



Article

# Culturally Diverse Street-Level Urban Activities through the Lens of Digital Footprints

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**Abstract:** Acknowledging and sustaining the ethnic and cultural diversity that the phenomenon of globalization has brought to the urban environment is one of the target objectives to seek spatial and social sustainability in today's cities. This study aims to build upon previous research approaches that sought to characterize culturally diverse, urban public spaces. For this purpose, a method that encompasses digital and physical layers of information has been proposed to gather signs of culturally diverse, street-level urban and economic activities. Geolocated data from three social media platforms, as well as field-work observations, were collected from two case study street segments with different socio-cultural, demographic profiles. The findings suggest that economic activities related to retail and restaurants, and especially those with higher levels of personalization that reflect "cultural specialisms", have a significative relevance in both the physical and virtual domains. However, unlike the case study area with the higher socio-economic profile, the urban vibrancy observed through field work throughout the more culturally diverse street segment was not found to be fully represented by social media data. There is still much room for research on the extent to which these sources are useful for characterizing fine-grain street-scale phenomena.



**Citation:** Martí, P.; Serrano-Estrada, L.; Abutorabi, M. Culturally Diverse Street-Level Urban Activities through the Lens of Digital Footprints. *Sustainability* **2021**, *13*, 11141. <https://doi.org/10.3390/su132011141>

Academic Editor: Hone-Jay Chu

Received: 1 September 2021

Accepted: 6 October 2021

Published: 9 October 2021

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## 1. Introduction

Globalization is a trend that is intensifying, while the urban environment is becoming ever more diverse with the flow of immigrants. However, more than ever, urban environments are experiencing homogeneity and vernacularisation [1]. There is a need to engage with these rapidly evolving changes, aiming, on the one hand, to create socially sustainable communities where locals integrate with the diversity brought by other ethnic groups and cultures from abroad and, on the other, to assume the challenge for urban designers and planners to create or preserve unique and appealing spaces for the various cultures represented in the population.

From this viewpoint, it is worth distinguishing between the concepts of culture and ethnicity. Culture is often defined by the social behaviour that is followed by people, while ethnicity is the fact of belonging to a group of people that share biological characteristics, common food habits, nationality, language, culture, physical attributes, and/or ancestry. Evidently, with the increase of ethnic diversity in cities, "the chances that different cultures will share public spaces have also increased" [2]. Therefore, creating socially sustainable and liveable urban spaces requires a context-specific understanding of the relationship between human behaviour and the physical setting. In line with this notion, and among the features that define this relationship, the authors recognise that culture, in particular, determines a good part of human behaviour in the space [3,4]. In order to achieve urban landscapes that foster integration among the varied cultural and ethnic values that coexist in city spaces, it is necessary, although challenging, to recognise and promote those aspects

in the physical setting that construct a shared identity and sense of belonging. In this respect, new skills and methods in professional practice are required to make modern cities work and find new forms of “intercultural dialogue”, planning for diversity, inclusion, and choice in cities [5].

With the above in mind, this study aimed to build on existing research that explores methods for characterising local features in physical environments. Specifically, an approach that adopts both digital and physical measurements of a case study has been proposed, supporting the notion that “combining the results of each method could provide a database that serves as a comprehensive spatial design for multicultural public spaces” [6]. On the one hand, social media data from Foursquare, Google Places, and Twitter were used as digital traces for identifying signs of cultural diversity in street-level urban and economic activities. Specifically, in this study, the types of these urban and economic activities were used as proxy indicators of multicultural urban contexts. On the other hand, field-work annotations and mapping, as the physical measurements, were used for validating, comparing, and discussing the findings obtained from online data. Through the intertwining of the digital and the physical representations of the urban reality, this research contributes to the understanding of (i) how user-generated social media data can be useful for urban- and field-related researchers and practitioners to characterise culturally diverse street-level urban activities and (ii) the extent to which the cultural features in the physical layer of urban environments are reflected in digital footprints.

### 1.1. Streets as the Physical Manifestation of the Socio-Cultural Context

Urban public spaces are containers of cultural, social, and individual relationships. These relationships promote the attachment of people to spaces [7,8]. This attachment, therefore, indicates people’s association with the space “either as a memory of direct experience of being there or indirect experience through words, stories, and images” [9]. The character and uniqueness of urban spaces are defined by the combination of social, spatial, and cultural features [10]. At the same time, this character often represents the cultural identity of the different groups that frequent the space [11,12]. In other words, each space embodies a set of meanings and symbols expressing its uniqueness in relation to the cultural identity of a group, which is a reference point to which they may belong [10,13]. In the city experience, streets are the basic unit of space [3] and the “vital container of the public life” [14]. They are “symbols of community and of its history; they represent a public memory” [15]. The direct experience of streets that have “strong local flavour, visual character, and clear boundaries” enables emotion and a “warm sentiment” [16]. These streets become more of a place than a path, and the movement of people is constantly being negotiated, especially when they begin to attract social life. Examples of these types of streets are those where there is a good quantity and variety of independently owned small businesses, or there is a physical manifestation of different cultures through storefronts and product display personalization that offers high levels of sensory stimuli to pedestrians [3]. Such stimuli are critical for communicating the socio-cultural context of the space [17]. Therefore, it is necessary to acknowledge and preserve the “symbolic ways of communicating cultural meanings” [1] in order to promote and sustain cultural diversity in urban public spaces. For this study, the “symbolic ways of communicating” are the culturally diverse urban and economic activities that offer spatial and social integrity [3] and have the potential to create opportunities for “local identity and for local people to influence the external image-creation process” [18]. These businesses and services reinforce the multicultural identity of the streets through their personalization: the fact that businesses express their “territorial claim” by personalizing their street interfaces with canopies, signs, planters, wares, etc. and the way the products are displayed [3].

### 1.2. Digital Footprints for the Study of Urban Phenomena

Nowadays, everyday behavioural patterns are highly influenced by mobile communication [19], just as social technologies have transformed spatiotemporal connections

between people. This transformation, which has reconfigured the “forms and practices through which the collective memory is transmitted”, has had a profound impact on social relations [20] and on the human–urban environment interaction.

Indeed, the development of technology and the spread of social media have created a new virtual environment for social life. These online social interactions leave digital footprints (spatiotemporal user-generated opinions, check-ins, photographs), which, once interpreted, are highly valuable for urban research purposes [21] and for informing decision-making processes. It has now been over a decade since the footprints generated by users of virtual social media platforms have proved to be useful for detecting key physical and behavioural aspects of the urban environment [22–24] and discerning phenomena that are hard to appreciate directly by the human senses: people’s perceptual responses to the environment [25,26], the cultural diversity of an urban setting [27], and other complex non-physical phenomena, such as the sense of place [28] and the character and vibrancy of local urban life [29–32].

Social media data have been used for analysing a wide variety of geographical scales. However, there is a recognised trend in research using these sources of information to cover extensive areas and, thus, use substantial datasets (Big Data) that require sophisticated software, or skills that are often beyond social science researchers, for pre-processing and conducting any type of analysis [33]. For instance, Palazzo et al. [34], Maurer [35], and Lv et al. [36] adopted, respectively, Instagram, Twitter, and Baidu datasets to assess global, cross-country and country-wide geographical scales of analysis.

