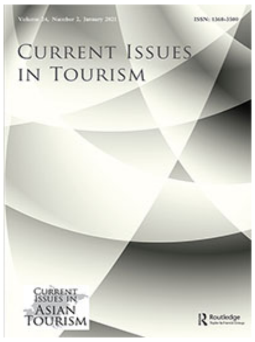

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Taking the urban tourist activity pulse through digital footprints

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ABSTRACT

An insight on urban tourism-related phenomena is provided in this study by analysing open and volunteered user generated content. A reference framework method is proposed and applied to an illustrative case study to meet a twofold objective: to identify Tourist Activity Centre – TAC – areas based on their functional character – sightseeing, shopping, eating and nightlife; and, to obtain an up-to-date fine-grain characterization of the most dynamic zones in an urban context. Instasights Heatmaps and data from Location Based Social Networks – Foursquare, Google Places, Twitter and Airbnb – were used to depict tourist urban activity. This reproducible method transcends Instasights generic visualization of popular areas by exploiting the benefits of overlapping LBSN data sources. This method facilitates a granular analysis of tourism-related places of interest and makes headway in bridging the gap between traditional approaches and user preferences, revealed through digital footprints, for urban analysis. The results indicate the potential of this method as a complementary tool for urban planning decision-making.

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Urban tourist activity pulse; user-generated content (UGC); tourist activity centre (TAC) areas; location-based social networks (LBSNs); Instasights Heatmaps

1. Introduction

Big Data have great potential for tourism research as they provide spatiotemporal information generated from large numbers of tourists (Salas-Olmedo, Moya-Gómez, García-Palomares, & Gutiérrez, 2018). Furthermore, geolocated Big Data sourced from tracking devices offer numerous possibilities for addressing research topics related to the tourism phenomena, such as tourist mobility (Sulis, Manley, Zhong, & Batty, 2018; Zheng, Huang, & Li, 2017), tourist consumption (Md Khairi, Ismail, & Syed Jaafar, 2019) and tourist spatial behaviour (Edwards & Griffin, 2013). Among these sources, social media is fast becoming an important information source for qualitative research in the field of urban studies (Puebla, 2018; Rose & Willis, 2018; Silva, Vaz de Melo, Almeida, & & Loureiro, 2014; Tasse & Hong, 2014; Van Canneyt, Schockaert, Van Laere, & Dhoedt, 2012) through which researchers conceptualize and represent the spatial structure of human society in the age of advanced Information and Communication Technologies (Shen, 2010). The user-generated content – UGC – retrieved from these sources is being streamed and archived in real time, thus creating immense volumes of spatiotemporal records: Big Data, 'larger than anything we have experienced in cities hitherto' (Batty, 2014).

For instance, Location Based Social Networks – LBSNs – have been broadly used as key big data sources (Stock, 2018) for urban analysis and for unveiling hidden traces related to user preferences (Hochman & Manovich, 2013; Padrón-Ávila & Hernández-Martín, 2017; Serrano-Estrada, Martí,

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Nolasco-Cirugeda, & Agryzkov, 2016), providing a means by which the city's activity pulse can be assessed (Martí, García-Mayor, & Serrano-Estrada, 2019).

Big Data retrieved from LBSN sources can be complementary to traditionally sourced data by providing reliable, up to date and more detailed information. Indeed, the reliability of these sources has been proved by several studies that have compared LBSN data with that of traditional fieldwork sources (Agryzkov, Martí, Tortosa, & Vicent, 2016b; Cranshaw, Schwartz, Hong, & Sadeh, 2012; Nolasco-Cirugeda & García Mayor, 2014) or with other government or administrative databases (Zhou, Hristova, Noulas, & Mascolo, 2018), recognizing the great potential offered by LBSNs for obtaining up to date information as they reflect social dynamics, whereas traditional sources rapidly become outdated (Chen & Roy, 2009).

Data retrieved from LBSNs are increasingly being used for researching tourism-related urban dynamics due to the ease with which locals and visitors alike are able to leave a digital footprint of their activities and preferences (Edwards & Griffin, 2013; Salas-Olmedo et al., 2018). Among the various research lines that explore UGC to approach urban dynamics, those that analyse clusters of activities to identify liveable neighbourhoods – *Livehoods* (Cranshaw et al., 2012) – and those that identify the most popular places (Agryzkov et al., 2016a; Bigné, Oltra, & Andreu, 2019; Martí, Serrano-Estrada, & Nolasco-Cirugeda, 2017; Salas-Olmedo et al., 2018; Van Canneyt et al., 2012) are of interest to this research as both approaches render possible the recognition of spatially aggregated most visited and most preferred points of interests – POIs.

Previous research has identified that an advantage of using Big Data, specifically LBSNs, for tourism-related research is that these sources reflect the online travel information search behaviour in general (Xiang & Gretzel, 2010), thereby implying that these sources can no longer be neglected in in the field and, arguably, user perception of tourist destinations is largely influenced by social media. In this respect, user perceptions have been dealt with from different perspectives. Thus far, a significant number of studies have focussed on photo-based social networks (Hu et al., 2015). In fact, online photo data retrieved from Social Networks such as Panoramio, Instagram and Flickr have been described as 'the rising stars' (Li, Xu, Tang, Wang, & Li, 2018) in this emerging phenomenon. Specifically, the assessment of tourist perceptions through the use of geolocated photographs retrieved from photo-sharing services as well as Geolocated Information Systems – GIS – (García-Palomares, Gutiérrez, & Mínguez, 2015) has been carried out to identify: (1) tourism attractiveness – i.e. cultural POIs – (Giglio, Bertacchini, Bilotta, & Pantano, 2019); (2) the impact of destination photography on perception (Kim & Stepchenkova, 2015); (3) the perception of the urban environment for urban planning purposes (|Dunkel, 2012, 2015); and, (4) the tourist experience through visual data – photography – (Balomenou & Garrod, 2019). Indeed, there is a general consensus in the scientific literature on the relevance of UGC to create tourism strategy models (Che, Safran, & Peng, 2013; Marine-Roig & Anton Clavé, 2015; Shelton, Poorthuis, & Zook, 2015).

The cross-referencing of data from various UGC sources to obtain different types of variables is also gaining momentum for several reasons. Firstly, as most of the UGC available is not generated or gathered for the specific purpose of addressing a research question, data could be biased when using a single source. Therefore, analysing various sources enables the crosschecking of data which is useful for drawing more robust conclusions (Lenormand et al., 2014). Secondly, using various data sources overcomes some of the associated limitations that may be uniquely inherent to a single source with respect to the representativeness and usage of data (Sulis et al., 2018). Thirdly, UGC data sources can be complementary as they offer unique and different content that is purposely created for each social channel (de Lange & de Waal, 2019, p. 145; Martí, Serrano-Estrada, & Nolasco-Cirugeda, 2019) – i.e. check-ins from Foursquare; text from Twitter; photos from Instagram; etc. Fourthly and lastly, the comparison of the results obtained from the analysis of different sources independently permits the search for data correlation (Silva, Horizonte, Salles, & Loureiro, 2013) that would thoroughly inform the object of study.

