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Identifying opportunity places for urban regeneration through LBSNs

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ABSTRACT

The use of location based social networks—LBSNs—for diagnosing phenomena in contemporary cities is evolving at a fast pace. However, methodological frameworks for informing urban regeneration at a fine-grain neighborhood scale through LBSNs is still by and large an unchartered territory, which this research seeks to address. This research bridges the knowledge gap by proposing a method to identify urban opportunity spaces for urban regeneration that involves pre-processing, analyzing and interpreting single and overlapped LBSN data. A two-fold perspective—people-based and place-based—is adopted. Data from four LBSNs—Foursquare, Twitter, Google Places and Airbnb—represent the people-based approach as it offers an insight into individual preferences, use and activities. The place-based approach is provided by an illustrative case study. Local unexpected nuances were gathered by the interlinking of data from different LBSNs, and opportunity places for urban regeneration have been recognized, as well as potential itineraries to boost urban liveliness and connectivity at both intra and inter- neighborhood scales. Findings show that overlapping data from various LBSNs enriches the analysis that would previously have relied on a single source.

1. Introduction

The liveliness of urban neighborhoods is, by and large, determined by the sensorial cues and experiences originating from the built environment (McAndrews & Marshall, 2018). Urban landscapes are built by both, the physical context and human activity. Thus, from the urban morphology perspective, analyzing built forms is as important as exploring how people impact their dynamism because "individual perceptions, histories and activities […] are both shaped and have reshaped the built form" (Jones, Isakjee, Jam, Lorne, & Warren, 2017). Acknowledging that this iterative process starts with the physicality of the built environment and is shaped by people's perceptions and activities therein is important for determining the priorities and directions of urban regeneration projects (Agryzkov, Oliver, Tortosa, & Vicent, 2017; Marmolejo & Cerda Troncoso, 2017).

Kuo, Sullivan, Coley, and Brunson (1998) suggest that the quantity and quality of informal social contact among neighbors is what builds neighborhood social ties. They argue that the characteristics of common spaces and their use are key factors to foster community links, which in turn, if well managed, have a positive repercussion on a city's standard of living. Therefore, the neighborhood scale is also where place attachment forms from the emotional bonds between people and their places of residence (Giuliani, 2002).

The "neighborhood scale" concept may be ambiguous in terms of scope because places differ in scale (Lewicka, 2010); however, the concept is intuitively understood and widely studied from an interdisciplinary research perspective including sociological, economic, geographical, or urban planning. Research papers that consider the neighborhood scale appropriate for the study of specific urban phenomena are on the increase. This is because the neighborhood scale is a spatially delimited area with several distinguishing morphological and demographic characteristics. George Galster (2001, p. 2113) argues that "the unifying feature of these attributes constituting the bundle called neighborhood is that they are *spatially based*." Additionally, Galster clarifies that this "spatially based" factor is not only related to the structural and physical characteristics of buildings and infrastructures—geographical features—, but also to the individuals that form a community—demographic characteristics of the residents—(Galster, 2001).

The objective of this paper is to propose a method for identifying opportunity spaces for urban regeneration at neighborhood level by analyzing overlapping information from four Location Based Social Networks —LBSNs— on urban physical features. The relevance of this research is grounded in the recognized lack of up-to-date data available on the spatial and territorial reality that is necessary to inform urban regeneration policies (European Commission, 2016); and, in the difficulty of addressing less tangible aspects of regeneration (Colantonio & Dixon, 2011) such as socio-spatial issues.

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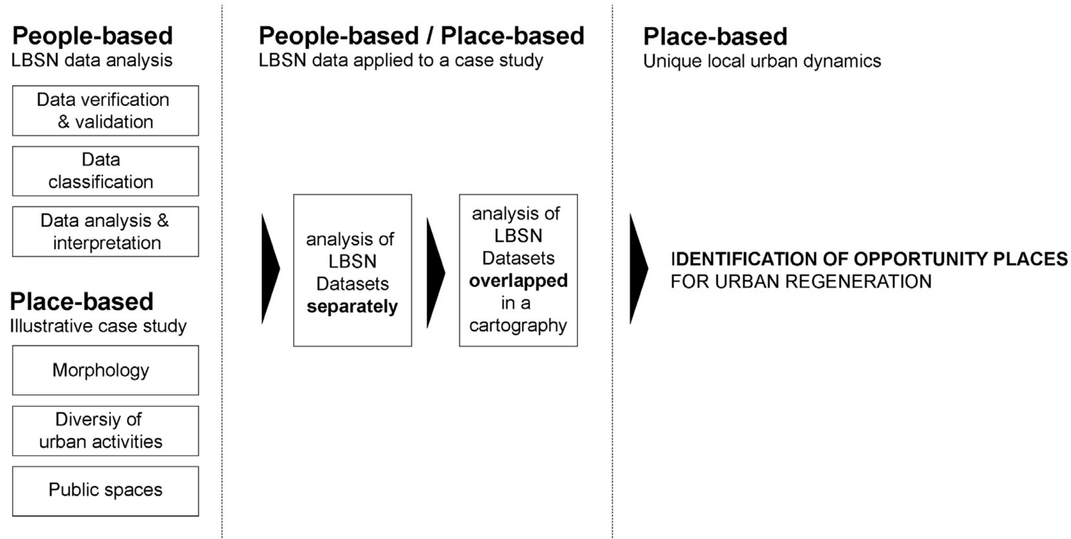


Fig. 1. Overall neighborhood scale method to identify opportunity places for urban regeneration through Location Based Social Networks—LBSNs—.

The paper's novel approach lies in the study of inner-city neighborhood spatial and functional dynamics and patterns from a two-fold perspective:

i. The **people-based**, involving trends related to people presence and the use of urban space preferences through LBSN data, which highlights appreciations and choices associated with places via a "multidimensional approach that goes beyond the traditional analysis of cities" (Wu, Wilkes, Silver, & Clark, 2018).
ii. The **place-based** which considers the physical reality—morphological features of the urban tissue, street network, facilities existence, public transport network, offices and retail business—at a neighborhood scale (Kropf, 2017).

The two-fold perspective, **place-based** and **people-based**, is reflected in both the illustrative case study and the method that involves user-generated data sources, respectively—Fig. 1—.

This research builds on the existing methodologies for the analysis and interpretation of LBSN data to identify potential spaces of opportunity for urban regeneration. It analyses and overlaps four well renowned social networks: Foursquare, Twitter, Google Places and Airbnb that are considered as layers of information in order to conduct an inner-city neighborhood analysis. The method proposed is applied to an illustrative case study.

This paper is structured as follows. First, a theoretical framework for this work is grounded in previous research that uses LBSNs to study the city. Second, the sources and overall method to prepare data for analysis are explained. Third, the illustrative case study is described. Finally, the results are presented followed by the discussion and the main conclusions of the study.

1.1. Literature review

The neighborhood scale is used in this study as the unit to measure the pulse of a community by understanding how people interact with each other in places for grasping both intra and inter-neighborhood dynamics. Hence, a people and place-based approach (Meegan & Mitchell, 2001) is adopted, and the reason for this is subsequently substantiated.

1.1.1. People-based perspective

The fact that citizens are considered volunteer sensors (Goodchild, 2007) has offered additional tools to analyze the city. Data gathered at a neighborhood scale through traditional fieldwork methods—synchronous interaction—can now be complemented by user-generated information, extracted from LBSNs—asynchronous interaction—. Precisely, virtual traces of people's activities in the physical space are being used by scholars in qualitative research to characterize urban environments (Agryzkov, Martí, Tortosa, & Vicent, 2016; Shelton, Poorthuis, & Zook, 2015; Silva, Vaz de Melo, Almeida, & Loureiro, 2014; Tasse & Hong, 2014; Van Canneyt, Schockaert, Van Laere, & Dhoedt, 2012). Thus, nowadays LBSNs represent an optimal resource for studying the spatial properties of user interests—they connect geographic locations and social connections—; and, for obtaining a large amount of data through social media listening (Crawford, 2009), which enables large-scale studies to deduce trends or general patterns (Scellato, Noulas, Lambiotte, & Mascolo, 2011).

Furthermore, the great variety of LBSN data available allows researchers to focus on different urban phenomena, such as: human behavior (Chen, Gao, & Xiong, 2016; Chen, Yang, Hu, & Zhuang, 2016; Fisher, 2011; Graham, Hale, & Gaffney, 2014; Hochman & Manovich, 2013; Huang & Wong, 2015); preferences (Agryzkov, Martí, Nolasco-Cirugeda, et al., 2016; Aliandu, 2015; Martí, Serrano-Estrada, & Nolasco-Cirugeda, 2017; Noulas, Scellato, Mascolo, & Pontil, 2010; Quercia, Schifanella, & Aiello, 2014); urban uses (Shelton et al., 2015; Zhou, Hristova, Noulas, & Mascolo, 2018); spatio-temporal patterns of people's activities (Noulas et al., 2010) and perception (Aiello, Schifanella, Quercia, & Aletta, 2016; Dunkel, 2015; Hess, Iacobucci, & Väiko, 2017; Hochman & Manovich, 2013; Quercia, Aiello, Mclean, & Schifanella, 2015).