Likewise, studies concerned with the cultural character of cities are often conducted in large geographical areas. For instance, the study by Wu et al. [27] analysed the cultural diversity of an entire country (328 cities in China), and the research by Hochman and Manovich [31] and Hochman and Schwartz [37] developed a city-scale computational analysis of user-generated social networks to study social and cultural urban phenomena [38].

Although there are some examples dealing with smaller scales, which focus on the analysis of specific public spaces through social media [39,40], there is still much to be learned about the extent to which these sources are useful for characterising street scale phenomena and, more specifically, for revealing signs of cultural diversity embedded in the urban environment.

In light of these facts, studies such as those proposed by López Baeza et al. [41] and Huang et al. [42], which incorporate mixed-method approaches combining digital layers (social media data sources) and physical layers (fieldwork), have proved effective for conducting fine-grain urban analysis. While comparisons between the digital and physical layers of information have long been commonplace for theoretical and empirical research [43,44], more, and ongoing, work is certainly needed in this area for several reasons: (i) field study sources allow verification of whether online user-generated data corresponds to reality; (ii) the amount and types of social media sources and, consequently, the opportunities for their use in the analysis of different urban phenomena, are constantly increasing; and (iii) the access to social media data, as well as their penetration in society, granularity of the information, and functionality are in constant change, allowing new methods of analysis to emerge.

This study contributes to the existing body of research in two main directions: firstly, it proposes a method for characterising cultural diversity of street-level urban and economic activities through digital and physical sources of information, and secondly, the digital footprints from different sources are explored to understand their potential and limitations for the analysis of public spaces and the extent to which the cultural diversity of cities is represented online.

## 2. Case Study

Stratford Road was selected as the case study. It is one of the main arteries of the southern part of the West Midlands conurbation area, connecting the city centre of Birmingham, with a population of 1,073,045 [45], with the Solihull metropolitan borough in

the south, where popular residential localities such as Shirley are located. Along this axis, both continuous and discontinuous settlements can be identified. The same patterns are followed by the presence of urban and economic activity along the axis. Specifically, this study focused on two segments of Stratford Road, where a significant amount of clustered economic activity is located. The spatial delimitation of these two case study segments was part of the actual research procedure and will be covered in the following Section 3.2.1. One of the selected segments was located in Sparkhill, a suburban area belonging to Hall Green, one of the 10 council constituencies of Birmingham metropolitan borough. The other segment was the street portion that divides Shirley East and Shirley West in the Solihull constituency. These two case study areas have visible and recognizable differences in their socio-economic status, which have been reflected in the use, behaviour, and activities that take place in the public space, including identifiable characteristics that provide useful clues for depicting the socio-cultural nature of the space [3]. These differences have been further supported by socio-economic indicators, such as the Index of Multiple Deprivation (IMD) [46], which evidenced the fact that neighbourhoods within Shirley East and West areas are amongst the 20% and 40% least deprived in the country respectively, whereas those in Sparkhill are amongst the 10% and 20% most deprived. Furthermore, although these areas are similar in population size and age group distribution, the population density is more than double for Sparkhill, and the ethnic distribution differs substantially. In Sparkhill, almost 80% of the population is Asian, whereas in Shirley East and Shirley West, 86% of the total population is white (Table 1).

**Table 1.** Population by age and ethnic group in Sparkhill and Shirley (East and West). Source: UK National Statistics via <https://www.citypopulation.de/en/uk/> (accessed on 23 June 2021).

	Sparkhill (Hall Green)	Shirley East and Shirley West (Aggregated) (Solihull)
Total population (2020 estimate)	21,650	22,770
Pop. Density (2020 estimate)	10,760/km <sup>2</sup>	4648/km <sup>2</sup>
Age group (2020 estimate)		(average)
18–64 years	60%	57%
0–17 years	31%	23%
65+	9%	20%
Total	100%	100%
Ethnic group (census 2011)		
White	12%	86%
Asian	77%	10%
Black	5%	1%
Other	3%	1%
Mixed	3%	2%
Total	100%	100%

### 3. Sources and Method

#### 3.1. Digital Footprints

As previously mentioned, this study considered both online and offline layers of information. The social media platforms Google Places, Foursquare, and Twitter were adopted as the online layer, whereas fieldwork observations were gathered as the offline layer, which allowed verification and validation of online collected data.

Even though each of the selected social media platforms meet very specific purposes, different from that of this study, they were selected for several reasons: (i) they include geolocated user-generated information, which means that the users' contributions are associated with a specific geographical space; (ii) their data are rich in spatiotemporal content, which allows a characterization of the data in a specific time frame; (iii) they are representative of different types of social media sources [47], thereby offering diverse information from the same geographical context; and (iv) although they have different functionalities, the three sources have proven to be complementary to each other for both analysing and diagnosing temporal and socio-spatial urban dynamics [48–50].

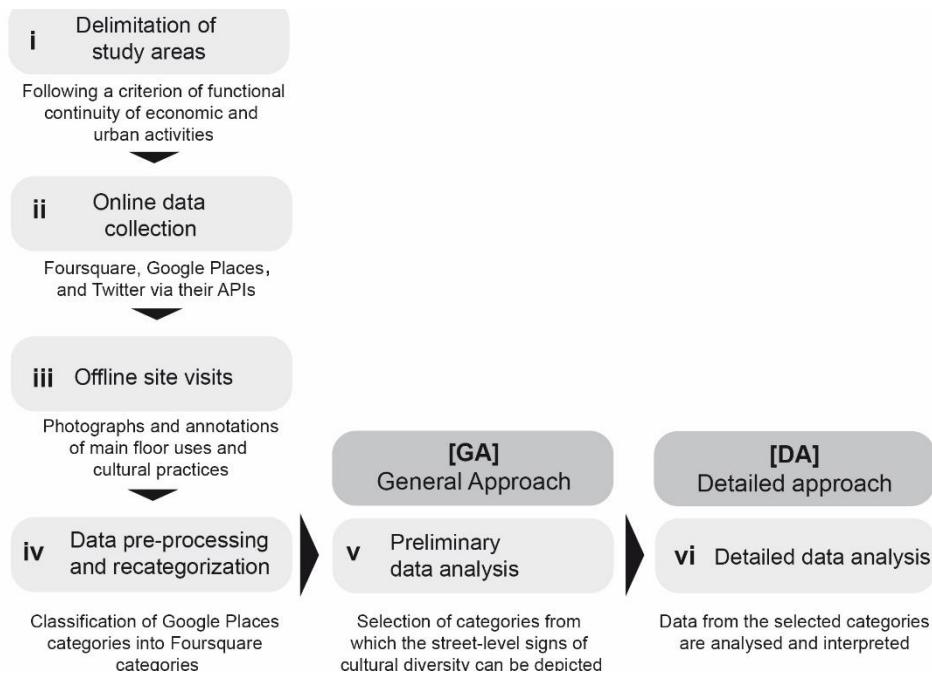
Google Places [51] is a place-based database linked to Google Maps' listing of points of interest (POIs), referred to as *places* by the platform. This source has become very popular among researchers for the collection of POIs, as it includes a rich list of commercial businesses, transit stations, landmarks, government buildings, etc. Specifically, this study focused on those locations that represent economic urban activities allocated inside buildings. Google Places prompts users to rate and/or review a place. This collaborative feature, which characterises social media platforms [47], allows users to connect and share opinions and feedback, which is why Google Places was considered a social media platform in this study.