This work enriches existing research – highlighted in the literature review in section 2 – from a different angle. The study incorporates a broader range of UGC sources, but focused on very specific areas thus reducing the dataset to smaller datasets, and thereby thoroughly addresses the role of different LBSNs in the context of retrieving UGC to identify and analyse tourist city hotspots (Cheng & Edwards, 2015; Hays, Page, & Buhalis, 2013; Nummi, 2018). Therefore, this work addresses the need for a more detailed approach in this context by developing a reference method that embraces the unique benefits of cross-referencing several LBSNs, as will be fully explained in the *Section 4 Sources and procedures*. This synthesis provides an insight on user activity in urban spaces, enabling the identification and analysis of locations where the concentration of tourism-related activities occurs, as well as the detection of inactive pockets within the urban area. This potentially provides urban planners and other stakeholders with up-to-date information to better promote and implement strategies that balance the existing offer by boosting connectivity and liveability for less appealing areas.

The novelty of this research is twofold: first, it focuses specifically on areas where eating, shopping, sightseeing and nightlife activities converge; and second, the reference framework proposed integrates LBSN data with a tool – Instasights – that is available to the general public. This framework can be used as a complementary instrument for planning and decision-making processes that aim to enhance city dynamics.

1.1. Objectives

The main objective of this study is to present a method for gauging the tourist activity pulse in cities based on the analysis of UGC data. This entails two ancillary objectives:

(1) To identify Tourist Activity Centre areas – TAC areas – through Instasights Heatmaps tool for pinpointing baseline areas with most tourism-related activity – i.e. sightseeing, shopping, eating and nightlife.
(2) To depict an up-to-date characterization of the urban activities and most tourist-related dynamic places within the obtained TAC areas through data from four LBSNs – Foursquare, Twitter, Google Places and Airbnb.

A case study approach is used to conduct an exploratory study in the cities of Valencia and Alicante, which are representative cities of urban tourism in the Spanish Mediterranean Arc. The remainder of the paper is structured as follows: Section 2 focuses on the literature review of previous work conducted by leading scholars that deal with the use of LBSNs for assessing tourist areas; Section 3 describes the context of the case study areas; Section 4 provides the sources and method applied to the case studies; Section 5 presents the results; and finally, Section 6 discusses the findings and concluding remarks.

2. Related literature review

A comprehensive review of the literature that deals with different types of big data related to tourism research is provided by Li et al. (2018) and Salas-Olmedo et al. (2018). Therefore, the studies that are cited in this section focus specifically on previous work that responds to a similar research question and/or deals with the same sources of information as those of this paper.

2.1. Instasights Heatmaps and the tourist city

The adoption of Instasights as a tool to understand the tourist city is quite recent and, thus far, studies have used this source for the following purposes: to determine areas with high concentration of users (Simancas-Cruz et al., 2017); to define user activities and urban dynamics after public spaces renewal (Martí & Garcia-Mayor, 2018); and, to analyse the location of Airbnb accommodation offer and tourist areas (Perez-Sanchez, Serrano-Estrada, Marti, & Mora-Garcia, 2018). In combination with TripAdvisor, Instasights has been tested to unveil the most photographed places (Padrón-Ávila & Hernández-Martín, 2017). However, despite the potential offered by this platform to provide a delimitation of touristic activity areas, the analysis of Instasights Heatmaps in the context of identifying the specific concentration of points of interest in a tourist city has not been explored. Arguably, one of the setbacks of this tool is that the four types of touristic activities defined by Instasights cannot be visualized simultaneously on a map, a problem that the method developed for this study seeks to address.

2.2. Foursquare, Twitter – user preferences – and the tourist city

Foursquare and Twitter potentially represent user demand for activities and places (Martí, García-Mayor, et al., 2019), and the geolocated data retrieved from these social networks provide evidence of people activity and a ranking of preferences (Martí, Serrano-Estrada, et al., 2019). The information obtained from these Big Data sources, shared publicly and voluntarily by users – from individuals to entire organizations, is considered as traces human activity (Chorley, Colombo, Allen, & Whitaker, 2013). For example, the spatiotemporal and dynamic nature of Twitter has rendered this LBSN a useful tool for the assessment of how destination marketing organizations affect hotel occupancy in Spanish tourist cities (Bigné et al., 2019; Brandt, Bendler, & Neumann, 2017).

More frequently, studies have relied exclusively on a single source despite evidence that superimposing different layers of information has proven to enrich urban analyses (Martí, García-Mayor, et al., 2019). Specifically, for the case of tourism related phenomena, among the very few studies that combine different LBSN sources, the study from Salas-Olmedo et al. (2018) retrieves data from Panoramio, Foursquare and Twitter using Madrid as case-study, 'one of the European cities with the highest volume of tourists'. It compared the three sources and identified tourist activities with respect to sightseeing – through Panoramio; consumption patterns – through Foursquare – and spatial connection-accommodation patterns – through Twitter.

2.3. Google Places, Airbnb – urban economic activity offer – and the tourist city

Google Places and Airbnb Big Data sources provide insightful information on the diversity and quantity of economic activities, revealing the urban activity offer of different services: retail, professional and peer-to-peer accommodation services, for example. The analysis of these social networks enables the identification, concentration and distribution patterns of urban tourism related economic activities (Agryzkov, Alvarez, Serrano-Estrada, Tortosa, & Vicent, 2015; Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017). Furthermore, a current wave of studies approaches the tourist city dynamics by looking at the accommodation offer, including Airbnb as a recent trend in this sector (Adamiak, Szyda, Dubownik, & García-Álvarez, 2019; Coyle & Yu-Cheong Yeung, 2017; Gutiérrez et al., 2017; Perez-Sanchez et al., 2018; Perles Ribes, Moreno Izquierdo, Ramón Rodríguez, & Such Devesa, 2018; Sans & Quaglieri, 2016).

2.4. Main contribution of this study

Considering the literature, an unexplored approach is the overlapping of several LBSNs to provide a fine-grain analysis of specialized areas of tourism-related activity, even in the exemplary studies dealing with LBSNs as sources for urban analysis in tourist cities. This is precisely the main contribution of this paper. A reference framework is proposed by highlighting the potential of using Instasights Heatmaps as a tool for establishing baseline TAC areas and retrieving data from open sources, such as LBSNs, for harnessing user preference data and characterizing urban activities and the most tourist-related dynamic places.

Table 1. Ratio of most visited cities by national tourists within the peninsular Spanish Mediterranean Arc.