Most of the above cited studies consider data from a single LBSN source. However, recent work has evolved from using only one source of information to introducing various layers of complementary data to acquire a broader picture of the analyzed urban phenomena. Nevertheless, from the international perspective, little has been published using several LBSNs in order to devise urban regeneration strategies. Instead, most research has taken a more retrospective approach to urban regeneration projects. For instance, Zhou et al. (2018) have used a combination of two large-scale datasets—Index of Deprivation and Foursquare data—to understand the impact of the 2012 Olympic Games on the regeneration of East London neighborhoods; and, López Baeza, Serrano Estrada, and Nolasco-Cirugeda (2016) have used both data gathered on field studies and data collected from Instagram to identify how a street that has recently been pedestrianized has impacted the overall perception of the place.

Among the studies that have introduced various layers of information, a distinction can be made between those whose data are sourced from "volunteered" and those sourced from "non-volunteered" information. The volunteered information is user-generated, such as social networks data; whereas the non-volunteered comes from sources that gather data from user activity, such as mobile data. The former is the case of unprompted user data, whereas the latter is being generated and collected without the user consent or awareness.

The studies that introduce **volunteered geographic information** (Campagna, 2016; Campagna, Floris, Massa, Girsheva, & Ivanov, 2015), are of two kinds. The first includes those studies where one single dataset is sourced from two social networks. For instance, Hasan, Zhan, and Ukkusuri (2013) uses Foursquare and Twitter to analyze activity and mobility patterns, taking advantage of each social network's attributes and characteristics—the number of check-ins and geolocation of *venues* from Foursquare; and the spatio-temporal data from Twitter—. The second extracts separate datasets from different social networks, such as Salas-Olmedo, Moya-Gómez, García-Palomares, and Gutiérrez (2018), who studied the digital footprints of tourists in Madrid—Spain—using three different LBSNs, Panoramio, Twitter and Foursquare. Also, the work of Scellato et al. compares similar social network services—Foursquare, Brightkite and Gowalla—(Scellato et al., 2011).

As for the studies that consider exclusively **non-volunteered geographic information**, these are mainly represented by data collected from telephone operating companies (Andris, 2016; Blondel et al., 2013; Calabrese, Ferrari, & Blondel, 2014; Ratti, Pulselli, Williams, & Frenchman, 2006).

Other examples where both **volunteered** and **non-volunteered** information are included in the same study are the work of Indaco and Manovich (2016) and Steiger, Westerholt, Resch, and Zipf (2015) that combined population census data and social networks data; and that of Sulis, Manley, Zhong, and Batty (2018) that conducted a study on urban mobility using public transport card data, Twitter data and OpenStreetMap data.

While all the above-mentioned studies have covered a wide range of urban phenomena through the use of various layers information, there is still a gap in the literature related to the use of different complementary LBSNs to identify potential spaces for urban regeneration.

1.1.2. Place-based perspective

Understanding the neighborhood scale as an urban functional unit, which entails recognizing spatial and socio-economic attributes, makes possible the identification of intra-neighborhood patterns of urban activity.

Given that the neighborhood could be the unit of organization of city planning, it is not surprising that urban phenomena is analyzed at this scale (Mehaffy, Porta, & Romice, 2014). Since the 1970s, there has been consistent research interest in a local scale approach to measure deprivation (Leary & Mccarthy, 2013); inner-city neighborhood decline and public investment (Zuk, Bierbaum, Chapple, Gorska, & Loukaitou-Sideris, 2018). Recent thematic approaches to urban regeneration policies at neighborhood scale have involved a variety of issues, among which are included the following: gentrification processes (Bridge, 2014); quality of life (Rogers, Halstead, Gardner, & Carlson, 2011); socioeconomic context and health outcomes (Pickett & Pearl, 2001); and, housing policy (Blasius, Friedrichs, & Galster, 2007). However, despite attempts to tackle urban decline, one of the major criticisms of urban regeneration, according to Colantonio and Dixon (2011), is that it has not entirely addressed the problem of social and physical inequality between inner-city neighborhoods.

In the European context, urban issues confined to the local scale that have a city-wide impact are a key consideration. Particularly, those at a neighborhood scale (Kennett & Forrest, 2006) where spatial, economic, social and environmental challenges must be faced (Kain et al., 2016). These concerns are translated into the Urban Agenda for the European Union—UAEU—, which aims to address current problems faced by cities across the EU (European Commission, 2016). It comprises twelve priority thematic issues. In an effort to refocus on balanced spatial distribution of goods and services that would then have a positive impact on social issues, the so-called *Regeneration of Urban Deprived Areas and Neighbourhoods* action—included in the UAEU's *Urban poverty* priority thematic issue—was defined. This action specifically aims to promote the quality of life in inner-city neighborhoods by adopting a "place-based approach" that "encourages mixed-use, complex and polycentric urban areas" (European Commission, 2018). In order to achieve these goals and a balanced territorial development, regeneration policies should consider, for example, the provision of necessary services and facilities at a walking distance; as well as lively and safe public spaces that encourage social interaction and diversity (European Commission, 2018).

With the above considerations, this study approaches the issue of identifying opportunity spaces through a place-based perspective that includes both, the aggregated neighborhoods within the illustrative case study, as well as each specific neighborhood in its own right.

2. The people-based perspective: data sources and method

LBSN user-generated data represent the people-based perspective as citizens use these platforms to register their activities, opinions, perceptions, and presence in urban spaces. Hence, data from four social networks—Google Places; Foursquare; Twitter; and Airbnb—were extracted to provide four layers of information, each of which was analyzed independently and then was visualized on the cartography. Each social network offers different but complementary variables—Table 1—. For instance, while Google Places includes a listing of all registered economic activity *places* in a certain area, Foursquare data only includes *venues*—economic activities and other places of interest—where at least one person has checked-in. Thus, with both the offer—Google Places—and the demand—Foursquare—, the degree of neighborhood liveliness in terms of urban activity can be more thoroughly depicted. Furthermore, the location of the tweets creates patterns of citizen presence by timeframes that, in turn, present great potential for detecting possible activity centralities. As for Airbnb listings, there are two main reasons why the analysis of non-regulated temporary accommodation is of relevance to this study. First, because there is a significantly higher offer of this type of accommodation

Table 1
Social Networks data variables selected for this study.

General variables	Foursquare	Twitter	Google Places	Airbnb
1. Location	Longitude	Longitude	Longitude	Longitude
	Latitude	Latitude	Latitude	Latitude
2.Temporal information	Cumulative data on *venues*	Time the tweet was posted	Updated data on registered *places*	–
3.User generated data	*Venue* name	Tweets text	*Place* name	Listing title/description
	Check-ins	–	–	–
	Users	–	–	–
4. Data categorization	Hierarchy of categories and sub-categories	–	Categories, sub-categories, sub-sub-categories	Listing type, Property type
5. Data ID	*Venue* ID and URL	Tweet ID	*Place* ID	Property ID

compared to the offer of regulated accommodation. Second, because the presence of this type of lodging is likely to become a catalyst for activity in an urban space.

Taking the above into account, each social network is approached from a specific angle, which does not necessarily conform to the one adopted by previous studies or to the rationale for the social network's existence. Specifically, Google Places data are used to find out the quantity and types of economic activities on offer, whereas Foursquare data are used to analyze venue quantity and types of demand. Geolocated Twitter data are used to analyze spatio-temporal patterns of human activity. Airbnb data are used to shed light on potential areas of alternative tourist accommodation in the city.

Four procedural phases were designed to deal with LBSN data for identifying urban opportunity places: (2.1) geolocated data retrieval; (2.2) verification and filtering of retrieved data; (2.3) data classification; and, (2.4) visualization in a cartography and interpretation of single and various overlapping combinations of the four data sources. Results from phases (2.1), (2.2), and (2.3), involving data processing and analysis for each LBSN, are presented in Section 3, which provides the exemplary results as applied to the illustrative case study. Results from phase (2.4) are explained in Section 4 and involve the analysis of the four overlapping layers.

2.1. Data retrieval

Geolocated data from Google Places, Foursquare and Twitter were retrieved through a self-developed desktop application: SMUA—Social Media Urban Analyzer—(Martí, Serrano-Estrada, & Nolasco-Cirugeda, 2018) which has been designed to request specific information and metadata from each social network—Table 1—. SMUA collects data within a delimited polygonal area, thus using a geographic boundary box as a filter so as not to exceed the size and amount of data request limitations imposed by each social network (Martí et al., 2018; Morstatter, Pfeffer, Liu, & Carley, 2013; Sloan & Quan-Haase, 2017). The data from Airbnb were acquired through a third-party business who uses web-scraping methods for data collection. SMUA's and Airbnb's datasets were retrieved on February and March 2018, respectively.