Foursquare [52] and Twitter [53] are similar in the sense that they combine people's social and spatial behavioural information. Although Foursquare is a place-based platform, like Google Places, its functionality differs in two aspects. First, one of the main functionalities of Foursquare is that once in a *venue*, as referred to by the platform, users can check in to broadcast their presence at a physical location. Second, Foursquare's listing of *venues* includes only those in which users have checked-in at least once. Therefore, not all economic and urban activities are listed in the platform database. Twitter is a micro-blogging service where users can broadcast posts limited to 280 characters (*tweets*) related to news, opinions, etc. to a public feed. Twitter users decide whether the shared *tweets* should include the exact location from which they have been sent. For this study, only geolocated *tweets* were considered.

With the above in mind, for the scope of this research, Google Places *places* represented the urban and economic activities on offer; Foursquare checked-in *venues* represented the urban activities on demand; and the geolocated *tweets* from Twitter were indicative of the presence of people at certain locations.

#### 3.2. Research Procedure

A six-stage methodological approach was adopted: (i) the delimitation of study areas; (ii) online data collection and curation; (iii) offline data collection; (iv) data pre-processing and recategorization; (v) preliminary data analysis ([GA] General Approach); and (vi) detailed data analysis ([DA] Detailed Approach). Stages ii to iv consisted of preparing data for analysis, and stages v and vi included both a broad and a more detailed analysis and interpretation of data, respectively (Figure 1). Specifically, the General Approach [GA] stage provided an overall picture of urban activity and social patterns present within the space, and the findings from this stage guided further interpretation of data at the Detailed Approach stage [DA].

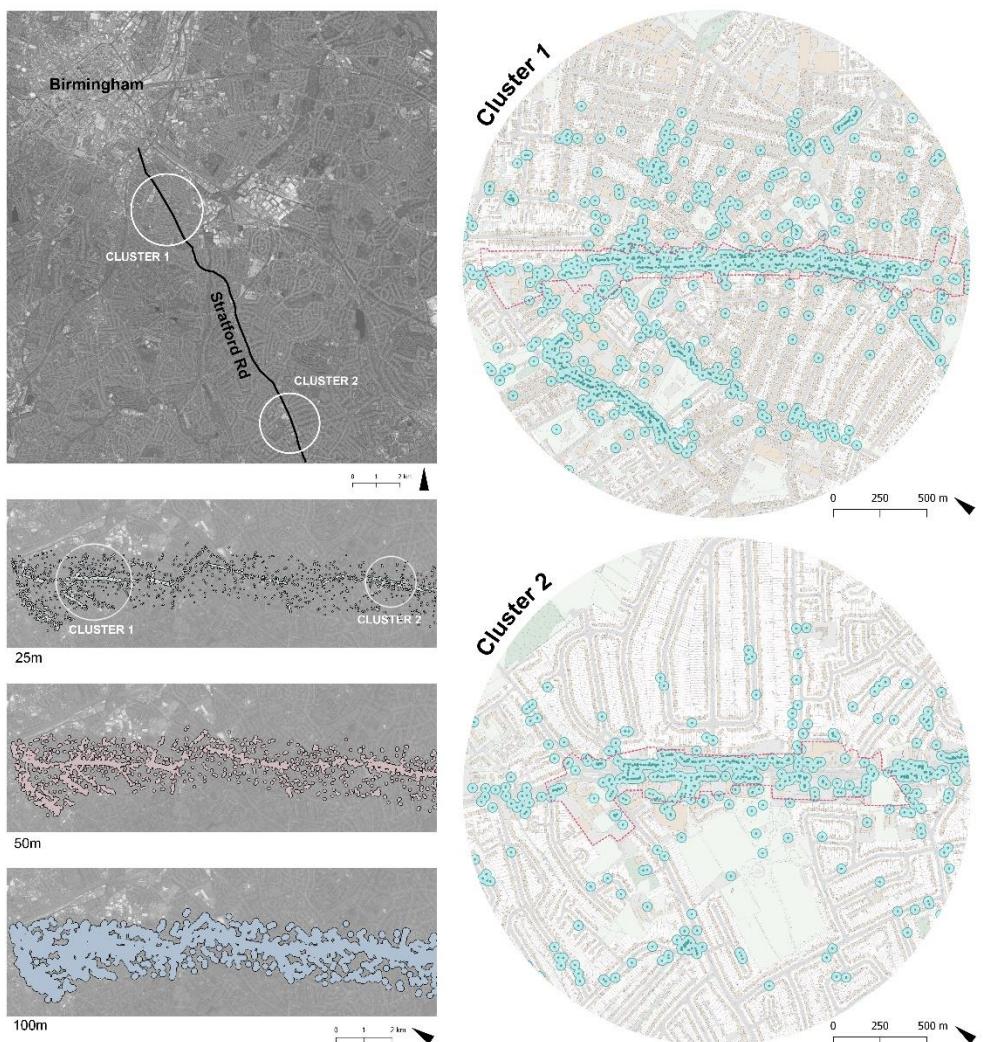


**Figure 1.** Research procedure stages.

### 3.2.1. Delimitation of Study Areas

Two representative road segments of Stratford Road were selected as study areas (Figure 2, upper left). The selection of these two area samples followed the criterion of functional continuity of street-level urban and economic activities, that is, the spatial clustering of Google Places datapoints. The procedure followed began with the visualization of Google Places datapoints in a Geographical Information System, considering an area spanning a one-kilometre distance from both sides of Stratford Road's central axis. Secondly, for determining the length of the road segments selected as sample areas, each datapoint was surrounded by different radius area sizes (25 m, 50 m, and 100 m) to identify clustering patterns (Figure 2, bottom left). Thirdly, the clustering patterns forming a continuous shape were closely analysed. Finally, the two longest road segments with the highest concentration of urban activities were selected, considering the 25m radius representation. This radius size criterion appeared to be more appropriate for the small street-scale analysis for two reasons. First, at a distance of 22–25 m, human vision is able to accurately read facial expression and dominant emotions. Short messages can be exchanged (hearing and seeing others), and so a degree of basic social interaction can happen [54]. Second, close observation of the clusters generated by the three radii sizes showed that with the 50 m and 100 m radius, there were cases in which two economic activities that appeared to be clustered together were too far from each other (up to a distance of 200 m) and thus did not meet the functional continuity criterion.

Once the length of the two sample road segments was defined (2478 linear metres for Cluster 1 and 1745 linear metres for Cluster 2), the width of the street area and adjacent urban blocks included on both sides was superimposed (Figure 2, right), as per the method proposed by Serrano-Estrada et al. [55].



**Figure 2.** Location of clusters 1 and 2 along Stratford Road (upper, left); visualization of the three trials with different radii area sizes surrounding each Google Places datapoint (bottom, left); spatial delimitation of Clusters 1 and 2 (right).