Province capital city	National tourists 2018	Population 2018	Ratio V/P
Alicante	**383,888**	**331,557**	**1.16**
Valencia	**774,454**	**791,413**	**0.98**
Barcelona	1,510,506	1,620,343	0.93
Málaga	477,670	571,026	0.84

3. Context of the study area: tourist cities in the Spanish Mediterranean Arc

In Europe, the Spanish Mediterranean Arc integrates one of the most relevant tourist destinations, whose contribution to Gross Domestic Product – GDP – is an average 9.2% (Costa, Panyik, & Buhalis, 2014). Within this context, the Valencian Community is one of the most relevant tourist regions with more than 9.2 million foreign tourists (Tourisme Comunitat Valenciana, 2018). Moreover, the Valencian Community is the first destination for national tourists in the Spanish peninsula (Agencia Valenciana de Turismo, 2019), whose coastal nature has traditionally attracted tourists from inland cities (Claver-Cortés, Molina-Azorín, & Pereira-Moliner, 2007).

From the 30 most visited Spanish cities in the Mediterranean peninsular coast (INE, 2018), Table 1 shows those most representative that are renowned for their urban tourism specialization (Moreno-Izquierdo, Ramón-Rodríguez, Such-Devesa, & Perles-Ribes, 2019) and have the largest ratio of national tourists per head of population.

Alicante and Valencia cities have been selected as highly suitable case studies for several reasons. They occupy a central location in the Spanish Mediterranean Arc and are the two main cities of the Valencian Community. Valencia is the third largest Spanish city with a population of 774,454 inhabitants and is the regional capital of the Valencian Community, followed by Alicante with 383,888 inhabitants (INE, 2018). Their attributes – good climate, cultural offer, calendar of events, leisure activities, infrastructure, important transport hubs, and tourist facilities – are decisive for competitiveness in the tourism sector (Sánchez & López, 2015). In the last decades, both Valencia and Alicante have experienced important territorial transformations in terms of their urban configuration (Font Arellano, 2006). Despite their different tourist projection, Valencia and Alicante are two well-known cities for their touristic resources, both involving a variety of accommodation types (Moreno-Izquierdo et al., 2019), which has led to the emergence of new and different types of tourism due to their rich cultural, architectural and gastronomic heritage at local level (Claver-Cortés et al., 2007).

4. Sources and procedure

Two types of sources were adopted for achieving the objectives set for this study: Instasights Heatmaps online platform and the LBSNs Foursquare, Twitter, Google Places and Airbnb.

4.1. Instasights Heatmaps

Instasights Heatmaps includes an 'Instant overview of the most popular areas within a city displayed in easy to understand map overlays' using collected and analysed data from 'more than 60+ public sources' (AVUXI LTD, 2018a) whose information is 'mainly tailored for online travel agencies and hotel metasearch sites'. This website is also an open service available to the general public. Instasights cartographies display four tourist activities, namely, *Shopping, Eating, Nightlife* and *Sightseeing* represented individually as a five-level coloured heatmap. The scale of colours shows the extension and density of activities. The softer colours green and yellow (Figure 1 Step 1 L1) represent activity areas with lower density, whereas the deeper red and pink (Figure 1 Step 1 L4) represent the opposite. However, Instasights does not permit the simultaneous overlapped visualization of different activity Heatmaps.

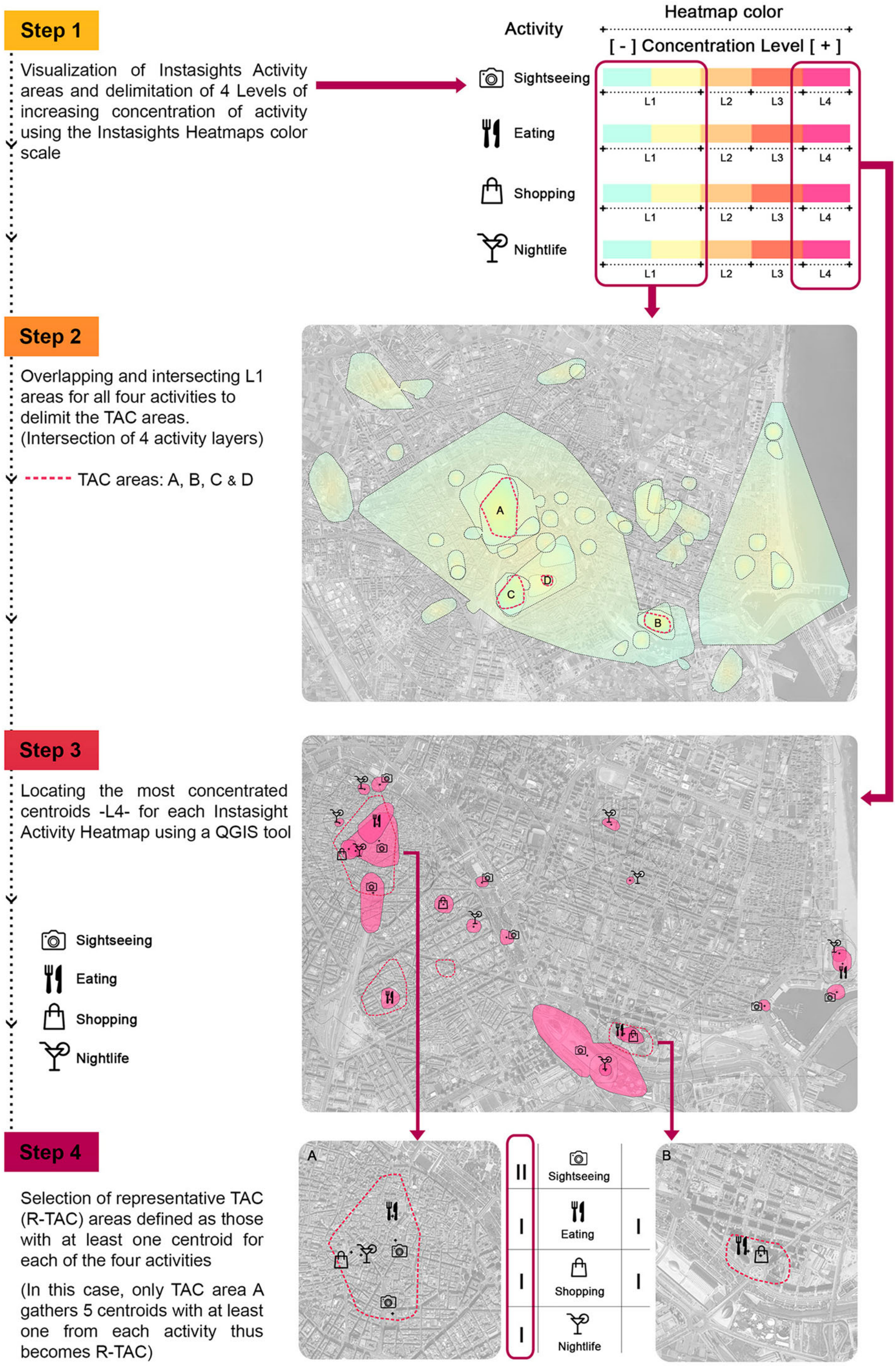

Figure 1. Identifying R-TAC areas with Instasights Heatmaps.