2.2. Data verification

All datasets were verified to avoid duplication and misrepresentation of data. This process differs from one social network to the other since user-generated data are created and shared on the social network with a different purpose. A general criterion adopted to avoid data duplication consisted of obtaining unique data items—items with unique ID and geographical coordinates—.

Twitter data had to be verified to avoid data misrepresentation caused by the following two frequent situations: i) tweets that are automatically generated from a single geographic coordinate due to the fact that there is an automatic tweet generator that is constantly tweeting information from a single place; and, ii) tweets that are automatically geolocated by Twitter and not by the user who generates them, which is the case of some users who do not wish to share their exact location and turn that function off on the Twitter app or on their GPS mobile device.

Likewise, the location of some of the Airbnb listings had to be adjusted to prevent data misrepresentation. Airbnb users—accommodation hosts—indicate the location of the accommodation and, in some cases, this location does not correspond to the exact coordinates of the lodging location. Instead, the host may choose to associate the accommodation to a nearby landmark or the geographical coordinates from which the photo of the property was taken.

2.3. Data classification prior to analysis. LSBN sources analyzed individually

The data collected from the social networks are, to some extent, classified by default. The *places* from Google Places, *venues* from Foursquare and accommodation listings from Airbnb are organized according to each respective social network's predefined categories. Google Places and Foursquare have hierarchical categories: over 90 main *place* types for Google Places (Google Developers, 2017); and, 10 main *venue* categories for Foursquare (Foursquare Inc., 2018). There are three types of Airbnb accommodation listings that indicate whether the property is completely or partially rented.

In the case of Google Places data, an exhaustive revision of the *places* categories assigned to each place had to be done and a re-categorization of the 90 main place types was necessary to streamline the data groupings and enrich the analysis of economic activities offered at an inter-neighborhood scale. To this end, the American Planning Association's functional Land Based Classification Standards—LBCS—categorization (American Planning Association, 2018a, b) was adopted. Even though there are many land use and land cover classification systems, the APA categorization was used in line with the work of Deng and Newsam (2017) and P. Martí et al. (2018), two of the few studies specifically concerned with the examination and reclassification of Google Places data economic activity categories into a fine-grain land-use taxonomy. Additionally, this fine-grain classification is relevant for this study because it permits identifying ground floor activities which have an influence on urban liveliness.

Twitter data are not necessarily categorized; however, the timestamp of every tweet allows grouping of data into temporary blocks. Specifically, for this study, tweets have been classified into four twelve-hour time slots: weekdays from Monday to Friday between 8 am and 8 pm; weeknights from Monday to Thursday between 8 pm to 8 am; weekends from Saturday to Sunday between 8 am to 8 pm; and, weekends from Friday to Sunday between 8 pm to 8 am. Finally, Airbnb introduces an additional classification related to offer categories of lodging: private room; shared room and entire home/apartment.

2.3.1. Google Places original and proposed categories

The hierarchical APA's functional LBCS includes nine main categories at the first level; 47 sub-categories at the second level; and over 120 sub-sub categories at the third level. The Level 1 categories are 1000- *Residence or accommodation functions*; 2000- *General sales or services*; 3000- *Manufacturing and wholesale trade*; 4000- *Transportation, communication, information and utilities*; 5000- *Arts, entertainment, and recreation*; 6000- *Education, public admin., health care, and other institutions*; 7000- *Construction-related businesses*; *8000- Mining and extraction establishments*; 9000- *Agriculture, forestry, fishing and hunting*. For the purpose of this study, only the first seven Level 1 categories—1000 to 7000—, and their corresponding Level 2 sub-categories, were adopted as they are concerned exclusively with urban uses.

Level 1 categories have sub categories—Level 2—and sub-sub-categories—Level 3—that allow a better definition of the place. For instance, the category 2000 *General sales or services* has 29 sub-categories that include: 2100 *Retail sales or service*; 2200 *Finance and insurance*; 2300 *Real estate, rental and leasing*; 2400 *Business, professional, scientific and technical services*; 2500 *Food services*. An example of the fine granularity of this hierarchical categorization is the sub-category 2500 *Food services* that includes eight Level 3 sub-sub categories. Some examples are: 2510 *Full-service restaurant*; 2520 *Cafeteria or limited service restaurant*; 2530 *Snack or nonalcoholic bar*. Indeed, the granularity offered by the Level 2 sub-categorization was considered detailed enough to discount the use of level 3 categorization, which provided additional detail that was not relevant to meet the objectives of this research.

The recategorization of Google Places dataset standard categories is not, however, without its limitations since a good number of *places* are originally assigned very generic categories. For instance, "*Point of Interest*", "*Establishment*" and "*Premise*". These tend to be businesses of any sort that must be revised and manually reassigned to a more precise Google Places category—i.e. hairdresser to "*hair_care*"—. The final assignment of categories was the result of discussion and agreement between the researchers involved in this work.

2.3.2. Foursquare's original and proposed categories

Foursquare categories are: Arts and Entertainment; College & University; Food; Nightlife Spot; Outdoors & Recreation; Professional & Other places; Residence; Shop & Service; Travel and Transport; and, Other. Three different types of venues in the Outdoors & Recreation category have been identified and reclassified into:

i. *Formal public spaces* are areas within the public realm that have been designed to promote social gathering and/or to become a community or neighborhood landmark
ii. *Informal public spaces* are areas within the public realm identified and checked-in as relevant outdoor *venues* by Foursquare users even though they have been designed for other functional uses. These spaces were not conceived to foster social gatherings. Thus, they are not provided with urban furniture or other elements found in plazas or parks, for example.
iii. *Private indoor spaces* are mostly recreation and sport establishments that are privately managed.

2.4. Visualization in a cartography and data interpretation

Once datasets from each social network have been verified and classified, they are individually visualized in a cartography and overlapped to obtain an interrelated approach to local urban dynamics. The interpretation and findings at this stage will largely depend on the particularities of the case study, the research question and the specific topic to be analyzed. The identification of spatio-temporal patterns in the distribution of datapoints in the visualization process provides insightful clues as to whether one urban dynamic is more relevant than others. The following sections present the results of the illustrative case study to which these processes have been applied.

3. The place-based perspective: illustrative case study

This section presents the findings of the method applied to an illustrative case study. Firstly, its geographic delimitation, main physical features and some social aspects are presented. The relevance of the adopted case study in the European context is also highlighted. Secondly, the results concerned with the collection, validation and classification of data are explained in quantitative and qualitative terms so that this research could be used as a reference point for future studies.

3.1. Case study

The Urban Agenda for the EU (European Commission, 2016) seeks to improve the quality of life in urban areas (Ferry & McMaster, 2018) by regenerating deprived neighborhoods. The European Regional Development Fund—ERDF—(European Council (EC), 2006), together with local administration, finance urban regeneration programs for vulnerable neighborhoods that are threatened by a lack of physical, social and functional connectivity to the rest of the city.

In Spain, sustainable and integrated urban development strategies have been incorporated into urban regeneration programs, such as the EDUSI—*Estrategias de Desarrollo Urbano Sostenible e Integrado*—(Matesanz Parellada & Hernández Aja, 2018).

The urban area selected is one of the EDUSI strategic areas referred to in this study as "Las Cigarreras"—Fig. 2—, in the city of Alicante—Spain—. This study area corresponds to a series of inner-city neighborhoods which have traditionally settled working-class and middle-class families in socially mixed population areas in the city's core.

Alicante, the capital of Alicante province, has 330,525 inhabitants within its municipal term (INE - Estadística de España, 2016). It is considered a Spanish benchmark city for two reasons. Firstly, it is a Spanish Mediterranean Arc city that has experienced an important territorial transformation in the last three decades in terms of its morphological configuration and increase in size (Font Arellano, 2006); and secondly, it is representative of the average European city model—midsize city scale—(Dehaene, Havik, & Notteboom, 2013), where 84% of the European population lives (Eurostat, 2017).

"Las Cigarreras" case study comprises seven neighborhoods, five of which are consolidated continuous urban fabric—namely, San Antón, Mercado Central, Carolinas Bajas, Campoamor, Fábrica de Tabacos-Plaza de Toros Complex—; and, the two remaining ones, which mainly take in the largest urban parks of the city—Monte Benacantil and Monte Tossal—including, respectively, the castles of Santa Bárbara and San Fernando—Fig. 2—. Both castles are highly relevant landmarks from an environmental, historical and heritage perspective, orographically delimiting the study area (Ayuntamiento de Alicante, 2017a).

Of the seven urban areas of the case study, the Mercado Central area—Fig. 2, neighborhood 2—was originally developed as part of Alicante's *Ensanche*, the first regulated urban planning extension. Furthermore, the Mercado Central area is currently the liveliest and has the most updated urban tissue. The remaining neighborhoods were considered periphery in the early 1900s and, therefore, were not integrated into the same *Ensanche* project. The least developed zone is San Antón, a 17th century area with the narrowest urban fabric, a lack of inner block green spaces and a limited number of small retailers mainly located at the periphery of this neighborhood.