### 3.2.2. Online Data Collection and Curation

Data from the three selected social networks (Foursquare, Google Places, and Twitter) were collected via their public Application Programming Interface (API) by means of a self-developed web application, SMUA (Social Media Urban Analyser). This application allows the delimitation of a geographical polygon area, within which all data are collected and then exported into a .csv file. The procedure for collecting data as well as the advantages and limitations of this application have been extensively covered in a previous work [48]. However, from the data collection process, there are a few aspects that should be noted. Only geolocated data available from the social networks are collected. Therefore, while all available Foursquare and Google Places registers are retrieved, only geopositioned *tweets* are queried by SMUA. Moreover, the data collection from Foursquare and Google Places is conducted through single requests to the REST API, meaning that datasets include the cumulative registers available up to the date of retrieval (whereas the data collected for Twitter is performed through the Twitter Streaming API), so real-time *tweets* are collected during a specific timeframe. For this study, Google Places and Foursquare datasets were collected on 30 September 2019, whereas the Twitter dataset included all those geolocated *tweets* generated between the 21 September 2018 and the 14 March 2019.

From the broad range of metadata offered by these platforms, the raw datasets retrieved from the three social networks only included very specific metadata (Table 2).

**Table 2.** Foursquare, Google Places, and Twitter dataset metadata used for this study.

General Variables	Foursquare	Google Places	Twitter
1. Location	Longitude	Longitude	Longitude
	Latitude	Latitude	Latitude
2. Temporal information	Cumulative data on <i>venues</i>	Updated data on registered <i>places</i>	Time the <i>tweet</i> was posted
	<i>Venue</i> name	<i>Place</i> name	<i>Tweet</i> text
3. User-generated data	<i>Venue</i> address	<i>Place</i> address (vicinity)	-
	Check-ins	Average <i>place</i> ranking	-
	Visits	-	-
4. Data categorization	Users	-	-
	Hierarchy of categories and sub-categories	Categories, sub-categories, sub-sub-categories	-
	<i>Venue</i> ID and URL	<i>Place</i> ID	<i>Tweet</i> ID
5. Data ID			

In the case of Foursquare and Google Places, the metadata comprised, respectively, the listing of *venues* and *places*, their predefined hierarchical classification into *venue* categories [56] and *place* types [57], the geographical coordinates, and the ID or identification number of each register. Foursquare datasets also included three other different metadata variables: *users*, *visits*, and *check-ins*. Firstly, the *users* value corresponds to the total number of unique individuals registered in the social network that have ever checked in at a *venue*. Therefore, in this study, the *users* value suggests whether the *venue* is popular or not. Secondly, the *visits* value refers to the total number of times that users pass by a *venue*. These registers are possible due to the fact that Foursquare tracks user whereabouts through location services; thus, the *visits* value provides an indication as to whether the area surrounding a *venue* is popular or not. Lastly, the *check-in* value represents the total number of times that users have voluntarily broadcast their presence in a *venue* through Foursquare's Swarm mobile application [58].

The metadata collected from Twitter included the ID or identification number, the geographical coordinates, the *tweet* language, and the temporal information (date and time the *tweet* was posted).

The data curation process consisted of removing duplicate records from the three social media raw datasets, as well as the retweets and *tweets* generated by bots (messages shared by automated accounts) in the case of Twitter. Only those *tweets* that were likely to have been shared by individuals were manually selected and kept as part of the dataset for further analysis.

### 3.2.3. Offline Site Visits

Offline information was gathered through unstructured direct on-site observations of the two selected road segments of Stratford Road, at different times of the day from the 5 to 26 March 2019. Specifically, the fieldwork data collection had a twofold purpose: first, the manual registration of economic activities, which allowed a verification of Google Places registers in terms of their location and types; and second, the comparison of results obtained through online data sources with regard to identified signs of culturally diverse street-level urban activities.

Therefore, prior to visiting the site, the online-sourced dataset was examined using the method proposed by Dobson [30] and Longan [59]. This included the visualization of the curated datasets over a cartography in a Geographic Information System program. A paper version of this map was used for annotating on-site observations and for comparing and identifying any discrepancies with the online sourced datasets.

### 3.2.4. Data Pre-Processing and Recategorization

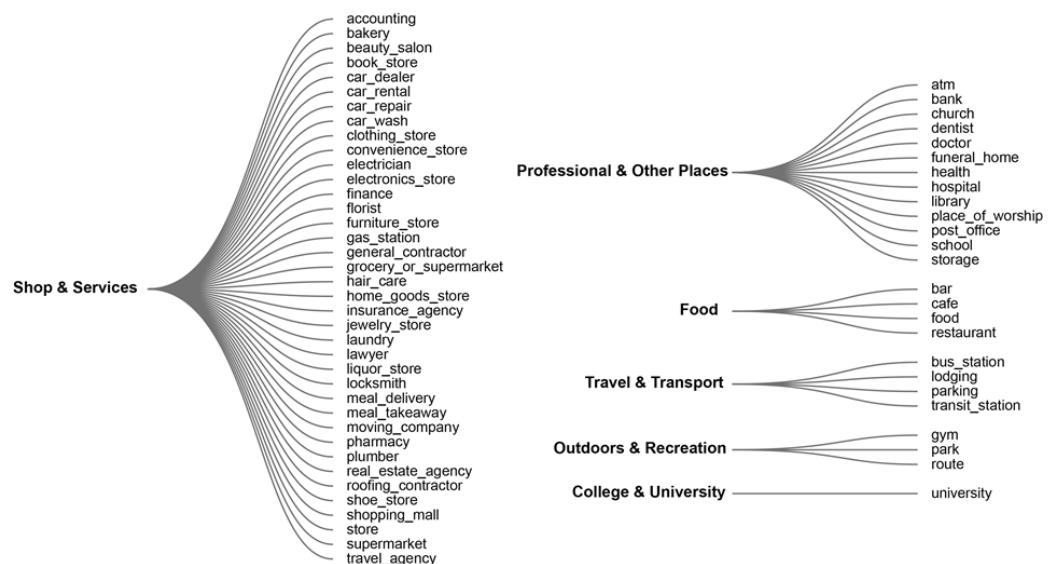
In total, after the data curation, the registers within the selected areas amounted to 41 Foursquare *venues*, 427 Google Places *places*, and 29 *tweets* for Cluster 1 in Hall Green and 73 *venues*, 298 *places*, and 87 *tweets* for Cluster 2 in Solihull (Table 3). The datasets from the three social networks were pre-processed and recategorized to facilitate the analysis.

The pre-processing of Foursquare and Google Places datasets was carried out to ensure that all the *venues* and *places* listed had an assigned category that corresponded to the type of location or activity they referred to. This task involved manual verification that resulted in only 5% of Foursquare *venues* requiring adjustment to their predefined categories. However, 20.1% and 22.8% of Google Places *places* in Clusters 1 and Cluster 2, respectively, had to be categorized into an existing Google Places category, either because the registers were not assigned to any category or because they had an ambiguous category assigned. For example, the category *point of interest* did not provide enough information about the place's type of activity but accounted for 21.4% and 23.4% of the total raw data in CL1 and CL2, respectively (See Table S1 in Supplementary Materials).

As for the Twitter dataset, the pre-processing consisted of cleaning the text and removing in-text symbols, weblinks, etc., that did not provide useful information for the purpose of the study. Then, *tweets* were classified into four-timeframes, as follows:

- I. weekdays morning/afternoon, from 08:00 to 20:00, Friday included;
- II. weekdays evening/night, from 20:00 to 07:59, Friday excluded;
- III. weekends morning/afternoon, from 08:00 to 20:00, Friday excluded;
- IV. weekends evening/night, from 20:00 to 07:59, Friday included.