In this study, these Heatmaps were used as baseline areas for identifying TAC areas as the intersection of the four tourist activities. For this purpose, a vector image file for each activity heatmap was downloaded from the AVUXI TopPlace Heatmaps service's demo website – www.instasights.com – (AVUXI LTD, 2018b), permitting the delimitation of a five-level heatmap. The two layers of low-density activity were merged into one (see Figure 1 steps 1 & 2), thereby resulting in a four-layer map representation. Additionally, for the location of the most concentrated spots of all four specific activities – L4, a QGIS tool (Open source Geospatial Foundation OSGEO, 2019) is used to calculate all the L4 area centroids (Figure 1 step 3).

4.2. LBSNs data

The LBSNs Foursquare, Twitter, Google Places and Airbnb were used as sources of information to obtain an up-to-date characterization of the urban activities and most tourist-related dynamic places in both case study cities. Similar to the study conducted by Martí et al. (2019), layers of data from all LBSNs were overlapped onto the Instasights Heatmaps baseline areas. Specifically, Foursquare data facilitated the identification of key city hotspots and their social relevance in the city, whereas the data from the other three social networks – Twitter, Google Places and Airbnb – provided complementary information for characterizing dynamic tourist places and specific connector axes – itineraries and landmark nodes – in relation to the economic activity on offer and users presence.

Among the various methods of LBSN data collection, a self-developed web-based application – SMUA: Social Media Urban Analyser – that retrieves data via the social networks' Application Programming Interface – APIs – was used for obtaining data from Foursquare, Twitter and Google Places. As in the case of previous studies (Adamiak et al., 2019; Coyle & Yu-Cheong Yeung, 2017; Ioannides, Röslmaier, & van der Zee, 2018; Perez-Sanchez et al., 2018; Simancas-Cruz et al., 2017), Airbnb data has was obtained via AirDNA (2018).

The data retrieval dates are as follows:

- Foursquare and Google Places- 4 March 2018
- Twitter- from 7 July 2016–8 November 2018
- Airbnb- 2 March 2018

4.3. Delimiting and selecting TAC areas with Instasights Heatmaps

The procedure followed for locating and delimiting TAC areas is graphically explained in Figure 1. The process can be summarized in four basic steps, namely: step 1- visualization and delimitation of activity areas based on the four Instasights Heatmaps activities; step 2- delimiting TAC areas through overlaying and intersecting all four Level 1 activity Heatmaps which resulted in the visualization of several differently sized TAC areas; step 3- locating Level 4 activity heatmap centroids using QGIS tools (Open source Geospatial Foundation. OSGEO, 2019), revealing the greatest points of concentration for each activity and subsequently locating the corresponding number of hotspots; and finally, step 4- from the TAC areas identified in step 2, only those that contained at least one centroid for each one of the four Instasights activities were selected as representative TAC areas for this study – R-TAC areas hereafter.

4.4. Assessing tourist hotspots through LBSNs

Once R-TAC areas have been selected for both case study cities, the following three aspects were analysed using LBSN data: (1) the proportion of Foursquare *venues* or registers accumulated compared to that of the city's total urban area; (2) the ranking of Foursquare's specific *venue Categories*; and, (3) the spatial distribution of data from all four LBSNs within the R-TAC area to identify recognizable patterns of dynamic touristic places – such as, data clusters forming nodes and itineraries.

As for the variables used from the social networks, Foursquare datasets included a list of geolocated *venues* and their associated metadata related to: a) specific *Categories* and sub-*Categories* predefined by the social network; and, b) total amount of people that have visited or c) checked-in a *venue*. Foursquare *venues* are hierarchically classified into ten main *Categories* and a wide range of sub-*Categories* that define the type of *venue* (Foursquare Inc., 2018). The main *Categories* are: Arts

Table 2. Correlation between Instasights and Foursquare *Categories*.

Instasights	Foursquare
Sightseeing	Outdoors & Recreation
	Arts & Entertainment
Shopping	Shops & Services
Eating	Food
Nightlife	Nightlife spot
Not selected	Event
	College & University
	Professional & Other places
	Residence
	Travel & Transport

& Entertainment; College & University; Event; Food; Nightlife Spot; Professional & Other Places; Travel & Transport; Outdoors & Recreation; Shop & Services; and, Residence.

Twitter, Google Places and Airbnb datasets include exclusively the variables related to the geolocation of *tweets, places* – related to economic activity, and *accommodation listings*, respectively. Additionally, LBSN data provide information that can be used to identify user activities and rankings of most popular places and activities within R-TAC area locations. The procedure involved the studying of LBSNs within the delimited R-TAC areas of both case study cities.

4.5. Foursquare

Foursquare data is measurable and enables both quantitative and qualitative analysis of the selected R-TAC areas. Therefore, matching the four Instasights Heatmaps activities with their equivalent in Foursquare *Categories* enabled a narrowing down of the data retrieved from Foursquare to exclusively represent tourist-related activities – Table 2. For comparative purposes, this process facilitated a better understanding of the selected areas' characteristics.

As indicated in Table 2, those Foursquare *Categories* that could not be matched were discarded as they were beyond the scope of this study.

The *venues* included within the selected *Categories* were then analysed to depict potential tourist hotspots. The amount of registered Foursquare users that have at least checked-in once in a *venue* is considered an indicative value of people presence and thus, of people preference of certain *venues* over others. Thus, *venues* within R-TAC areas, ranked per number of users, can potentially be considered the most socially preferred *venues*. Following this consideration, the extent to which the most relevant *venues* within R-TAC areas corresponded to the top ten *venues* at city-scale was crosschecked.

4.6. Twitter, Google Places and Airbnb

Twitter, Google Places and Airbnb data were processed as follows: (1) analysed in terms of their presence in the R-TAC areas; (2) visualized and overlapped as layers in QGIS; and, (3) used as complementary geolocated databases to inform and, to some extent, verify the findings obtained from the combined analysis of Instasights and Foursquare. The overlapped visualization and close analysis of the data distribution allowed the identification of spatial patterns of LBSN activity – i.e. the presence of people – Twitter – and the offer of economic activities – Google Places and Airbnb. Specifically, the obtained cartographies facilitated the characterization of concentration patterns of activity and the identification of most preferred hotspots – landmark nodes – and itineraries – connector axes – within the R-TAC areas.

5. Results

The results are presented in line with the set objectives in Section 1.

Figure 2. Valencia City. Identification of TAC areas and location of centroid hotspots.