Apart from the two neighborhoods including the city's biggest green areas, the remaining neighborhoods constitute zones with similar public space configuration in terms of street dimensions and connection with the city center, residential accommodation, and retail and professional businesses. They include more cultural, educational and private and public healthcare facilities than the other zones, although the public scene is declining, as demonstrated by the lack of green areas and the poorly designed public spaces.

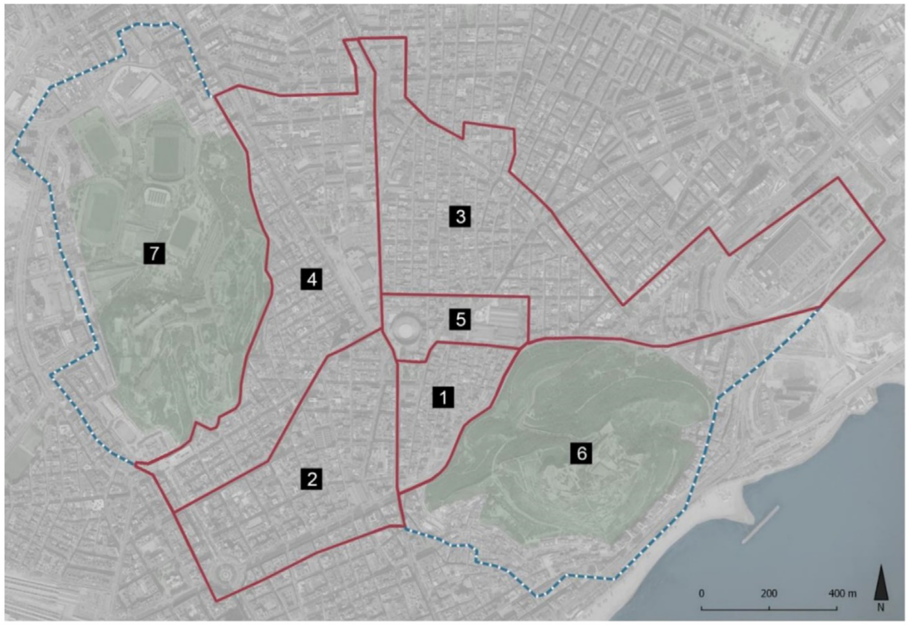
All studied neighborhoods indicate population decline together with an aging population, in line with national trends. Spanish nationality predominates but there is some variation of nationalities within the neighborhoods as follows: San Antón has the youngest population with the richest mix of nationalities; Mercado Central has the oldest population with the lowest number of different nationalities; and, the remaining neighborhoods have a similar distribution in terms of population age and mixture of nationalities (Ayuntamiento de Alicante, 2017a).

The central location of "Las Cigarreras" area within the city of Alicante is considered an opportunity to develop and promote integrated actions, affecting intra-neighborhood regeneration and inter-neighborhood dynamics. The location of these inner-city neighborhoods is a strategic factor that links the city center to the outlying urban areas, forming a fundamental structural part of the city's continuous urban fabric.

Having an allocated budget of just over €11 million, managed by the Alicante city council (Ayuntamiento de Alicante, 2017b), this area is selected as an illustrative case study for this research as it could be representative of other neighborhoods within European consolidated cities currently on track to design strategies for urban regeneration.

3.2. "Las Cigarreras" LBSN data retrieval and verification

This section presents the results of the data retrieval, verification and classification phases of the method proposed for the illustrative case study. Table 2 shows the total datapoints initially collected—raw



Neighborhood	Area (ha)	Inhabitants	Density Inhabitants per (ha)
1. San Antón	15.8	1,600	101.4
2. Mercado Central	45.3	6,000	132.5
3. Carolinas Bajas	85.1	12,200	143.3
4. Campoamor	65.2	12,800	196.4
5. Fábrica de Tabacos - Plaza de Toros	11.4	450	39.6
6. Monte Benacantil	84.9	2,500	29.4
7. Monte Tossal	105.8	1,200	11.3
TOTAL	**413.4**	**36,750**	

Fig. 2. Neighborhoods within "Las Cigarreras" case study.

Table 2
Data retrieved from LBSNs: raw and valid datapoints.

LBSN	Total data retrieved	Retrieval date/period	Total validated data	
	Raw data			Percentage
Foursquare	1030	23-Apr-18	1030	100%
Twitter	22,463	From 15-Mar-18 to 23-Apr-18	7385	33%
Google Places	5272	23-Apr-18	3525	67%
Airbnb	1555	02-Mar-18	1555	100%

data—from selected LBSNs—Foursquare, Twitter, Google Places, and, Airbnb—and the timeframe/date of retrieval. Additionally, the number of unique datapoints after the data validation is shown in the last column to the right of Table 2 and detailed per neighborhood in Table 3, upper table.

It is worth highlighting that no duplicate datapoints were observed in datasets from Foursquare and Airbnb. Instead, Google Places had the most duplicates—37% of initial datapoints—and Twitter had the most misrepresentation—67% of initial datapoints—. This is because for Google Places, people register the same *place* twice, and for Twitter some users are represented by a twitter account that automatically send tweets from a single spot. These tweets were recognized because they had the same geographic coordinates, and/or the tweet text is rather similar in content and/or style. Those tweets that have been identified as generated massively were discarded since they do not represent urban activity.

As for Airbnb datasets, there was no duplication in the listings. However, while carefully verifying the geolocation of the listings, approximately 8% had to be relocated since the owner registering the listing may not have georeferenced it appropriately. For instance, some of the properties were geolocated to the sloped unbuilt green areas of the Monte Benacantil.

Table 3
Number and density of LBSN valid datapoints.

Number of valid datapoints per LBSN	Google Places		Foursquare		Twitter		Airbnb	
	vd	%	vd	%	vd	%	vd	%
1. San Antón	130	3.7	28	2.7	126	1.2	91	5.9
2. Mercado Central	1547	43.9	473	45.9	2459	33.3	435	28.0
3. Carolinas Bajas	902	25.6	241	23.4	723	7.0	290	18.6
4. Campoamor	545	15.5	133	12.9	650	6.3	313	20.1
5. Fábrica de Tabacos – Plaza de Toros	66	1.9	17	1.7	664	6.4	60	3.9
6. Castillo de Santa Bárbara	237	6.7	78	7.6	2038	19.6	312	20.1
7. Castillo de San Fernando	98	2.8	60	5.8	725	7.0	54	3.5
Total	3525		1030		7385		1555	

Table 4
Frequency of places and *venues* per category for Google Places and Foursquare datasets.

Google Places valid data points – *places* – and APA categories assignment

Code	APA categories	Amount	Percentage
APA1000	Residence or accommodation functions	11	0.31%
APA 2000	General sales or services	2622	74.38%
APA 3000	Manufacturing and wholesale trade	128	3.63%
APA 4000	Transportation, communication, information, and utilities	123	3.49%
APA 5000	Arts, entertainment, and recreation	102	2.89%
APA 6000	Education, public admin., health care, and other institutions	359	10.18%
APA 7000	Construction-related businesses	180	5.11%
	Total	3525	100.00%

Foursquare valid data points –*venues*– and their assigned categories

Code	Foursquare categories	Amount	Percentage
FQ1	Arts & entertainment	68	6.60%
FQ2	College & university	16	1.55%
FQ3	Food	290	28.16%
FQ4	Nightlife spot	71	6.89%
FQ5	Outdoors & recreation	74	7.18%
FQ6	Professional & other places	139	13.50%
FQ7	Residence	34	3.30%
FQ8	Shop & service	268	26.02%
FQ9	Travel & transport	47	4.56%
FQ10	Other	23	2.23%
	Total	1030	100.00%

3.3. Data classification

The frequency of *places* in the Google Places dataset whose original categories have been reassigned to the APA's level 1 categories is shown in both, Table 4—upper table—. In the same table—Table 4, lower table—, the frequency of Foursquare *venues* with their corresponding categories is indicated.

Fig. 3 shows the most representative types of *places*—upper diagram—and *venues*—lower diagram—by category, respectively, for each neighborhood. The same APA level 1 categories were found across all neighborhoods indicating that they have a similar offer of economic activities. However, the demand for activities, as shown by the Foursquare categories, suggests some degree of specialization and citizen preference. For instance, there is significantly more demand for *venues* related to the category *Food* in neighborhoods 1, 2, 3, 4 and 6; whereas for neighborhood 5, this activity is as relevant as *Arts & Entertainment*. By contrast, for neighborhood 7, the category *Food* is not significant.

As for Google Places, despite the similarity found in the predominant APA Level 1 categories—Figs. 3 and 5, upper diagram—, the frequency of *places* of each category differs from one neighborhood to another, showing that, for example, the *Construction-related services* category in neighborhood 4 is more relevant than in any other neighborhood.