Once all datasets had been pre-processed, a reclassification of Google Places' place types (63 initial categories) into the predefined Foursquare categories (6 categories) was conducted (Figure 3) for two reasons: first, to streamline the analysis and, second, to be able to compare the information from both sources [55].



**Figure 3.** Recategorization of Google Places *places* into Foursquare categories.

### 3.2.5. General and Detailed Approaches to Data

Two analyses with different degrees of insight were conducted to depict signs of cultural diversity in street-level urban activities within the areas of study.

**Table 3.** Upper: frequency of Foursquare *venues* and Google Places *places* by category and Twitter *tweets* by time frame. Bottom: economic activity registered on field visit.

		Cluster 1 Hall Green 2478 Linear Metres	Cluster 2 Solihull 1745 Linear Metres
Foursquare <i>venues</i>			
Demand for urban activities	Average <i>venues</i> /100 linear metres	1.7	4.2
Retrieval date: 30 September 2018			
	<b>Categories</b>		
	Arts and Entertainment	2	5%
	College and University	2	5%
	Food	13	32%
	Nightlife Spot	2	5%
	Outdoors and Recreation	1	2%
	Professional and Other Places	7	17%
	Residence	1	2%
	Shop and Services	9	22%
	Travel and Transport	4	10%
	Total <i>venues</i>	41	100%
Google Places <i>places</i>			
Urban activities on offer	Average <i>places</i> /100 linear metres	17.2	17.1
Retrieval date: 30 September 2018			
	<b>Categories</b>		
	Arts and Entertainment	3	1%
	College and University	17	4%
	Food	34	8%
	Nightlife Spot	-	-
	Outdoors and Recreation	15	4%
	Professional and Other Places	75	18%
	Shop and Services	266	62%
	Travel and Transport	17	4%
	Residence	-	-
	Total <i>places</i>	427	100%
Twitter <i>tweets</i>			
Spatiotemporal patterns of people presence	Average <i>tweets</i> /100 linear metres	1.2	5
Retrieval period 20 September 2018 to 5 March 2019			
	<b>Timeframes</b>		
	Weekdays Evening (Friday EXCL)	6	21%
	Weekdays Morning (Friday INCL)	11	38%
	Weekends Evening (Friday INCL)	2	7%
	Weekends Morning (Friday EXCL)	10	34%
	Total <i>tweets</i>	29	100%

**Table 3.** Cont.

		<b>Cluster 1</b> Hall Green 2478 Linear Metres	<b>Cluster 2</b> Solihull 1745 Linear Metres
Field study collected data	Average field study registers/100 linear metres	14.3	14.1
	-Google Places data points misplaced	7	14
	-Not in Google Places dataset	44	9
	-Could not be found on field visit	58	38
	Total registers collected through field visits	356	246
			100%

The general approach ([GA] in Figure 1) consisted of an overall first comparison between the urban and economic activities of the two clusters, considering the average datapoints per 100 linear metres. Then, a second comparison was made based on (i) the amount and diversity of urban and economic activities on offer for both clusters, which have been highlighted by both the Google Places *places* and the records collected during field observations; (ii) the amount and diversity of the *venues* on demand according to Foursquare datasets; and (iii) the amount of social activity and patterns of people's presence as reflected by geolocated *tweets* as per the defined timeframes.

The detailed approach ([DA] in Figure 1) entailed recognizing and identifying *venues*, *places*, and *tweets* from which signs of culturally diverse street-level urban activities could be detected. Specifically, the metadata from social-media-gathered datasets were manually revised for that purpose. Foursquare *venues* ranked by *check-ins* provided an indication of socially preferred urban activities [50]. Then, the frequency of Foursquare *venues* within the Food and Shop and Services categories was analysed. Lastly, a word cloud showing frequent words in *tweet* messages related to both case study areas provided an indication of common topics related to urban activities.

#### 4. Results

The case study selected included two areas with high urban activates along Stratford Road in Birmingham: cluster 1 (CL1) in Hall Green (See Figure S1 in Supplementary Materials), with a higher percentage of Asian population registered, and cluster 2 (CL2) in Solihull, with a predominantly white population (See Figure S2 in Supplementary Materials). Both clusters surpassed the average of 7–8 Google Places *places* (i.e., economic activities on offer) for every 60 linear metres, an indicator that suggests that these segments can be considered "active" [3]. This demonstrates their functional continuity, the methodological criterion followed for the delimitation of study areas.

Two other methodological considerations concerning the information sources and the data classification are worth highlighting.

First is that which related to the comparison between the proportion of economic and urban activities on offer as per Google Places datasets and those collected during field observations (Table 3). Indeed, Google Places datasets included 19% and 20% more activities for CL1 and CL2, respectively. The difference in the amount of information retrieved from both sources was potentially due to the fact that social media data include activities that are not appreciable from the street level. For instance, during fieldwork, it was not possible to know whether professional activities were taking place on upper floors with no signage on the façade.

Second, the data recategorization of Google Places *places* into Foursquare categories facilitated the comparison between the two clusters in terms of quantity, availability, and preferred types of urban and economic activities.

#### 4.1. General Approach to Data [GA]

Findings from the General Approach to data are presented in Table 3, which shows the quantity and types of economic and urban activities that were analysed for each source and cluster. Two relevant findings were observed. First, with respect to the quantity, the average amount of urban activity on offer (*places*) per linear metre in CL1 and CL2 was rather similar, being 17.1 and 17.2, respectively, whereas the demand for activities was 2.4 times less in CL1 than CL2.

Second, in relation to the diversity of activities, although in a different order, the *venue* categories and *place* types that ranked the first, second, and third position with most registers were *Shop and Services*, *Professional and Other places*, and *Food* for both clusters. However, there seemed to be more diversity in the urban and economic activities on offer for CL2 than for CL1, whereas the opposite scenario was observed for the demand for these activities, in which more diversity was found in CL1 than in CL2.

As for the comparison between the number of Google Places *places* and Foursquare *venues* per category and cluster, the proportion of registers under the *Food* category was almost the same for both clusters in both social networks: 8% for CL1 and 10% for CL2 in Google Places and 32% for CL1 and 33% for CL2 in Foursquare. However, the category *Shop and Service* was far less well-represented in Foursquare than in Google Places, especially in CL1. This possibly suggests that local and proximity retail in CL1 was not fully represented in the Foursquare datasets.

Moreover, although a more exhaustive user behaviour analysis would be necessary to confirm this in quantitative terms, no apparent correlation was found during fieldwork between the very few registers collected from Foursquare and Twitter in CL1 and the actual vibrancy observed in this street segment, especially when compared to CL2. Indeed, CL1 was appreciated to be at least as active and vibrant as CL2 in terms of street-level pedestrian activity during the day and night, even though the number of *users*, *check-ins*, and *visits* registered in the Foursquare Nightlife Spot category *venues* (Table 4) was relatively small.

