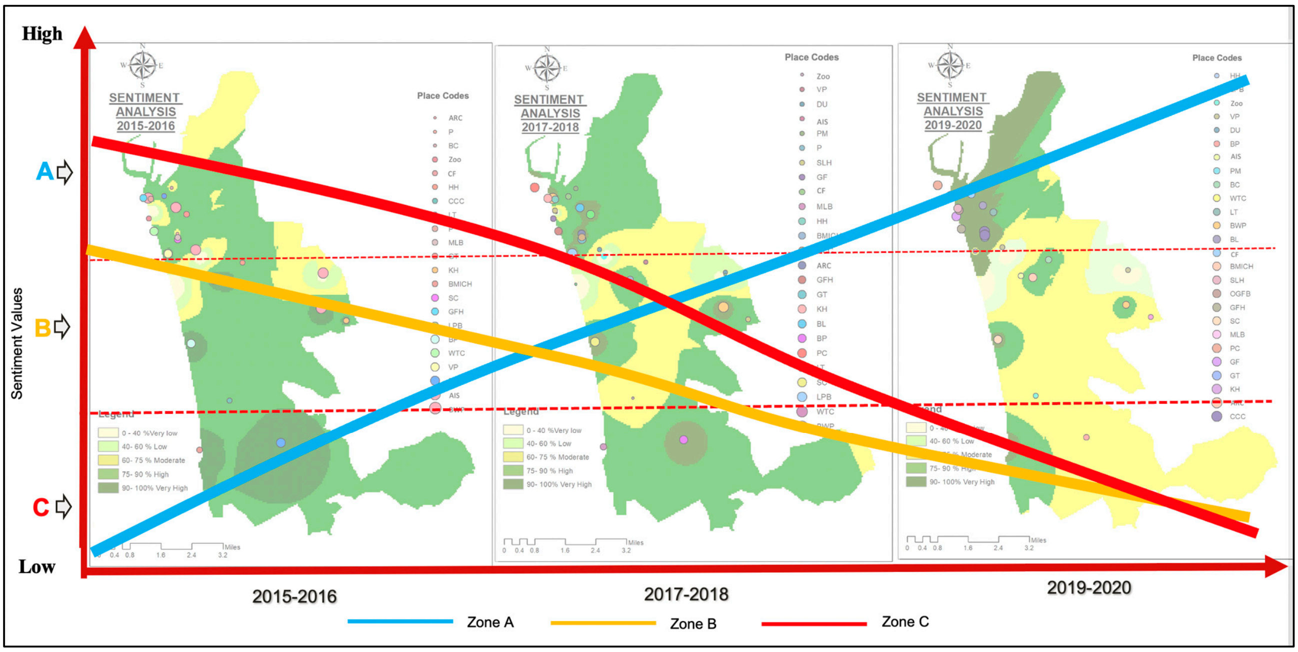


Figure 9. Temporal changes of the sentiment values by zones.

5. Discussion

The image of a city is a cognitive representation of space that emerges from cognitive processes that strongly interact with the community's perceptions and observations of a city [68–70]. Mostly, city images were evaluated through small data using mental maps, walking tours, interviews, questionnaires, and sketch maps [71,72]. Still, the study findings revealed that the use of social media data act as a promising data source to be used to examine city images in detail with more facts in this digital age.

Supported by the descriptive analysis and the image processing exercise, this study conducted two main analyses—sentiment and popularity analyses. Although both analyses reflected the positive perceptions borne by the public, the temporal changes of the community's sentiments have changed significantly with the emergence of new landmarks, paths, nodes, edges, and districts. For further discussion, the case study area was divided into three hypothetical zones (Figure 9)—Zones A, B, and C—to better understand the temporal changes of community sentiments.

Zone A consists of the highest number of Lynchian elements compared to Zone B and C each year. For instance, from 2015 to 2016, 45% (10 out of 22) of the total places identified were from Zone A. This number continuously and gradually increased from 2017 to 2018 to 48% (12 out of 24). Within the period of 2019–2020, the total Lynchian elements identified were 57% (16 out of 28). Especially, most of the highly perceived Landmarks, such as CF, GF, and PM, were in Zone A. Even the newly emerged Lynchian elements of ARC (Landmark), CCC (Landmark), and OGFB (Landmark) were from Zone A.