Depending on the case study, it can be a challenging task to assign the APA level 2—sub-categories—to Google Places original categories since the description of the *place* in the Google Places retrieved data may not be entirely clear.

Level 2 sub-categorization allows recognition, to a good extent, of the functional specialization of an area and a more thorough understanding of the type of economic activities on offer. For example, commercial activities, such as proximity retail, can be distinguished from those of food service establishments—Figs. 4 and 6—or other uses in upper floors, thereby allowing more granularity in the study of urban activity patterns of public spaces.

In terms of quantity of datapoints, a simple comparison between the amount of LBSN datapoints in each of the seven neighborhoods cannot be made since these areas vary considerably in dimensions—surface area—and population. However, when datapoints are visualized on a map, spatial concentration patterns are readily recognizable. Fig. 5—indicates the distribution patterns and concentration of *places*—economic activity offer—and *venues*—the demand for establishments and other spaces—. The neighborhood 2, Mercado Central, is where both the economic offer and demand are most relevant, followed by neighborhood 3, Carolinas Bajas, with less business density and significantly less *venues*. In the former case, most *places* are concentrated along specific urban axis leaving some underserved areas. In the latter case, a concentration of *venues* is recognized in proximity to the most relevant *Outdoors and recreation* category *venues*—see the circles and dotted arrows in Fig. 5, bottom image—.

As previously explained, Foursquare *venues* within the "outdoors & recreation" original category have been classified into three types of spaces: *Formal public spaces*; *Informal public spaces*; *and*, *Private indoor spaces*.

For the case study, the *Formal public spaces* include: 21 squares; 6 urban axes; 4 landmarks; 6 gardens or parks; and, 2 controlled-use outdoor activities. Furthermore, considering the ranking of the 20 most relevant urban public spaces, 10 of them are plazas. This indicates the important role of plazas in the urban fabric in terms of preferences and suggests that these urban spaces should be integrated in future urban regeneration projects. The three landmarks that represent a symbolic reference point on a citywide scale are the castles—Santa Bárbara and San Fernando—and the bullring—Plaza de Toros—.

The *Informal public spaces* category includes those places that are gathering points, even though they do not meet the design conditions of a staying space—lacking urban furniture, for example—. Their liveliness is derived from both optional and necessary activities (Gehl, 2010). In the first case—optional activities—there are small stairs, stairways and footbridges—6 *venues*—connecting neighborhoods and main green areas. Moreover, these *Informal public spaces* are intermediate points leading to several cultural or educational facilities, which is the reason why users perceive them as reference gathering points. In the second case, some urban spots are identified as staying *venues* as a result of necessary activities such as centrally located bus stops for the university bus service.

Airbnb's offer is well distributed across all neighborhoods—Fig. 7, lower image—. However, there are differences among the inner-city neighborhoods in terms of the proportion of Airbnb dwellings listed compared to the total dwellings in the area. For example, neighborhood 2 Mercado Central has 30% of the total of Airbnb offer, but this represents only 9% of total dwellings in the area. By contrast neighborhood 5 has 3% of the total of Airbnb offer, but this represents 25% of total dwellings. The implication is that one of the less popular areas in terms of Airbnb listings—neighborhood 5—is in fact the most greatly impacted by Airbnb as one in four dwellings are destined for Airbnb accommodation.

The Airbnb platform provides a classification of non-regulated temporary accommodation into three types of offer: *entire home* or *apartment*; *room* for single or double occupancy; and bed in a *shared room*—Table 5—. Both, the number of these lodgings as well as the distribution within the neighborhoods gives us an indication of economic activity related to tourism that runs parallel to the regulated tourist offer. In this case, Table 5 shows that the 81% of the total offer is concentrated in four of the seven neighborhoods, with Mercado Central as the inner-city neighborhood with the greatest number of Airbnb offers.

As for the spatio-temporal patterns of presence and activity observed with Twitter data, the four time slots considered have allowed the identification of urban activity patterns during the daytime and evening/night time. The visualization of geolocalized tweets—Fig. 6—during working hours on weekdays shows citizen presence, especially in urban nodes and axes where there is economic

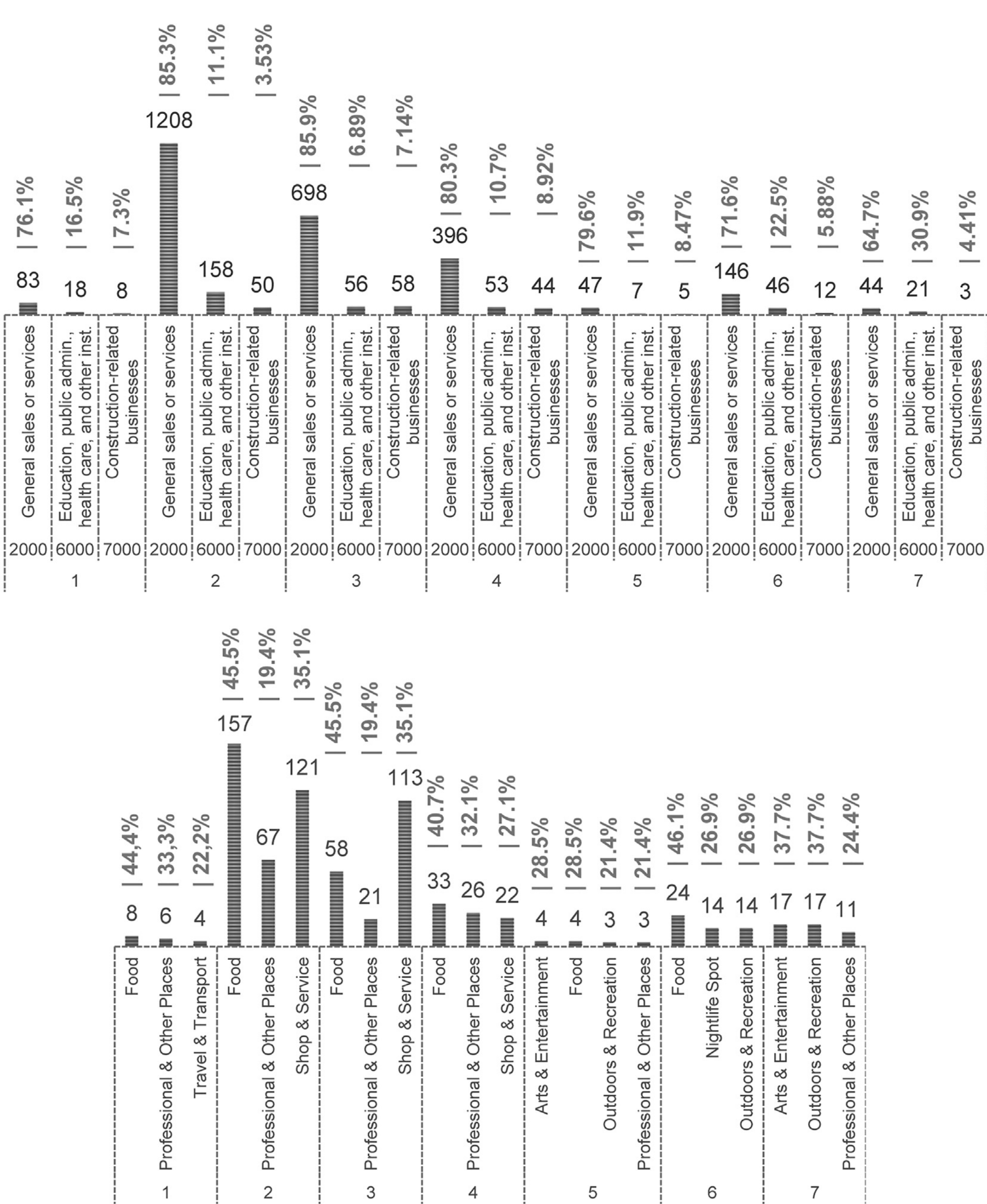


Fig. 3. Most frequent APA Level 1 category *places*—upper diagram—and Foursquare category *venues*—lower diagram—in the seven neighborhoods of the case study.

activity. This presence remains constant during the daytime weekend time slot in almost the entire Mercado Central area—neighborhood 2—since there is a good commercial offer that remains open on Saturday.

The activity found in neighborhoods 6 and 7 is mainly outdoors, leisure and entertainment activities. This type of activity during the day and most of the evening is not necessarily linked to economic activities, and therefore, would have been difficult to identify by using the other social networks. The concentration of tweets in these time frames also points to differences in the type of activities that occur in both areas. For instance, Monte Tossal—neighborhood 7—offers sport and educational facilities, which keep the area active during weekday and weekend evenings, whereas the area that comprises the Monte Benacantil—neighborhood 6—accommodates leisure and cultural activities associated with the existence of the city's heritage landmark—Santa Barbara Castle—. Area 6 also includes most of the historic city center and is located near the beachfront, one of the most popular nightlife areas.