**Table 4.** Foursquare *venues* within the Nightlife Spot category.

CL1 (Hall Green)	Users	Check-ins	Visits
Rangin	2	4	4
Farahzad Lounge	5	2	24
Total	7	6	28
<b>CL2 (Solihull)</b>			
Red Lion	45	60	93
Saracens Head	126	136	211
The Pump House (Wetherspoon)	212	216	509
Royal British Legion	41	75	126
Total	424	487	939

At this point, two considerations should be highlighted. First is that CL1 is located in a culturally rich area in which the penetration and use of the Foursquare social media platform might be different from that of CL2. Second, the socially oriented data included in this social network was not necessarily generated by neighbourhood residents, but by outsiders that may not be interested in registering or checking in to those retail *venues* found in CL1. These observations can be further supported by Twitter data (considered an indicative of the spatiotemporal presence of people), where CL1 presented three times fewer geolocated *tweets* than CL2 over a six-month span of streaming data collection.

#### 4.2. Detailed Approach to Data [DA]

Further analysis of the more socially oriented social media platforms selected (i.e., Foursquare and Twitter) evidenced traces of culturally diverse street-level urban activities for both clusters. Relevant observations are presented in relation to both field work annotations and key theoretical and empirical work from previous research.

The detailed approach to data included a ranking, by number of check-ins, of the 15 most active locations in Foursquare *venues* for both clusters (Table 5).

**Table 5.** Ranking of Foursquare *venues* by amount of *check-ins*.

Cluster 1 (Hall Green)					Cluster 2 (Solihull)					
	Venue Name	Visits	Check-ins	Users	Main Category	Venue Name	Visits	Check-ins	Users	Main Category
1	M.Y.Travel & Money Services Ltd.	2844	1751	407	Professional and Other Places	1 Costa Coffee	976	543	323	Food
2	Sparkbrook	278	192	86	Residence	2 Nando's	339	321	200	Food
3	Mushtaq's	190	178	35	Food	3 Morrisons Shirley	367	240	110	Shop and Service
4	Stratford Road	170	170	53	Travel and Transport	4 The Pump House (Wetherspoon)	509	216	212	Nightlife Spot
5	Barclays	173	169	23	Shop and Service	5 Aldi	736	172	209	Shop and Service
6	Sparkhill	170	163	46	Outdoors and Recreation	6 Lloyds Bank	254	170	86	Shop and Service
7	ShahiNan Kebab	388	113	132	Food	7 The Shirley Centre	239	148	50	Professional and Other Places
8	Aldi	239	100	108	Shop and Service	8 Saracens Head	211	136	126	Nightlife Spot
9	Caspian Pizza Complex	107	80	25	Food	9 The Gym	216	130	42	Outdoors and Recreation
10	Yaqub's Halal Steak House and Grill	215	63	135	Food	10 M&S SimplyFood	130	122	54	Shop and Service
11	Hajee's Spices	99	58	68	Food	11 Desco Lounge	393	121	201	Food
12	Mighty Q	54	43	20	Shop and Service	12 Big John's	125	106	50	Food
13	Faithful Neighbourhood Centre	36	36	9	Professional and Other Places	13 NatWest	156	88	66	Shop and Service
14	Guru Nanak Gurdwara	63	20	38	Professional and Other Places	14 Post Office	166	86	74	Professional and Other Places
15	Subway	105	18	45	Food	15 Domino's Pizza	76	76	42	Food

The highest ranked *venues* in CL2 were retail chain stores, whereas in CL1, most stores were locally oriented *venues*, which seemed to be aimed at very different target groups to those in CL2. Indeed, in view of this information, these types of urban activities are, to a great extent, indicative of the demographic and socio-economic profile of the area. Considering the number of users as indicative of the *venues'* popularity, the most popular *venue* in CL1 (Hall Green) was "M.Y. Travel & Money Services Ltd" (Figure 4 left), a travel and foreign currency office. For CL2 (Solihull), "Costa Coffee" (Figure 4, right), a coffee house chain, was the *venue* with most users.



**Figure 4.** Superimposed site visit and online retrieved photographs. Left and right pictures show the most checked in *venue* in Cluster 1 (Hall Green) and Cluster 2 (Solihull), respectively.

A closer examination of *venues* and *places* indicated that the categories from which signs of cultural diversity were more evident were *Food* and *Shop and Services* (See Figure 3 and Table 5). Table 6 shows the diversity of the type of food Foursquare *venues* per frequency and number of people that had walked by (visits), checked in (*check-ins*), or visited (users). CL2 had more diversity of Food *venues* registered in Foursquare. Furthermore, the most checked-in venues in CL1 under this category were Asian and Pakistani restaurants; whereas in CL2, the preferred types of Food venues were coffee shops, followed by Nando's (a multinational food chain) and other Fast-Food Restaurants.

**Table 6.** Foursquare's *Food* category *venues* and their cumulative visits, *check-ins*, and users.

Cluster 1 Hall Green	Visits	Check-ins	Users	Cluster 2 Solihull	Visits	Check- ins	Users
<b>Asian Restaurant</b>	<b>444</b>	<b>127</b>	<b>173</b>	<b>Asian Restaurant</b>	<b>28</b>	<b>24</b>	<b>22</b>
Dipyum	2	2	2	Chop Wok	10	9	10
Lahore KarahiChopstix	54	12	39	Good Wok	18	15	12
ShahiNan Kebab	388	113	132	<b>Bistro</b>	<b>407</b>	<b>130</b>	<b>208</b>
<b>Dessert Shop</b>	<b>57</b>	<b>9</b>	<b>37</b>	Desco Lounge	393	121	201
Cravings	57	9	37	Parksidebistro	14	9	7
<b>FastFood Restaurant</b>	<b>5</b>	<b>5</b>	<b>5</b>	<b>Café</b>	<b>23</b>	<b>12</b>	<b>19</b>

**Table 6.** Cont.

<b>Cluster 1 Hall Green</b>	<b>Visits</b>	<b>Check-ins</b>	<b>Users</b>	<b>Cluster 2 Solihull</b>	<b>Visits</b>	<b>Check- ins</b>	<b>Users</b>
Karachi	5	5	5	Alba Sandwiches	5	5	4
<b>Indian Restaurant</b>	<b>25</b>	<b>19</b>	<b>17</b>	CoffeeRoaster	18	7	15
Bab-E-Khyber	2	2	2	<b>Coffee Shop</b>	<b>985</b>	<b>550</b>	<b>329</b>
Deepalis	23	17	15	Costa Coffee	976	543	323
<b>Pakistani Restaurant</b>	<b>289</b>	<b>236</b>	<b>103</b>	KairosCoffee	9	7	6
Hajee'sSpices	99	58	68	<b>Fast Food Restaurant</b>	<b>186</b>	<b>163</b>	<b>84</b>
Mushtaq's	190	178	35	Big John's	125	106	50
<b>Pizza Place</b>	<b>107</b>	<b>80</b>	<b>25</b>	Shirley Kebab House	61	57	34
Caspian Pizza Complex	107	80	25	<b>North IndianRestaurant</b>	<b>114</b>	<b>103</b>	<b>60</b>
<b>Sandwich Place</b>	<b>105</b>	<b>18</b>	<b>45</b>	DosaVillage	2	2	1
Subway	105	18	45	Indico Street Kitchen& Bar	7	6	6
<b>Steakhouse</b>	<b>221</b>	<b>69</b>	<b>140</b>	Oasis Restaurant	30	23	24
G3 Steak& Grill	6	6	5	Shah'sBistro	9	9	4
Yaqub's Halal Steak House & Grill	215	63	135	ShaplaTandorri	66	63	25
<b>Total</b>	<b>1253</b>	<b>563</b>	<b>545</b>	<b>Italian Restaurant</b>	<b>76</b>	<b>57</b>	<b>46</b>
				Little Italy	23	13	13
				Prezzo	53	44	33
				<b>Pizza Place</b>	<b>160</b>	<b>145</b>	<b>82</b>
				Domino's Pizza	76	76	42
				perfetto pizza	7	7	3
				PizzaExpress	77	62	37
				<b>Portuguese Restaurant</b>	<b>339</b>	<b>321</b>	<b>200</b>
				Nando's	339	321	200
				<b>SandwichPlace</b>	<b>132</b>	<b>48</b>	<b>74</b>
				Subway	132	48	74
				<b>Turkish Restaurant</b>	<b>146</b>	<b>39</b>	<b>78</b>
				Istanbul Restaurant	146	39	78
				<b>Vegetarian/Vegan Restaurant</b>	<b>14</b>	<b>13</b>	<b>7</b>
				Falafel Munch	14	13	7
				<b>Total</b>	<b>2610</b>	<b>1605</b>	<b>1209</b>