Zone B has the second-highest number of Lynchian elements. Unlike Zone A, the number of Lynchian elements (n = 9) has not changed since 2015 in Zone B. Zone C has the lowest number of Lynchian elements (n = 9). Like Zone C, the number of Lynchian elements in Zone C have also not changed over time.

Additionally, the popularity is agglomerate in this respected area. This can be identified as a major concern when considering the whole city's image. As of Figure 9, Zone A is enriched with many Lynchian elements—GF, CF, and KH, with an increasing number of tweets over the years. This reflected that the community has perceived such Lynchian elements with increasing popularity in a positive manner.

This has created an agglomeration of Lynchian elements into Zone A, while other Zones remain unchanged in quantity. For better utilization, the city elements should be evenly distributed along the city and, hence, these 'Poles' must be avoided. The advantages of well-distributed Lynchian elements, especially with positive community perceptions, are much higher than proximity spatially concentrated Lynchian elements. Additionally, it can be observed that the city branding elements like 'Lotus Tower' are adding advantages to the city's popularity. To achieve an evenly distributed city image throughout the area, adding these branding elements can be an option to consider.

For new forms of territorial governance, the objective of place branding is no more limited only to economic gains but also to the development of a positive image of the place that facilitates a sense of place and satisfies the potential desires and needs of the public [73]. In the purview of place branding, the socio–cultural and anthropological differences contribute to highlighting as well as promoting uniqueness as a tool for place branding [74]. In recent years, there has been a growing consensus amongst scholars that considers the objective of place branding in terms of linking place image to aspects of place identity and developing a sense of pride and belonging within the spatio–temporal global context [75,76].

6. Conclusions

The image of a city changes over time due to social, environmental, economic, and political changes that take place in an urban environment [77,78]. According to [79,80], social media plays a key role in place marketing activities. Therefore, analyzing and understating the changing city image is important as it affects a city in different aspects. For instance, a popular and positively perceived city image attracts tourists and investors to a city, which could ultimately lead to branding the cities locally and internationally [81–83].

As this study emphasized, in this digital era, researchers or policymakers do not have to adopt time-consuming methodologies to examine the city image. Instead, the use of social media messages with or without images and emojis act as an effective and accurate method to understand community perceptions of the city's image.

Especially, by examining the sentiment or the emotional values hidden in the tweets and the images shared, the study was able to emphasize the validity of using community-generated social media messages to examine the city image often. This study suggested the lasting value of the city image theory amidst the prevalence of novel technologies such as social media, hand-held mobile devices, and Google Maps. Further technological innovation will also help in the accuracy and ease of undertaking social media big data analytics and planning accordingly for smarter urban environments [84–86].

Lastly, the following limitations of this study should be considered when interpreting the findings. This study only used open API to access the Twittersphere which provides limited access to the Twitter database. Secondly, this study did not conduct a ground survey to validate its findings through social media analytics, which further researchers can be focused on. Further, this study did not conduct an analysis to investigate the differences between the results obtained via Twitter and those obtained via Instagram, which future studies can extend on. Additionally, these research findings create a new platform for more research that needs to understand the use of social media data toward city branding.

Author Contributions: Conceptualization, S.A. and N.K.; Methodology, S.A.; Software, N.K.; Validation, N.K.; Formal analysis, S.A.; Investigation, S.A.; Resources, N.K. and S.A.; Data curation, S.A.; Writing—original draft preparation, S.A.; Writing—review and editing, N.K., T.Y. and S.P.; Supervision, N.K. and T.Y.; Project administration, N.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sectors.

Data Availability Statement: Not applicable.

Acknowledgments: The authors thank the managing editor and anonymous referees for their constructive comments on an earlier version of this paper.

Conflicts of Interest: The authors declare no known competing financial interest or personal relationship that could have appeared to influence the study reported.