5.1. Identified TAC areas

The method described in Figure 1 was applied to the case study cities and the results are represented in Figure 2, for Valencia, and Figure 3, for Alicante. The maps visualize all four Instasights activities, identifying several TAC areas: there are four in Valencia, labelled as A, B, C and D; and, two in Alicante,

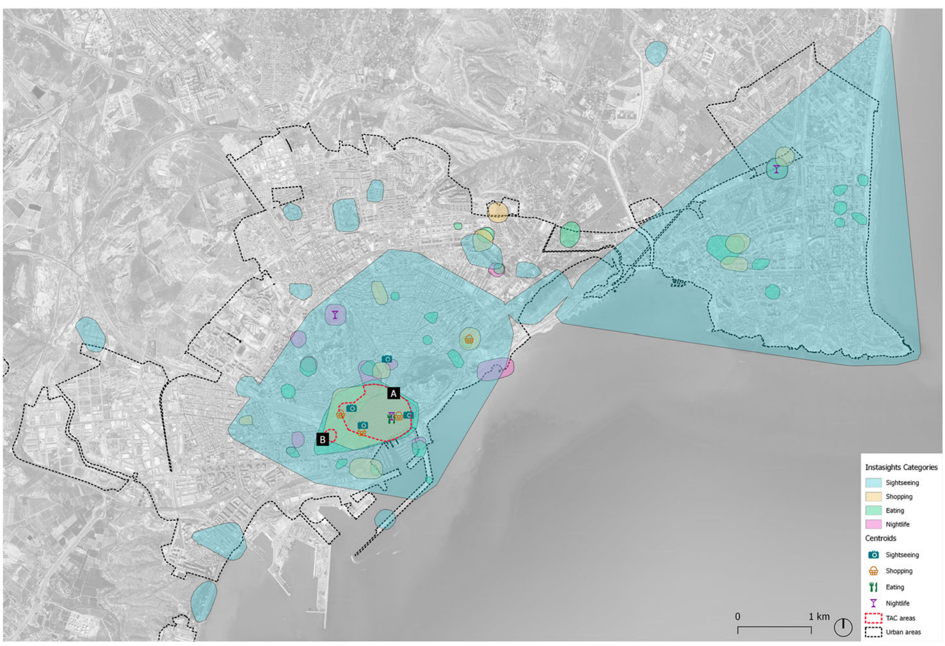

Figure 3. Alicante City. Identification of TAC areas and location of centroid hotspots.

Table 3. Instasights activity extension and correlation between R-TAC areas and centroids.

City	Urban area ha	Instasights activities	Activity area ha	Activity area %	Number of activity centroids within TAC areas A	B	C	D
Valencia	4,658.3	Sightseeing	2,621.3	56.3	2	–	–	–
		Shopping	148.6	3.2	1	1	–	–
		Eating	327.3	7.0	1	1	–	–
		Nightlife	214.6	4.6	1	–	1	–
Alicante	3,500.9	Sightseeing	2,863.4	81.8	3	–	–	–
		Shopping	144.1	4.1	3	–	–	–
		Eating	195.1	5.6	1	–	–	–
		Nightlife	106.6	3.0	1	–	–	–

labelled as A and B. These maps also include the location of activity centroids, represented by their respective icons, providing a complete picture of activity hotspots. Surprisingly, it can be observed in both city maps that not all the TAC areas include activity centroids, and not all the centroids are situated within a TAC area. These results are summarized in Table 3.

Table 3 shows the size of each Instasights activity area with respect to the city's urban area. The *Sightseeing* activity occupies the largest area of both case study cities – more than 50% in Valencia and more than 80% in Alicante. The other three *Categories* are much less extended. *Eating* accounts for the second largest area in both cases – 7% in Valencia and 5.6% in Alicante, whereas the area extension of *Shopping* and *Nightlife Categories* are ranked differently, namely, Alicante indicates a greater concentration of *Shopping* activities and Valencia of *Nightlife* activities.

As for the selection of TAC areas, L4 centroid location and diversity were considered. Table 3 shows the type and number of centroids found in each TAC area. In Valencia, out of the four identified TAC areas, only the TAC area A included at least one centroid for each activity. The remaining TAC areas – B, C, D – had only 2, 1 or none, respectively. A similar result was found in the case of Alicante where, out of the two areas, only the TAC area A had at least one centroid from each activity. Thus, in both cases, TAC area A are considered R-TAC representative examples.

These findings evidence the functional diversity of TAC areas, not only because of the range of activities they include, but also the presence of specialized concentration of activities, represented by multiple centroids of a single *Category* – i.e. *Sightseeing* in Valencia and *Sightseeing* and *Shopping* in Alicante.

5.2. LBSN data

Both selected R-TAC areas are relatively small urban zones situated in the city centre. They represent less than 1% of the total surface area of Valencia city – 41.1 ha – and 1.5% of Alicante city – 52.9 ha (Table 4, Figures 4 and 5).

The following figures – Figure 4 Valencia city and Figure 5 Alicante city – show how the concentration of LBSN data throughout the city centre for both case studies coincide with the spatial delimitation of R-TAC areas, reinforcing the information provided by Instasights. The figures show the tourism offer product within the R-TAC areas. These maps are an overlapped visualization of all four LBSN datasets used in this research: Google Places, Airbnb, Twitter weekdays and weekends, together with Top-10 Foursquare most popular venues within these areas.

The presence of LBSN activity within the R-TAC areas is reflected in Table 4, where the different concentration and spatial distribution of LBSN data are shown. The main findings are subsequently presented in line with: (1) the proportion of Foursquare *venues* and accumulated registered users compared to those of the city's total urban area (Table 4 and Table 5, respectively); (2) the ranking of Foursquare's specific *venue Categories* (Table 6); and, (3) the identification of spatial patterns of LBSN activity and dynamic touristic places within the R-TAC areas, such as, data clusters forming nodes and itineraries (Figures 6 and 7).

Table 4. LBSN presence within R-TAC areas.

	LBSN data within R-TAC areas											
	Valencia						Alicante					
	Urban Area			R-TAC area			Urban Area			R-TAC area		
Area	4,658.3	ha	100%	41.1	ha	0.9%	3,500.9	ha	100%	52.9	ha	1.5%
Foursquare	15,264	Venues		804	Venues	5.3%	6,434	Venues		1,101	Venues	17.1%
Twitter	1,84,514	Tweets		25,353	Tweets	13.7%	66,210	Tweets		9,992	Tweets	15.1%
Google Places	70,214	Activities		3,322	Activities	4.7%	30,758	Activities		4,971	Activities	16.2%
Airbnb	14,142	Lodgings		1,068	Lodgings	7.6%	5,186	Lodgings		889	Lodgings	17.1%