As for the *Shop and Services* category *venues* (Table 7), as previously observed in the general analysis of data, CL1 had three times fewer registered *venues* (9) compared to CL2 *venues* (33).

**Table 7.** Types and amount of Foursquare Shop and Services category *venues*.

Cluster 1 Hall Green	Total Venues	Visits	Check-ins	Users	Cluster 2 Solihull	Total Venues	Visits	Check-ins	Users
Bank	1	173	169	23	Bank	7	691	390	275
Convenience Store	1	54	43	20	Food and Drink Shop	5	206	168	106
Furniture/Home Store	1	25	4	18	Shopping Mall	1	79	72	26
Food and Drink Shop	1	6	6	5	Salon/Barbershop	4	76	51	24
Pharmacy	1	3	3	2	Sporting Goods Shop	1	30	22	20
Betting Shop	1	2	2	2	Gift Shop	1	29	29	12
Clothing Store	1	2	2	2	Optical Shop	1	25	24	11
Smoothie Shop	1	2	2	2	Auto Dealership	1	18	17	12
Bridal Shop	1	1	1	1	Furniture/Home Store	2	17	13	9
<b>Total</b>	<b>9</b>	<b>268</b>	<b>232</b>	<b>75</b>	<b>Clothing Store</b>	<b>1</b>	<b>14</b>	<b>13</b>	<b>7</b>
					<b>Pharmacy</b>	<b>1</b>	<b>12</b>	<b>11</b>	<b>1</b>
					<b>Convenience Store</b>	<b>2</b>	<b>11</b>	<b>11</b>	<b>9</b>
					<b>Thrift/Vintage Store</b>	<b>1</b>	<b>3</b>	<b>3</b>	<b>2</b>
					<b>Photography Lab</b>	<b>1</b>	<b>3</b>	<b>3</b>	<b>2</b>
					<b>Miscellaneous Shop</b>	<b>1</b>	<b>2</b>	<b>2</b>	<b>1</b>
					<b>Mobile Phone Shop</b>	<b>1</b>	<b>2</b>	<b>2</b>	<b>1</b>
					<b>Real Estate Office</b>	<b>1</b>	<b>1</b>	<b>1</b>	<b>1</b>
					<b>Shoe Repair</b>	<b>1</b>	<b>1</b>	<b>1</b>	<b>1</b>
					<b>Total</b>	<b>33</b>	<b>1220</b>	<b>833</b>	<b>520</b>

The economic activity with the most Foursquare *check-ins*, *visits*, and *users* for both clusters within the *Shop and Services* category was Bank: one registered in CL1 and seven in CL2. The next most popular *venue* type was Convenience Store, where the only *venue* in CL1 had double the number of registered users than the combined number of both *venues* in CL2.

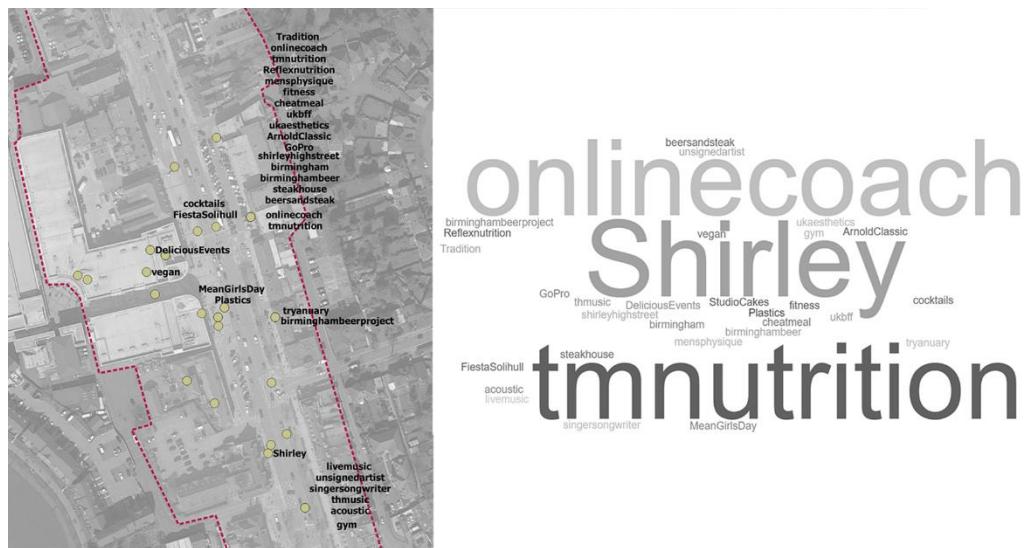
As evidenced by Foursquare datasets, “Betting” and “Bridal Shops” were noteworthy economic activity types identified in CL1. This was corroborated by fieldwork observations, as well as through Google Places and Twitter data (Figure 5, left). In fact, of the total Google Places *places* registered and originally categorized as “Clothes Store” (representing 30% of the total number of *places* in CL1), 85% specialized in Indian and Asian bridal gowns and accessories (See Table S1 in Supplementary Materials). This was further supported by the topic frequency shown in the word cloud generated from *tweets* shared in CL1 (Figure 5,

right), albeit the number of *tweets* was significantly lower than the amount of data retrieved from the other two social networks.



**Figure 5.** Left: the most active Twitter profile of CL1, and right: word cloud of CL1 topics included in *tweet* texts by frequency.

Lastly, the second, third, and fourth most popular type of *venues* within the *Shop and Services* Foursquare category in CL2 were “Food and Drink Shop”, “Shopping Mall”, “Salon/Barbershop”, and “Sporting Goods Shop”, respectively (Table 7). Precisely these types of urban activities were reflected in the trending topics included in CL2’s shared *tweets* that were geotagged at the area where the highest concentration of datapoints from all social networks was found (Figure 6).