References

1. Lynch, K. *The Image of the City*; MIT Press: Boston, MA, USA, 1964.
2. Pancholi, S.; Yigitcanlar, T.; Guaralda, M. Public space design of knowledge and innovation spaces: Learnings from Kelvin Grove Urban Village, Brisbane. *JOItmC* **2015**, *1*, 13. [CrossRef]
3. Zenker, S. How to Catch a City? *J. Place Manag. Dev.* **2011**, *4*, 40–52. [CrossRef]
4. Asur, S.; Huberman, B.A.; Szabo, G.; Wang, C. Trends in social media: Persistence and decay. In Proceedings of the International AAAI Conference on Web and Social Media, Barcelona, Spain, 17–21 July 2011.
5. Evans, G. Hard-branding the Cultural City. *Int. J. Urban Reg. Res.* **2003**, *27*, 417–440. [CrossRef]
6. Zhang, L.; Zhao, S.X. City Branding and the Olympic Effect. *Cities* **2009**, *26*, 245–254. [CrossRef]
7. Eraydin, A.; Taşan-Kok, T. State response to contemporary urban movements in Turkey: A critical overview of state entrepreneurialism and authoritarian interventions. *Antipode* **2014**, *46*, 110–129. [CrossRef]
8. Anholt, S. Place Branding and Public Diplomacy. *Place Brand.* **2008**, *4*, 1–6. [CrossRef]
9. Zimmerbauer, K. From Image to Identity. *Eur. Plan. Stud.* **2011**, *19*, 2243–2260. [CrossRef]
10. Zagoruyko, S.; Komodakis, N. Wide residual networks. *arXiv* **2016**, arXiv:1605.07146.
11. Raszkowski, A. Selected aspects of investment attractiveness of regions. *ACC J.* **2013**, *2013*, 116–127.
12. Yigitcanlar, T.; Kankanamge, N.; Preston, A.; Gill, P.S.; Rezayee, M.; Ostadnia, M.; Ioppolo, G. How can social media analytics assist authorities in pandemic-related policy decisions? Insights from Australian states and territories. *Health Inf. Sci. Syst.* **2020**, *8*, 37. [CrossRef]
13. Statcounter. Social Media Statistics Sri Lanka. Available online: https://gs.statcounter.com/social-media-stats/all/sri-lanka (accessed on 15 November 2022).
14. Portugali, J. Geography, environment and cognition: An introduction. *Geoforum* **1992**, *23*, 107–109. [CrossRef]
15. Al-Ghamdi, S.A.; Al-Harigi, F. Rethinking image of the city in the information age. *Procedia Comput. Sci.* **2015**, *65*, 734–743. [CrossRef]
16. Filomena, G.; Verstegen, J.; Manley, E. A computational approach to 'The Image of the City'. *Cities* **2019**, *89*, 14–25. [CrossRef]
17. Huang, J.; Obracht-Prondzynska, H.; Kamrowska-Zaluska, D.; Sun, Y.; Li, L. The image of the city on social media: A comparative study using "Big Data" and "Small Data" methods in the Tri-City Region in Poland. *Landsc. Urban Plan.* **2021**, *206*, 103977. [CrossRef]
18. Yigitcanlar, T.; Kankanamge, N. *Urban Analytics with Social Media Data: Foundations, Applications and Platforms*; Chapman and Hall/CRC: London, UK, 2022.
19. Jang, K.M.; Youngchul, K. Crowd-sourced cognitive mapping: A new way of displaying people's cognitive perception of urban space. *PLoS ONE* **2019**, *14*, e0218590. [CrossRef]
20. Meier, S.; Glinka, K. Psychogeography in the Age of the Quantified Self—Mental Map Modelling with Georeferenced Personal Activity Data. In *Advances in Cartography and GIScience*; International Cartographic Association: Bern, Switzerland, 2017.
21. Bahrehdar, A.R.; Adams, B.; Purves, R.S. Streets of London: Using Flickr and OpenStreetMap to build an interactive. *Comput. Environ. Urban Syst.* **2020**, *84*, 101524. [CrossRef]