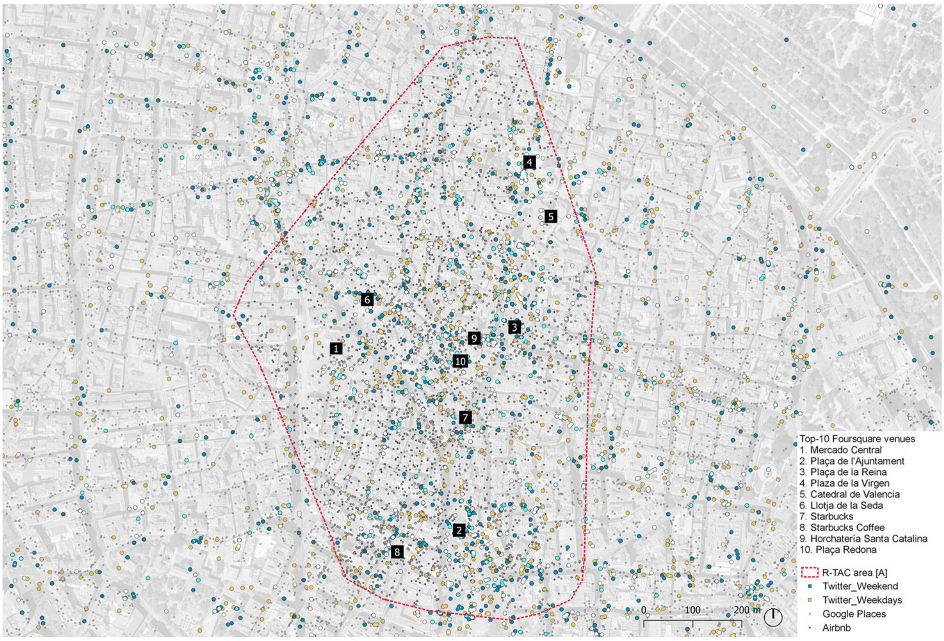

Figure 4. Valencia city. Overlapped visualization of all LBSN datasets – Google Places, Airbnb, Foursquare and Twitter weekdays and weekends – and the Top-10 Foursquare venues.

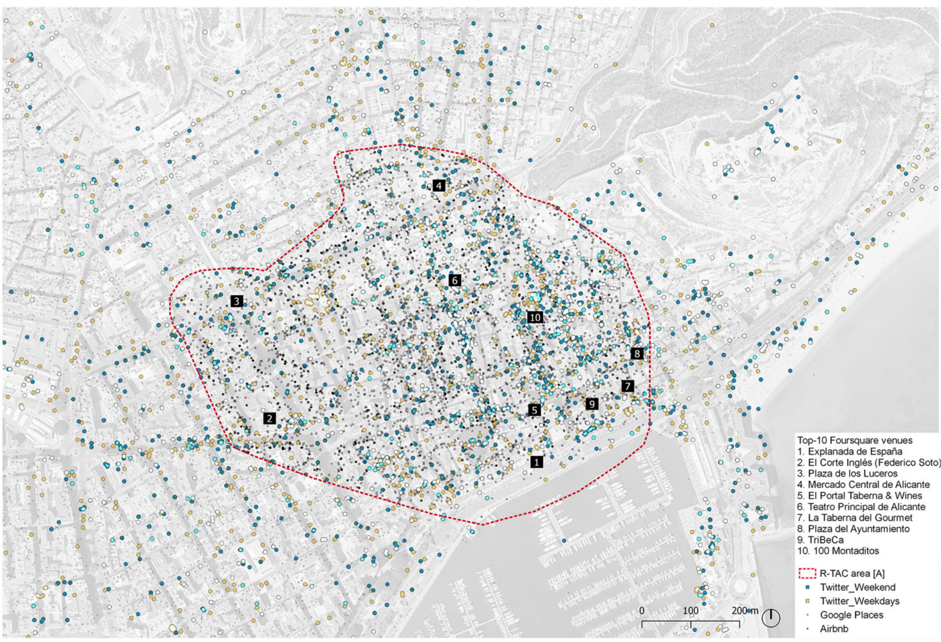

Figure 5. Alicante city. Overlapped visualization of all LBSN datasets – Google Places, Airbnb, Foursquare and Twitter weekdays and weekends – and the Top-10 Foursquare venues.

The Foursquare *venues* considered were those whose *Categories* could be correlated to Instasights *Categories* as indicated in Table 2. Data obtained show that, despite occupying a small part of the total city area – 0.9% and 1.5% of the overall urban area, R-TAC areas concentrate

Table 5. Top ten ranked Foursquare *Categories* and number of *venues* within R-TAC areas.

	Foursquare	Valencia		Alicante	
		venues		venues	
	Categories	number	%	number	%
Instasights activities correlation	Arts & Entertainment (A&E)	41	5.1%	38	3.5%
	Outdoors & Recreation (O&R)	84	10.4%	49	4.5%
	total (A&E + O&R)		15.5%		7.9%
	Food	289	35.9%	407	37.0%
	Shop & Service	144	17.9%	234	21.3%
	Nightlife spot	66	8.2%	134	12.2%
	total venues categories related to Instasights activities	**624**	**77.6%**	**862**	**78.3%**
Total TOP 10 categories		804	100%	1,101	100%

more than the 5% and 17% of the total *venues* for Valencia and Alicante, respectively. Moreover, these areas include a significant proportion of registered Foursquare *venue* users (Table 5) – 17% for Valencia and 33% for Alicante.

Table 5 shows the detailed proportion of Foursquare *Categories* for each case study city. Findings indicate that, in Valencia's R-TAC area, the distribution is as follows: *Outdoors and recreation* – 10.4% – together with *Arts and Entertainment* – 5.1%, totalling 15.5%, which corresponds to Instasights *Sightseeing* activity; *Food* 36%; *Shop and Services* 18%; and, *Nightlife Spots* 8.2%. In the case of Alicante's R-TAC area, which is 30% larger in extension compared to Valencia's, there are, proportionally, three times more Foursquare *venues* grouped into the following *Categories*: *Outdoors and recreation* – 4.5% – together with *Arts and Entertainment* – 3.5%, totalling 8% of *venues,* which corresponds to *Sightseeing* activity; approximately 40% belong to the *Food Category*; *Shop and services* 21.3%; and, lastly, *Nightlife Spots* 12.2%.

Table 6. TOP-10 Foursquare *venues* ranked by users.