4. Overlapping LBSNs geolocated data: urban diagnosis

Individual layers representing each social network indicated different distribution patterns in each one of the neighborhoods. This underscores the importance of an overlapping approach so that findings from the individual source can be contrasted and/or complemented by other sources. The results explained hereafter are exemplary of how the information from different LBSN data can be interpreted when overlapped—Figs. 6, 7 and 8—.

4.1. Google Places vs Foursquare: offer and demand of economic activities

There were similarities found in terms of concentration patterns from the analysis of the demand for economic activity through Foursquare and the economic activity offer using Google Places. The

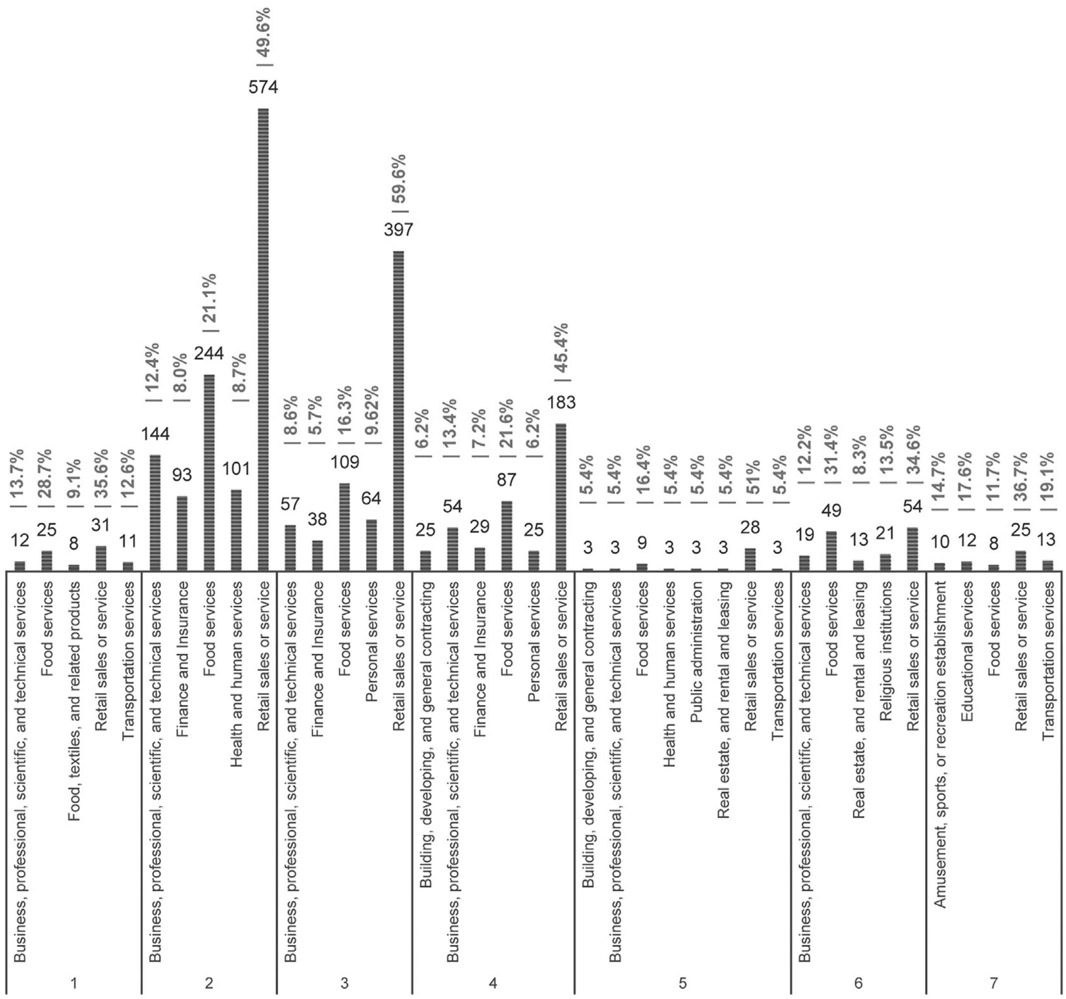


Fig. 4. The five Level 2 most recurrent Google Places categories within the 2000 General sales or services classification.

denser clusters of economic activity were appreciable in the Mercado Central neighborhood—area 2—. For all remaining neighborhoods, there were clusters of *places* linked to *Formal* and *Informal public spaces* as identified in Foursquare's *outdoors and recreation* categories. Respectively, the plazas and pedestrian walkways and public urban stairs were found to be spatially linked to *places* that belong to the APA Level 2 categories 2500 *Food services* and 2100 *Retail sales or services*—Fig. 6—which are activities that enrich the visual information and thus the livability of the urban environment.

Furthermore, by overlapping data from these two LBSNs the identification of underserved areas with lack of activity was made possible. In addition, linking ties between economic activity offer and *venues* ranked by users—demand—permits the relevant clusters of activity to be visualized. In this way, connecting urban paths with retail activity can be detected, or whether paths are isolated places surrounded by non-active areas.

In the case of neighborhoods 6 and 7—Monte Tossal and Monte Benacantil, respectively—both areas comprise *informal urban public spaces*, namely: two urban stairways near several public-school facilities in the first area; and, a pedestrian walkway connecting the old town from the mountain side with the beach promenade in the second area. These unexpected *Informal public spaces* identified through user-generated data are reinforced as gathering places by Twitter activity data.

4.2. Twitter vs Google Places & Foursquare: spatio-temporal patterns of presence and activity

Spatio-temporal patterns of people presence can be identified by overlapping data from Twitter, Foursquare and Google Places. Once more, tweets reinforce the previously identified distribution of urban activity with some specific nuances in terms of temporality.

Day-time distribution of activity is clearly associated with small retail distribution areas. As for activity and citizen presence at night, according to the tweets analyzed, the following results can be highlighted: tweets are practically non-existent in the vicinity of both parks, Montes Benacantil and Tossal, with the exception of the *Informal public spaces* in which the tweets are an indicator of social activity. Night-time activity is closely linked to Foursquare's nightlife *venues* and the food category establishments registered in Google Places; evidently, in locations where there is people presence. In the Mercado Central area, the activity and people presence at night is noteworthy and continues throughout the week, especially around the Mercado Central landmark, which falls within the area where there are most night-time Foursquare *venues* registered.

4.3. Airbnb & Foursquare. Spatial patterns of regulated and non-regulated temporary accommodation

A considerable share of the Airbnb offer is located outside the area where regulated hotel accommodation is based—Fig. 7, lower image—, thus decentralizing the economic benefit of tourism to non-touristic