22. Fan, W.; Gordon, M. The power of social media analytics. *Commun. ACM* **2014**, *57*, 74–81. [CrossRef]
23. Lynch, K. Reconsidering the image of the city. In *Cities of the Mind*; Springer: Boston, MA, USA, 1984; pp. 151–161.
24. Sainz, M. (Re) Building an Image for a City: Is A Landmark Enough? Bilbao and the Guggenheim Museum, 10 Years Together 1. *J. Appl. Soc. Psychol.* **2012**, *42*, 100–132. [CrossRef]
25. Radosavljević, U.; Đorđević, A.; Lalović, K.; Živković, J.; Đukanović, Z. Nodes and networks: The generative role of cultural heritage for urban revival in Kikinda. *Sustainability* **2019**, *11*, 2509. [CrossRef]
26. Whyte, W.H. The design of spaces. In *The City Reader*; Routledge: London, UK, 2015; pp. 631–639.
27. Gehl, J.; Kaefer, L.J.; Reigstad, S. Close encounters with buildings. *Urban Des. Int.* **2006**, *11*, 29–47. [CrossRef]
28. Creswell, T. *Place: A Short Introduction*; Wiley-Blackwell: London, UK, 2011.
29. Meyer, M.; Kuusisto, J.; Grant, K.; De Silva, M.; Flowers, S.; Choksy, U. Towards new Triple Helix organisations? A comparative study of competence centres as knowledge, consensus and innovation spaces. *RD Manag.* **2019**, *49*, 555–573. [CrossRef]
30. Cuff, D. *The Provisional City: Los Angeles Stories of Architecture and Urbanism*; MIT Press: Boston, MA, USA, 2000.
31. Castells, M. *Power of Identity*; Wiley-Blackwell: London, UK, 2009.
32. Meshur, H.F.A. Evaluation of urban spaces from the perspective of universal design principles: The case of Konya/Turkey. *TeMA-J. Land Use Mobil. Environ.* **2016**, *9*, 191–208.
33. Ng, E.; Yuan, C.; Chen, L.; Ren, C.; Fung, J.C. Improving the wind environment in high-density cities by understanding urban morphology and surface roughness: A study in Hong Kong. *Landsc. Urban Plan.* **2011**, *101*, 59–74. [CrossRef] [PubMed]
34. Ciuccarelli, P.; Lupi, G.; Simeone, L. *Visualizing the Data City: Social Media as a Source of Knowledge for Urban Planning and Management*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2014.
35. Zander, K.K.; Sibarani, R.; Lassa, J.; Nguyen, D.; Dimmock, A. How do Australians use social media during natural hazards? A survey. *Int. J. Disaster Risk Reduct.* **2022**, *81*, 103207. [CrossRef]
36. Alalwan, A.; Rana, N.; Dwivedi, Y.; Algharabat, R. Social media in marketing: A review and analysis of the existing literature. *Telemat. Inform.* **2017**, *34*, 1177–1190. [CrossRef]
37. Ahmad, N.; Musa, R.; Harun, M. The impact of social media content marketing (SMCM) towards brand health. *Procedia Econ. Financ.* **2016**, *37*, 331–336. [CrossRef]
38. Kankanamge, N.; Yigitcanlar, T.; Goonetilleke, A. How engaging are disaster management related social media channels? The case of Australian state emergency organisations. *Int. J. Disaster Risk Reduct.* **2020**, *48*, 101571. [CrossRef]
39. Saroj, A.; Pal, S. Use of social media in crisis management: A survey. *Int. J. Disaster Risk Reduct.* **2020**, *48*, 101584. [CrossRef]
40. Nadeem, M. Social customer relationship management (SCRM): How connecting social analytics to business analytics enhances customer care and loyalty? *Int. J. Bus. Soc. Sci.* **2012**, *21*, 1–15.
41. Liu, Y. Big data and predictive business analytics. *J. Bus. Forecast.* **2014**, *33*, 40.
42. Bennett, W. The personalization of politics: Political identity, social media, and changing patterns of participation. The annals of the American academy of political and social science. *SAGE J.* **2012**, *644*, 20–39.
43. Wolfsfeld, G.; Segev, E.; Sheafer, T. Social media and the Arab Spring: Politics comes first. *Int. J. Press/Politics* **2013**, *18*, 115–137. [CrossRef]
44. Oboler, A.; Welsh, K.; Cruz, L. The danger of big data: Social media as computational social science. *First Monday* **2012**, *17*, 1–10. [CrossRef]
45. Ruths, D.; Pfeffer, J. Social media for large studies of behavior. *Science* **2014**, *346*, 1063–1064. [CrossRef]
46. Huynh, H.T.; Nguyen, H. Joint age estimation and gender classification of Asian faces using wide ResNet. *SN Comput. Sci.* **2020**, *1*, 1–9. [CrossRef]
47. Kankanamge, N.; Yigitcanlar, T.; Goonetilleke, A.; Kamruzzaman, M. Determining disaster severity through social media analysis: Testing the methodology with Southeast Queensland Flood tweets. *Int. J. Disaster Risk Reduct.* **2020**, *42*, 101360. [CrossRef]
48. Kolar, T.; Cater, B. Managing group flow experiences in escape rooms. *Int. J. Contemp. Hosp. Manag.* **2018**, *30*, 2637–2661. [CrossRef]
49. Bertrand, K.; Bialik, M.; Virdee, K.; Gros, A.; Bar-Yam, Y. Sentiment in new york city: A high resolution spatial and temporal view. *arXiv* **2013**, arXiv:1308.5010.
50. Martí, P.; García-Mayor, C.; Serrano-Estrada, L. Identifying opportunity places for urban regeneration through LBSNs. *Cities* **2019**, *90*, 191–206. [CrossRef]
51. Wang, J.; Cao, S.; Yu, C.W. Development trend and challenges of sustainable urban design in the digital age. Indoor and Built Environment. *SAGE J.* **2021**, *30*, 3–6.
52. Nolasco-Cirugeda, A.; García-Mayor, C. Social dynamics in cities: Analysis through LBSN data. *Procedia Comput. Sci.* **2022**, *207*, 877–886. [CrossRef]
53. Dufty, N. Twitter turns ten: Its use to date in disaster management. *Aust. J. Emerg. Manag.* **2016**, *31*, 50–54.
54. Guan, X.; Chen, C. Using social media data to understand and assess disasters. *Nat. Hazards* **2014**, *74*, 837–850. [CrossRef]
55. Kankanamge, N.; Yigitcanlar, T.; Goonetilleke, A.; Kamruzzaman, M. Can volunteer crowdsourcing reduce disaster risk? A systematic review of the literature. *Int. J. Disaster Risk Reduct.* **2019**, *35*, 101097. [CrossRef]