	Valencia	**City**		**R-TAC area**	
	Total users	827,046		1,37,778	17%
R-TAC area [A] – TOP 10 Venues by Users					
	Venue name	**Users**	**Checkins**	**Main category**	**Subcategory**
1	**Mercat Central**	8,968	13,128	Shop & Service	Market
2	**Plaça de l'Ajuntament**	8,415	21,097	Outdoors & Recreation	Plaza
3	**Plaça de la Reina**	7,928	12,075	Outdoors & Recreation	Plaza
4	**Plaza de la Virgen**	7,410	11,377	Outdoors & Recreation	Pedestrian Plaza
5	**Catedral de Valencia**	6,903	7,970	Professional & Other places	Spiritual Center
6	**Llotja de la Seda**	2,545	3,099	Arts & Entertainment	Historic Site
7	Starbucks	2,469	3,501	Food	Coffee Shop
8	Starbucks Coffee	2,362	4,750	Food	Coffee Shop
9	Horchatería Santa Catalina	2,116	2,391	Food	Dessert Shop
10	**Plaça Redona**	2,085	2,609	Outdoors & Recreation	Plaza
	Alicante	**City**		**R-TAC area**	
	Total users	234,576		77,907	33%
R-TAC area [A] – TOP 10 Venues by Users					
	Venue name	**Users**	**Checkins**	**Main category**	**Subcategory**
1	**Explanada de España**	2,085	4,216	Outdoors & Recreation	Plaza
2	El Corte Inglés (Federico Soto)	1,939	5,604	Shop & Services	Department Store
3	**Plaza de los Luceros**	1,783	7,130	Outdoors & Recreation	Plaza
4	**Mercado Central de Alicante**	1,663	4,585	Shop & Services	Food & Drink Shop
5	El Portal Taberna & Wines	1,002	1,772	Nigthlife Spot	Bar
6	**Teatro Principal de Alicante**	947	3,121	Arts & Entertainment	Performing Arts Venue
7	La Taberna del Gourmet	932	1,432	Food	Restaurant
8	**Plaza del Ayuntamiento**	872	1,716	Outdoors & Recreation	Plaza
9	TriBeCa	844	1,634	Food	Burger Joint
10	100 Montaditos	748	1,190	Food	Spanish Restaurant

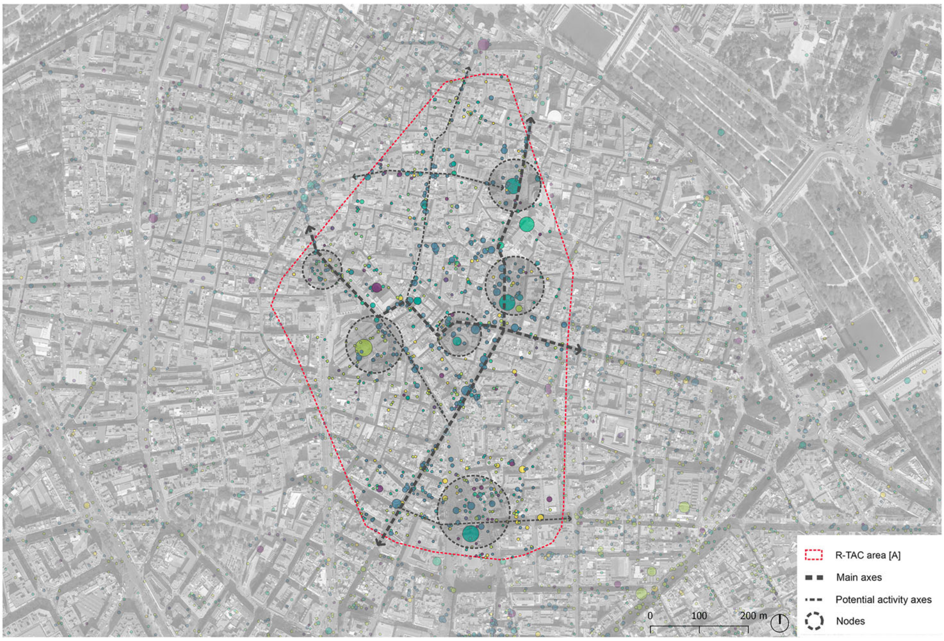

Figure 6. Valencia City. Concentration of mixed activities following itineraries or in specific plazas.

Table 6 shows the Top-10 ranked *venues* by number of users for Valencia and Alicante. It is noticeable that the best ranked public spaces and relevant buildings at the R-TAC scale are also some of the most relevant *venues* at the city scale – depicted by bold typeface. These findings suggest both the great influence of the R-TAC areas over the entire city, and evidence the validity of the method proposed for identifying key areas of activity.

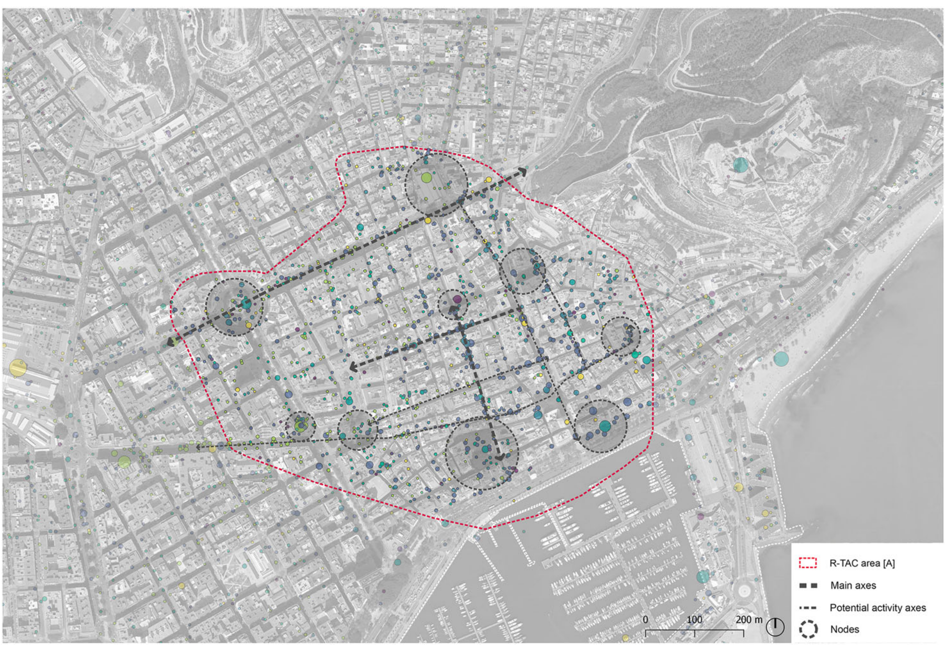

Figure 7. Alicante City. Concentration of mixed activities following itineraries or in specific plazas.

Indeed, the overlapping of LBSN layers corroborated the findings previously addressed. In terms of the data presence, as shown in Table 4, a 13.7% and a 15.1% of the total Twitter activity for Valencia and Alicante, respectively, are concentrated within the R-TAC areas. The tourist activity is reflected in Twitter by the large number of different languages – 32 and 38 different languages – used for sharing tweets in Alicante and Valencia R-TAC areas, respectively.

Following on with the other LBSNs, the number of economic activities offered, Google Places and Airbnb show similar results in terms of data presence in both case studies.

Firstly, the top ten most frequent types of registered Google Places businesses coincide in both cities. These correspond to the following Google Places dataset *Categories*. For Alicante and Valencia respectively: *store* – 12% and 18%; *restaurant* – 11% and 12%; *bar* – 8% and 7%; *clothing_store* – 8% and 5%; *real_estate_agency* – 7% and 5%; *health* – 5% and 4%; *cafe* – 4% in both cities*; local_government_office* – 3% and 5%*; jewellery store – 3% and 3%;* and*, bank – 3% and 4%*.