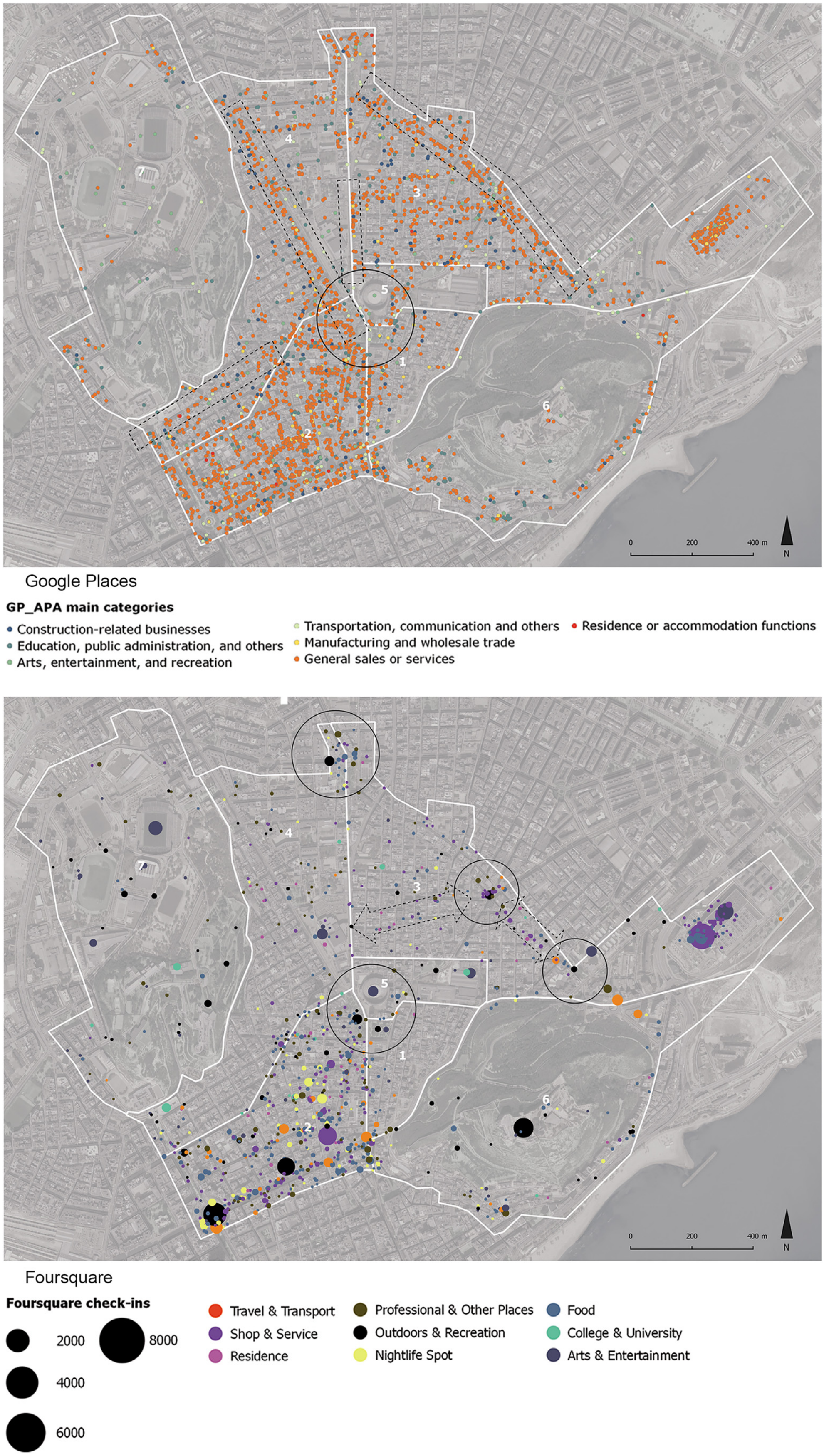


Fig. 5. Concentration of economic activities in nodes and axes. Google Places economic activities corresponding to APA main categories; and Foursquare main categories.

Table 5
Airbnb lodgings. Distribution by typology, neighborhood, and as a percentage of the total lodgings.

		Number of dwellings	Dwellings in Airbnb	Lodgings distribution by typology			Offer distribution within neighborhoods	
				Private room	Shared room	Entire home/ apartment	Number lodgings	Percentage
1	San Antón	1466	6%	43%	2%	55%	91	6%
2	Mercado Central	4413	9%	46%	2%	51%	419	30%
3	Carolinas Bajas	6952	4%	37%	1%	62%	288	20%
4	Ladera del Tossal-Campoamor	6314	5%	49%	2%	48%	295	21%
5	Fábrica de Tabacos- Plaza de Toros	167	25%	37%	5%	59%	41	3%
6	Monte Benacantil- Castillo Santa Bárbara	2552	10%	17%	0%	83%	253	18%
7	Monte Tossal- Castillo San Fernando	2056	1%	43%	0%	57%	21	1%
		23,920	6%	Total lodgings Airbnb			1408	100%

areas (Moreno Izquierdo, Ramón Rodríguez, & Such Devesa, 2016; Perez-Sanchez, Serrano-Estrada, Marti, & Mora-Garcia, 2018; Perles Ribes, Moreno Izquierdo, Ramón Rodríguez, & Such Devesa, 2018). When overlapping Airbnb data with Foursquare, the panorama of the city changes. There is an extended distribution of Airbnb lodging offer across all neighborhoods—Table 5—, including those that previously had indicated a lack of activity in the other LBSNs. These areas represent a potential for attracting associated services, and therefore, can

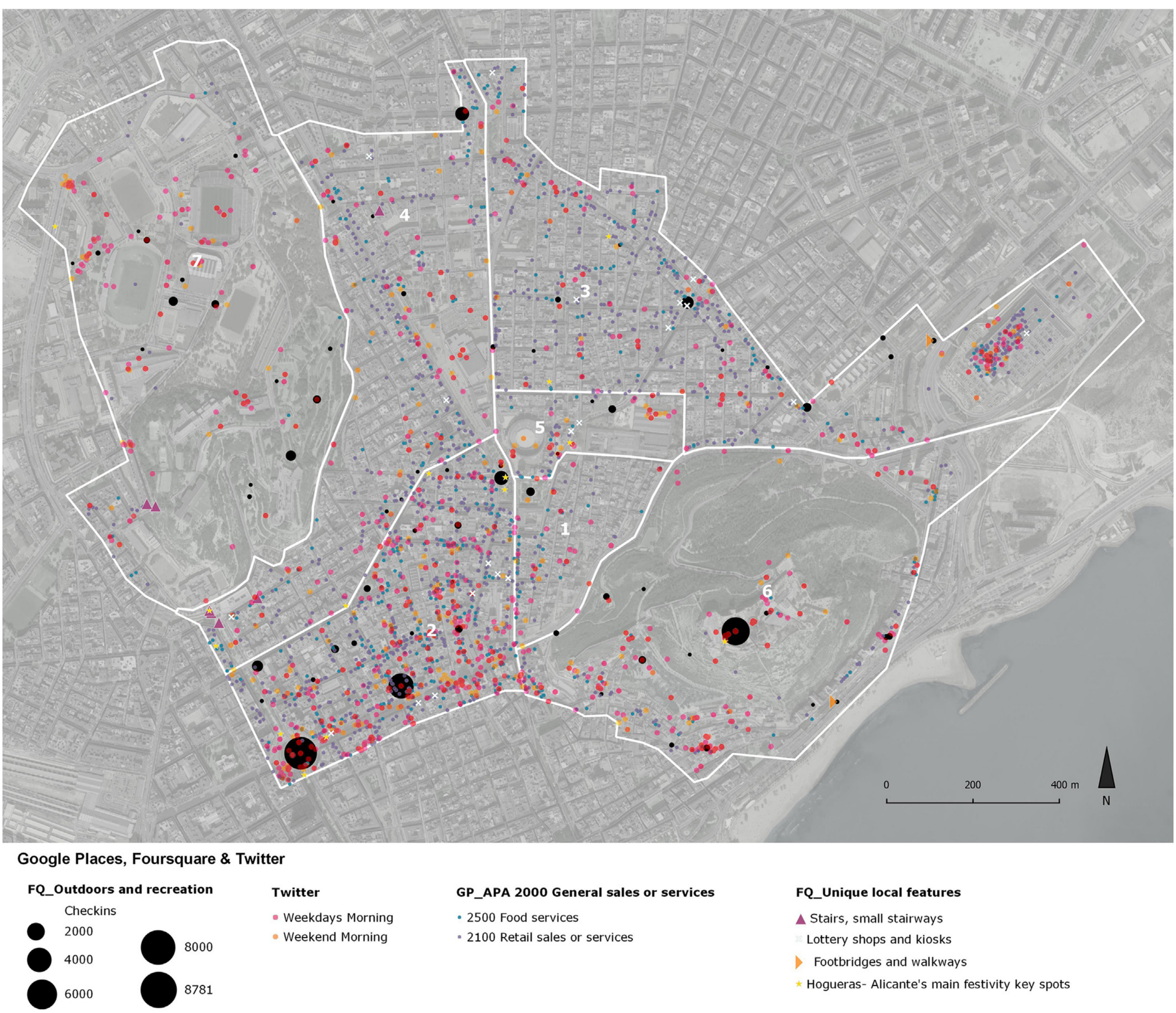


Fig. 6. Google Places, Foursquare and Twitter geolocated datapoints.

Fig. 7. Upper image—Spatial distribution of tweets in relation to the *Outdoors and recreation* Foursquare *venues*—by number of check-ins. Lower image—Airbnb non-registered accommodation versus the officially registered hotels and Tripadvisor's accommodation offer.