56. Cebeillac, A.; Rault, Y. Contribution of geotagged twitter data in the study of a social group's activity space. The case of the upper middle class in Delhi, India. *Netcom. Réseaux Commun. Territ.* **2016**, *30*, 231–248.
57. Lin, J.; Cromley, R.G. Evaluating geo-located Twitter data as a control layer for areal interpolation of population. *Appl. Geogr.* **2015**, *58*, 41–47. [CrossRef]
58. Brandt, H.; Turner-McGrievy, G.; Friedman, D.; Gentile, D.; Schrock, C.; Thomas, T.; West, D. Examining the role of Twitter in response and recovery during and after historic flooding in South Carolina. *J. Public Health Manag. Pract.* **2019**, *25*, E6–E12. [CrossRef] [PubMed]
59. Yuan, F.; Liu, R. Identifying damage-related social media data during Hurricane Matthew: A machine learning approach. In *Computing in Civil Engineering 2019: Visualization, Information Modeling, and Simulation*; American Society of Civil Engineers: Reston, VA, USA, 2019; pp. 207–214.
60. Chapman, A. *Principles and methods of data cleaning*; GBIF Publishing: Towoomba South, QLD, Australia, 2005.
61. Yigitcanlar, T.; Kankanamge, N.; Regona, M.; Ruiz Maldonado, A.; Rowan, B.; Ryu, A.; Desouza, K.C.; Corchado, J.; Mehmood, R.; Li, R. Artificial intelligence technologies and related urban planning and development concepts: How are they perceived and utilized in Australia? *J. Open Innov. Technol. Mark. Complex.* **2020**, *6*, 187. [CrossRef]
62. Zhou, A.; Yao, A.; Guo, Y.; Xu, L.; Chen, Y. Incremental network quantization: Towards lossless CNNs with low-precision weights. *arXiv* **2017**, arXiv:1702.03044.
63. Jiang, Y.; Li, Z.; Cutter, S. Social network, activity space, sentiment, and evacuation: What can social media tell us? *Ann. Am. Assoc. Geogr.* **2019**, *109*, 1795–1810. [CrossRef]
64. ArcMap. How IDW Works. Available online: https://pro.arcgis.com/en/pro-app/2.8/tool-reference/3d-analyst/how-idw-works.htm (accessed on 4 May 2022).
65. Yigitcanlar, T.; Guaralda, M.; Taboada, M.; Pancholi, S. Place making for knowledge generation and innovation: Planning and branding Brisbane's knowledge community precincts. *J. Urban Technol.* **2016**, *23*, 115–146. [CrossRef]
66. Mohammed, A.I.; Tahir, A.A. A New Optimizer for Image Classification using Wide ResNet (WRN). *Acad. J. Nawroz Univ.* **2020**, *9*, 1–13. [CrossRef]
67. Vasavi, S.; Vineela, P.; Raman, S.V. Age detection in a surveillance video using deep learning technique. *SN Comput. Sci.* **2021**, *2*, 1–11. [CrossRef]
68. Brunec, I.K.; Moscovitch, M.; Barense, M.D. Boundaries shape cognitive representations of spaces and events. *Trends Cogn. Sci.* **2018**, *22*, 637–650. [CrossRef]
69. Breckler, S.J.; Pratkanis, A.R.; McCann, C.D. The representation of self in multidimensional cognitive space. *Br. J. Soc. Psychol.* **1991**, *30*, 97–112. [CrossRef]
70. Omer, I. Effect of city form and sociospatial divisions on cognitive representation of an urban environment. *J. Urban Aff.* **2018**, *40*, 560–575. [CrossRef]