As for the presence of Airbnb accommodation activity, notably, Valencia's R-TAC area concentrates almost 8% of Airbnb's total offer, whereas for Alicante, the comparable figure is 17% – Table 5. Despite, this difference, when analysing the accommodation types in the R-TAC areas of both cities, similar figures were obtained. For Alicante and Valencia respectively, the *Entire home/apartment* accounted for 70.75% and 74.4%; the *Private room* category had a 28.8% and 24.63%; and, the *Shared room* category had a 0.45% and a 0.47%.

In terms of the spatial distribution of LBSN activity, as can be observed in Figures 4 and 5, it is not evenly distributed across both R-TAC areas. Moreover, the presence of clusters and specific city hotspot connectors, emerging from overlapping the LBSN data layers are visible. Itineraries and key landmark nodes with most social media activity were identified and proved to have a complex nature, that is, a mixture in the type of activities and the presence of various degrees of intensity in the social activity – the larger and smaller dots represented in Figure 4 for Valencia, and in Figure 5 for Alicante. This visualization provides a deeper insight and finer granularity in relation to tourist activity.

6. Discussion and conclusions

This research builds and broadens previous studies that have demonstrated that LBSNs are a powerful means by which the concentration of tourism related activities and their urban spatial patterns can be depicted in a way that accounts for user experiences and opinions (Salas-Olmedo et al., 2018). Furthermore, the findings concur and reinforce previous research suggesting that Big Data generated from UGC sources offer numerous possibilities for addressing tourism-related phenomena. In this study, the datasets retrieved from these LBSNs were strictly limited to those falling within the study areas, allowing a more focused and specific approach. This approach to data supports Bibri's observation: 'while data reduction involves loss of information under normal conditions, the trade-off for enhanced insights remains of importance' (2018, p. 215).

As a result, the method proposed facilitates an up-to-date and highly granular characterization of urban activities. Specifically, the reference framework introduces two different types of UGC sources for identifying and measuring TAC areas in terms of their functional diversity: Instasights Heatmaps and the selected LBSNs – Foursquare, Twitter, Google Places and Airbnb.

The findings show that compared to the merely generic visualization available from Instasights Heatmaps, the analysis and interpretation of LBSN data reveal specific tourism-related dynamics and places of interest. Precisely, one of the limitations of Instasights Heatmaps is that, in general, the colour gradient tends to extend over large urban stretches – especially for the sightseeing category heatmaps – that neither allows pinpointing specific spots where urban activity occurs, nor provides any indication of other types of related information, such as spatiotemporal variations of urban phenomena, or tourist movement and behaviour, which are frequent topics dealt with by the relevant literature (Salas-Olmedo et al., 2018). In this respect, and similar to the work of Lee, Wakamiya, and Sumiya (2013), once R-TAC areas are delimited and specific points of interest are highlighted, future work could benefit from incorporating the analysis of spatiotemporal trends and tourist flow patterns during the day, week or a certain period of time using Twitter data, for example.

Nevertheless, Instasights Heatmaps website has proven its worth as a valuable information source. It is an open and readily available tool for defining effective baseline areas of, specifically, four functional activities – sightseeing, eating, shopping and nightlife. This is a useful resource for the urban studies field for mainly three reasons: (1) it facilitates the analysis and diagnosis of the tourist activity pulse by providing a delineation of specific target areas on which to focus; (2) it provides a tool for analysis, open and available to any researcher, thus potentially reproducible in any urban setting; and, (3) it is a dynamic source as it gets frequently updated. According to AVUXI (2018b), Instasights Heatmaps feed from sources that include UGC, thus, just like the user opinion and perception of a place can change from time to time, Instasights Heatmaps is constantly changing as well.

The selected LBSNs are also accessible but require some degree of technical knowledge for data collection via APIs, web scraping, or other retrieval methods (Sloan & Quan-Haase, 2017). Overcoming this challenge provides two important benefits: first, LBSN data represent a sample of user preferences and uses of city spaces; and second, the overlapping of data from several LBSNs provides further granularity, thereby enriching the results, especially, in the study of tourist-related complex phenomena (Salas-Olmedo et al., 2018).

Focusing on the key findings in relation to the TAC areas, the first observation is that their size is not proportional to that of the city. Surprisingly, multiple TAC areas emerged in both case study cities, but when locating the centroids – highest concentration of a given activity, not all of them fell within the TAC area delimitation. Precisely, that was a key consideration in the criteria set for the selection of TAC case study areas – R-TAC areas for this study. These were, exclusively, those TAC areas where centroids of the four activities converged – sightseeing, eating, shopping and nightlife. The location of the top-10 ranked Foursquare venues is evidence of both, the great influence of the R-TAC areas over the entire city and the validity of the procedure adopted for identifying key urban areas of activity.

Concurrently for both case study cities, the selected R-TAC areas are within the historic city centre, where several landmarks are located. Specifically, social media data allowed the identification of certain singularities among which three can be highlighted. Firstly, all the activities related to *Sightseeing* encompass both outdoor and indoor Foursquare *venues*, whereas those related to *Shopping, Eating* and *Nightlife* are all indoor *venues*. Secondly, the types of activities – Foursquare and Google Places *Categories* – detected in the fine grain data analysis are essential for the city's touristic offer, and thereby linked to the dynamics of the city's tourism. Thirdly, the information provided by the four LSBN data has made possible the representation of multi-activity clusters and main itineraries based on user traces in social networks. These digital footprints reveal that, within the R-TAC areas, the urban activity is not homogenous in terms of type, intensity or spatial distribution. Instead, multiactivity clusters, as well as their connecting itineraries, depict urban polarities and potentially socially vibrant connections with the rest of the city. Indeed, the identification of these clusters and itineraries was only possible through the analysis and interpretation of the four LBSN data sources selected.

Overall, the recognition of existing R-TAC areas and the identification of fine-grain nuances and distinguishing features by using UGC sources are the main contribution of this paper.

This research is potentially valuable to tourism managers, urban planners, urban scientists, and other professionals interested in the analysis and diagnosis of urban dynamics. However, knowledge of the city is important for an accurate interpretation of the findings within the context of the city. The reference framework developed in this paper could be useful for the design of urban policies that may be more effective in strategically balancing tourism-related activities. For instance, this could entail identifying the need for activities around important landmarks that are located outside the existing TAC areas or assessing and diagnosing specialized areas in order to promote the diversity and complexity of the urban activity on offer.

Finally, this study sets in motion several directions for future research. The first could be to apply this method to areas that include centroids without diversity of activity, as these have been excluded in this study. The second line would involve exploring the interconnectivity between different city TAC areas to identify zones which show potential for increasing urban dynamism at a city scale. Lastly, the method developed could be adapted to address the over-tourism issue, for example. For this purpose, additional datasets would be required for detecting spatiotemporal congestion patterns related to specific city activities or events.

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