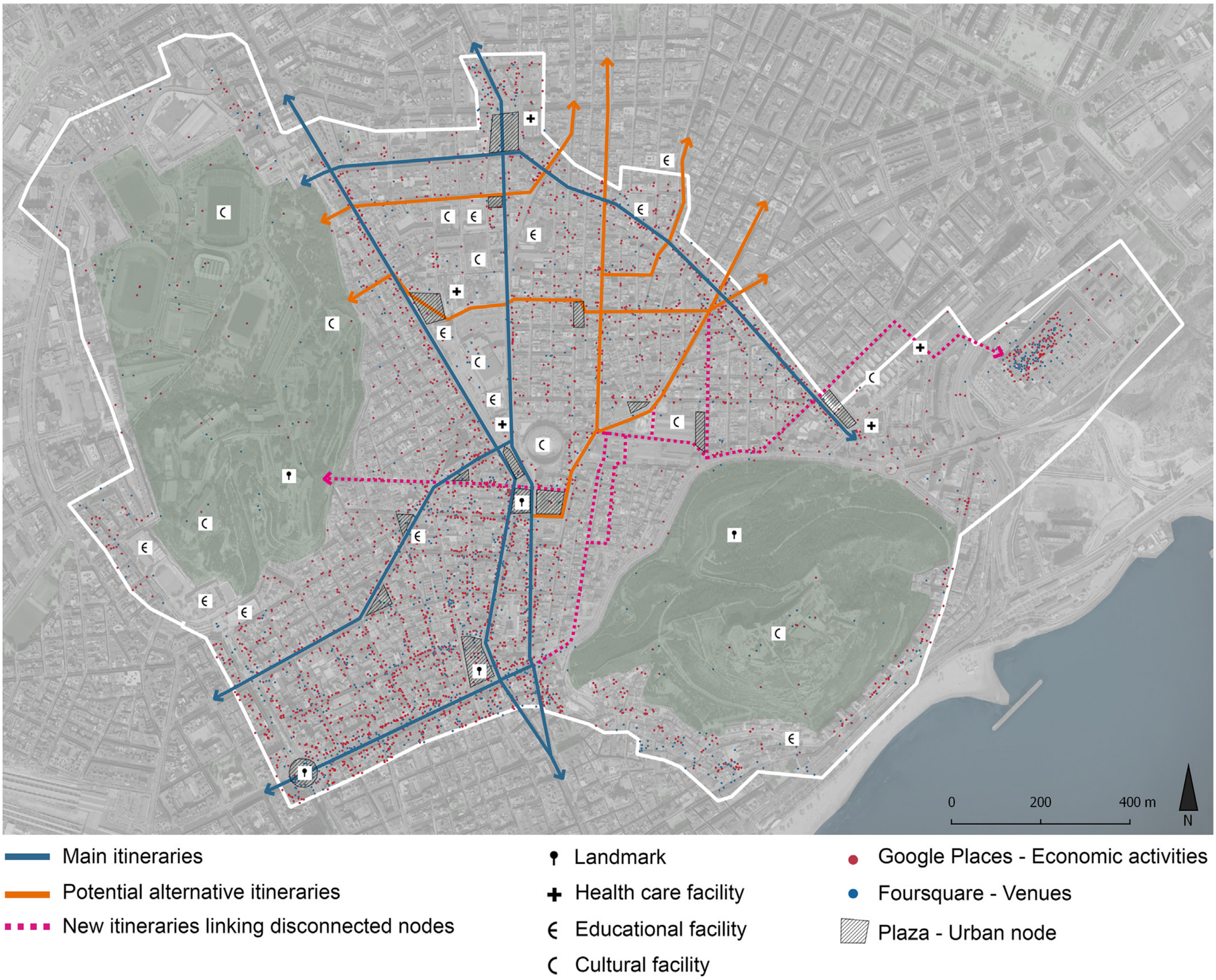


Fig. 8. Emergent inter-neighborhood itineraries resulting from the place-based and people-based perspectives.

be considered a catalyst for urban activity. Some examples are neighborhoods 1, 4 and 6 and the adjacent historical urban tissue pocket-area that, despite indicating little or no economic activity in other social networks, have a considerable offer of Airbnb accommodation.

5. Discussion. The LBSN contribution to finding urban opportunity places

The four studied LBSNs constitute supplementary layers of information for reading place-based nuances from a people-based perspective. Specifically, when overlapping data, specific trends are shown in relation to user preferences and demand for services—Foursquare and Twitter—, as well as the existing offer—Google Places and Airbnb—.

Overlapping several LBSNs consolidates the information provided by single sources in relation to spatial patterns, facilitating richer analysis and interpretation of the results in a case study. This is mainly because the overlapping approach facilitates a transversal view of urban dynamics. For instance, tweets are most likely to be present where Foursquare *venues* are located, whereas many of the axes with Google Places economic activity—offices, and upper floor uses in compact city areas—lack geolocated tweet presence after the daytime slot. In this process, the *places* and *venues* categorization is important for understanding the type of activities in the space. These considerations have assisted interpretation and helped to reveal urban opportunity places.

Moreover, identifying inactive areas in contrast to activity nodes provides a diagnosis that can better guide solutions to balance the diversity and quantity of activity throughout an urban area. This would allow an amelioration of intra-neighborhood and inter-neighborhood dynamics by encouraging mixed use, and thereby, urban activity. For example, the findings indicate a strong correlation between location and diversity for the identified places of interest—as reflected in Foursquare and further reinforced through geolocated tweet patterns—.

From the intra-neighborhood perspective, one unanticipated finding has been the detection of informal meeting places in unexpected locations through Foursquare data—*Informal public spaces*—. While *formal urban public spaces* in all inner-city neighborhoods have a significant role, *informal public spaces* have the potential to make an important contribution to urban regeneration processes. Several registered *venues* from Foursquare O*utdoors and recreation* category such as 'stairs', 'small stairways', 'walkways' and 'footbridges' were identified as meeting and social gathering points. This was also evidenced by Twitter activity. They are flexible public urban spaces in terms of their capacity to accommodate spontaneous activities of various kinds, given their physical attributes. These *venues* are located close to pedestrian paths that connect urban areas to sports and education facilities or commercial areas.

Furthermore, regarding the Foursquare dataset, certain public transport bus stops are registered as *venues*, highlighting their relevance as social spaces. Specifically, the most checked-in bus stops in central locations are those running along the route from the city center to the University of Alicante.

The place-based perspective enables the analysis of morphological attributes of places (Singleton, Spielman, & Folch, 2018). However, traces of pedestrian custom practices would be more difficult to detect through fieldwork. In this line, urban regeneration policies should consider both, the physical aspects as well as LBSN user-generated data that represent the people-based perspective from citizens using these platforms. Specifically, the latter provides information on activities, opinions, perceptions, and people presence registered in urban spaces.

From the inter-neighborhood scale of analysis, geolocated LBSN data have revealed relevant itineraries for residents which connect specific urban nodes corresponding to plazas and urban axes between neighborhoods. Moreover, if connected, areas lacking activity between nodes have the potential to introduce liveliness.

Depending on the density and spatial distribution of LBSN data, the following three scenarios have been identified to design potential itineraries for urban regeneration—Fig. 8—:

i. Main urban axes whose role is already reinforced by the density of LBSN data main itineraries—, where specific strategically located stretches can be promoted for boosting urban liveliness and new activity routes;
ii. Potential urban itineraries with some LBSN data presence along axes that connect urban public spaces as well as the core of adjacent neighborhoods—potential alternative itineraries—, where suitable walkway design solutions that consider existing virtual traces would potentially enliven a zone's dynamism; and,
iii. Weakly connected areas with scarcely scattered LBSN data between inter-neighborhood nodes—itineraries lacking presence of activities—were identified. By connecting main public facilities to already existing itineraries ingrained in local pedestrian customs, the definition of new walkways through inactive areas may act as an urban-life catalyst.

6. Conclusions

Intertwining people-based with place-based approaches for city neighborhood analysis has proven to be a valuable method for identifying opportunity places for urban regeneration strategies. From the people-based perspective, LBSN data have provided an insight on people use of the city that would have been more difficult and time-consuming to obtain through fieldwork.

Data verification, validation and classification phases are important for accurately understanding the nature of the information shared by users. These phases are necessary for further diagnosis and represent a methodological approach that can be applicable and reproducible to other case studies.

In line with previous studies, the visualization in a cartography of each LBSN individually is recognized as an effective way of detecting the inner-city neighborhood pulse. Nevertheless, findings of this study show that overlapping data from various LBSNs enriches the analysis that would previously have relied on a single source.

The present study appears to be one of the first attempts to identify opportunity spaces for urban regeneration by thoroughly examining, at the neighborhood scale, the geographical distribution of four LBSNs—Foursquare, Twitter, Google Places and Airbnb—in overlapped combinations. Besides, in relation to user preferences, use and activities, these data help to overcome problems associated with the need for finer granularity in research of this type. Indeed, the insights gained from the resulting analysis contribute to a more accurate understanding of local nuances that would improve the diagnosis of urban areas.

One of the greatest advantages of the overlapped approach is that not all social networks have the same penetration in all places, and therefore, when there is a scarcity of data in one social network it may be supplemented by other LBSN sources. Addressing the evaluation of inner-city problems or imbalances can be facilitated by using overlapped data from LBSNs to support analysis and assessment in urban planning decision-making. All in all, LBSN data applied to the urban studies field permit a thorough and up to date diagnosis of neighborhood liveliness.

Applying the method proposed to an illustrative case study suggests both the reproducibility and validity of this approach for revealing social activity and local nuances, which would better inform neighborhood urban regeneration processes. Moreover, the relatively small scale of the area of study, in relation to the size of the city, made possible an in-depth treatment of the data.

In the case of "Las Cigarreras", potential spaces of opportunity for urban regeneration have been revealed. This method has permitted the identification of nodes and axes, recognizing them as new activity centers. Specifically, the discovery of people presence through the emergence of their virtual traces has provided relevant clues on how to prioritize areas for urban regeneration. These clues are important because they are better aligned with the actual behavior of locals and passers-by.

Overall, the findings provide evidence to suggest that the proposed method could also be applied to other case studies. As interpretation and findings largely depend on the case study's unique characteristics, future research could benefit from comparing results and conclusions from different cities to establish common ground on neighborhood regeneration policies.

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Declarations for interest

None.

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