71. O'Brien, D.T. Using small data to interpret big data: 311 reports as individual contributions to informal social control in urban neighborhoods. *Soc. Sci. Res.* **2016**, *59*, 83–96. [CrossRef]
72. Qin, X.; Zhen, F.; Gong, Y. Combination of big and small data: Empirical study on the distribution and factors of catering space popularity in Nanjing, China. *J. Urban Plan. Dev.* **2019**, *145*, 05018022. [CrossRef]
73. Kavaratzis, M.; Ashworth, G.J. City branding: An effective assertion of identity or a transitory marketing trick? *Place Brand.* **2006**, *2*, 183–194. [CrossRef]
74. López-Lita, R.; Benlloch, M.T. De la marca comercial a la marca territorio. *Recer. Rev. De Pensam. I Anàlisi* **2005**, *5*, 87–100.
75. Govers, R.; Go, F. *Place Branding: Virtual and Physical Identities, Glocal, Imagined and Experienced*; Palgrave-Macmillan: Basingstoke, UK, 2009.
76. Fernández-Cavia, J. Ciudades, regiones y países como marcas: Luces y sombras del place branding en J de San Eugenio (Coord). In *Manual de Comunicación Turística. De la Información a la Persuasion. de la Promoción a la Emoción*; Documenta Universitaria: Barcelona, Spain, 2011; pp. 103–113.
77. Laaksonen, P.; Laaksonen, M.; Borisov, P.; Halkoaho, J. Measuring image of a city: A qualitative approach with case example. *Place Brand.* **2006**, *2*, 210–219. [CrossRef]
78. Li, J.; Webster, D.; Cai, J.; Muller, L. Innovation clusters revisited: On dimensions of agglomeration, institution, and built environment. *Sustainability* **2019**, *11*, 3338. [CrossRef]
79. Papp-Váry, Á. The Anholt-GMI city brand hexagon and the saffron European city brand barometer: A comparative study. *Reg. Bus. Stud.* **2011**, *3*, 555–562.
80. Fernández-Cavia, J.; Kavaratzis, M.; Morgan, N. Place branding: A communication perspective. *Commun. Soc.* **2018**, *31*, 1–7. [CrossRef]
81. Ginesta, X.; de San Eugenio, J. The use of football as a country branding strategy. Case study: Qatar and the Catalan sports press. *Commun. Sport* **2014**, *2*, 225–241.
82. Govers, R. Rethinking virtual and online place branding. In *Rethinking Place Branding*; Springer: Singapore, 2015; pp. 73–83.
83. Go, F.; Govers, R. *International Place Branding Yearbook 2010: Place Branding in The New Age of Innovation*; Springer: Singapore, 2010.
84. Yigitcanlar, T.; Sabatini-Marques, J.; da-Costa, E.; Kamruzzaman, M.; Ioppolo, G. Stimulating technological innovation through incentives: Perceptions of Australian and Brazilian firms. *Technol. Forecast. Soc. Change* **2019**, *146*, 403–412. [CrossRef]

85. Yigitcanlar, T. Planning for smart urban ecosystems: Information technology applications for capacity building in environmental decision making. *Theor. Empir. Res. Urban Manag.* **2009**, *4*, 5–21.
86. Butler, L.; Yigitcanlar, T.; Paz, A. Barriers and risks of Mobility-as-a-Service (MaaS) adoption in cities: A systematic review of the literature. *Cities* **2021**, *109*, 103036. [CrossRef]