**Figure 6.** Left image: geolocated *tweet* hashtags; right image: word cloud of CL2 trending topics of *tweet* texts.

## 5. Discussion

This study contributes to the existing body of research that characterises culturally diverse urban environments through digital footprints collected from social media platforms. Specifically, Google Places was used as a listing of urban and economic activities on offer; Foursquare was used as a means by which socially preferred places were recognised; and geolocated Twitter *tweets* were used as indicating the presence of people at certain locations and as a textual representation of social activities.

Two levels of data analysis were adopted in the proposed method: a general and a detailed approach. Google Places, which is a place-centred social network, was quite useful for the general approach to data, as it provided an up-to-date listing of urban and eco-

nomic activities. From this, it became evident that both retail (Shop and Services category) and restaurants (Food category) have significative relevance in both road segments, with 12% more retail in CL1 (Hall Green), the most ethnically diverse and socioeconomically disadvantaged cluster. As previous findings from empirical research have confirmed, by analysing social preferences through behavioural mapping and personal interviews, culturally diverse shops and restaurants are important spaces for social and leisure activities, and in particular, “retail activities are the main concern of people in multi-cultural streets” [60]. Indeed, these are the types of businesses that often incorporate physical characteristics that support sociability and liveability, such as personalization of storefronts and street fronts, thereby creating unique ambiances [3]. As shown in Figure 7, the personalization of the most checked-in commercial establishments in both clusters differed in terms of how the products are displayed. Mighty Q, the most checked-in Convenience Store in CL1 was “extending the interior territory of the store to the exterior street space” [3], whereas the Convenience Store with most users in CL2 had a high permeability, but product display was restricted to the inner store space.



**Figure 7.** Superimposed site visits and online retrieved photographs. From left to right, the most popular Convenience Stores in Cluster 1 and Cluster 2.

This information is valuable for designing businesses management strategies for retail activities and services that aim for a pluralistic approach towards inclusionary retail activity in multicultural contexts [6].

As for the detailed approach to data, despite the small-size of the dataset from Twitter in CL1 (Hall Green) and CL2 (Solihull) and of Foursquare in CL1, the data from both social networks highlighted relevant social preferences in terms of *venues* popularity and signs of cultural diversity embedded in urban and economic activities. This was found through a close examination of Foursquare *venues* and the hints detected about the nature of the activities that took place in each of the clusters through the textual information included in the *tweets*. For instance, the social relevance of Pakistani restaurants in CL1, along with the character and type of preferred *venues*, coincided with the Twitter trending topic word cloud. Although generalisation was not possible, in the light of the socioeconomic context of the case study areas (see Section 2), these results concurred with those obtained from the research of Yuan et al. [61], which suggested that “low-income communities have a distinctive restaurant culture that the high-income areas do not have”.

There are a few aspects worth highlighting regarding the opportunities and limitations of data retrieved from the three social media platforms for depicting cultural diversity in street-level urban activities.

First, this study proved that “identities and power relationships [...] are not always visible from the online prospective” [58]. In particular, this “visibility” largely depends,

among other things, on the penetration and popularity of the social media platform in the case study areas, the age group that uses these platforms, and whether only one source of information is to be used for the analysis. Indeed, for this street-scale study, it was necessary to include several sources of data. This is a well-known strategy to “thicken” small data corpuses [61]. However, it is often not necessarily a matter of sample size, since a large data sample does not guarantee that better insights will arise [62]. Rather, it is more about the quality and content of the data.

This study, as has been the case for others that deal with small samples of data [63,64], has demonstrated the importance of not disregarding small datasets. For small-scale analysis, data cannot be dismissed before making sure it is not useful. For instance, a Twitter “influencer” is a user who is likely to generate noisy *tweets*, which is why some studies tend to eliminate the *tweets* generated by these users, especially in large-scale studies. However, in the case of street-scale analysis, it seems convenient to further investigate whether such users are posting content that could be useful. For instance, the most active user in Twitter of CL1, R F Chohan, a jewellery store user profile, provided what appeared to be an accurate picture of commonly found urban and economic activities within the street segment. This economic activity reflects the “cultural specialisms” of the area, one of the key cultural indicators pointed out by Montgomery [65], as it represents “the presence of peculiar and specialized art forms, crafts, or even manufacturing and services, jewellery, ceramics, cuisine, etc.”. Similarly, an example of unexpected traces detected from Foursquare datasets was the social relevance of *venues* such as “Bus stops” in CL1, which were non-existent in CL2. These potentially contributed to the social life of the street and reflected a socio-economic difference between the two street segments.

## 6. Conclusions

This study has explored the potential of social media data sources for depicting culturally diverse street-level urban and economic activities. Specifically, the types of urban and economic activities reflected in Foursquare, Google Places, and Twitter have been used as proxy indicators of multicultural urban contexts.

Findings from Google Places data at a general stage provided a good understanding of the urban environment analysed. However, it must be acknowledged that the amount of geolocated data available from Foursquare and Twitter did not correlate with the amount of ground-observed liveability and ethnic and cultural richness in CL1. Although more exhaustive field data gathering and behavioural analysis would be required to quantitatively measure this assertion, it could be affirmed that, unlike in the case of CL2 (the area with the higher socio-economic profile), the urban vibrancy observed in CL1 remained mostly physical and, as such, was not found to be entirely represented by these social media platforms. The degree of socialization and people presence observed in CL1 remained mostly in the physical space and did not extend to the virtual space, whereas in CL2, the social activity found in the virtual space seemed to mirror the physical one. Therefore, it is worth insisting on the fact that insights from these sources cannot be extrapolated to a society, nor can it be assumed that there is a single meaning to them. The reproducibility of the method proposed for other street-level case studies largely depends on the geographical context. For instance, the *Food* category was relevant for identifying and comparing urban and economic activities of distinct natures between the two case study areas. However, this may not necessarily be the case in other geographical contexts without such a strong and rich cultural character.

All in all, future research along the lines of small-scale analysis in multicultural urban environments could consider including a behavioural analysis and semi-structured interviews as an additional layer of information to deepen the conclusions drawn from the social media small-data analysis (as opposed to Big Data analysis for entire cities). This would provide a more comprehensive understanding of the socio-spatial relation between local people (and not only social media users) and the urban setting, which is valuable

information for decision making aimed at preserving a unique, appealing, and socially inclusive urban environment.

**Supplementary Materials:** The following are available online at <https://www.mdpi.com/article/10.3390/su132011141/su132011141/s1>, Figure S1: Visualization of datasets retrieved from the three social networks in CL1 (Hall Green): Foursquare venues (by check-in value ranking); Twitter; and Google Places places, Figure S2: Visualization of datasets retrieved from the three social networks in CL2 (Solihull): Foursquare venues (by check-in value ranking); Twitter; and Google Places places, Table S1: Google Places types of activities per cluster.

**Author Contributions:** Conceptualization, P.M., L.S.-E. and M.A.; methodology, P.M. and L.S.-E.; formal analysis, P.M., L.S.-E. and M.A.; investigation, P.M., L.S.-E. and M.A.; data curation, P.M. and L.S.-E.; writing—original draft preparation, P.M., L.S.-E. and M.A.; writing—review and editing, P.M., L.S.-E. and M.A.; funding acquisition, P.M. and L.S.-E. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by Conselleria de Innovación, Universidades, Ciencia y Sociedad Digital, Generalitat Valenciana (GV/2021/177).

**Conflicts of Interest:** The authors declare no conflict of interest.

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