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A near Real-Time Monitoring System Using Public WI-FI Data to Evaluate COVID-19 Social Distance Measures

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Abstract: This study assessed the applicability of geolocation data provided by public Wi-Fi infrastructures as information sources that can contribute to urban planning and management. We focused particularly on modeling and monitoring real-time mobility and congestion using geolocation capabilities of Wi-Fi public networks in Smart cities. The proposed methodology combines a detailed geographic analysis of the space with high-frequency indicators generated from network data. This study emphasizes the importance of Wi-Fi infrastructures as noninvasive monitoring systems, and describes how network data can be applied to generate useful indicators for urban planning and management. The methodology was empirically implemented in the city of Palma (Balearic Islands, Spain), where the social distance level was measured to identify conflicting areas. We demonstrate how the proposed solution can estimate pedestrians' density efficiently and precisely through high-frequency monitoring (5 min or less) and the construction of comprehensive indicators. In this context, we suggest several public policies that can be implemented by using this methodological approach to monitor dynamic patterns of pedestrian mobility, especially during health crises or during high tourist seasons.

Keywords: Wi-Fi network data; real-time urban monitoring; pedestrian mobility; COVID-19 social distancing measures

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1. Introduction

The huge increase in the usage of digital mobile devices has led to several methodological approaches being proposed for generating new types of data. In this paper, we focus on high-frequency monitoring of mobile devices through a Wi-Fi infrastructure platform. One trend in most modern cities has been the promotion of Wi-Fi communication infrastructure in public spaces to improve local connectivity and boost the introduction of digital services [1].

Wi-Fi data has two novel characteristics: real-time frequency and precise geolocation. With the appropriate transformations, this information has many applications, including planning for smart cities, use of resources and services in retail settings, contribution to a better understanding of the city through behavioral analysis of its citizens, and dynamic traffic-management systems [2]. If we consider the example of a city hosting an event, we could count in real time the number of devices being used, and by making appropriate adjustments estimate the number of participants. Thus, we could improve event management by identifying and eliminating critical obstacles, designing mechanisms to limit the physical proximity of participants, and implement time slots. Similarly, understanding the flow of participants can be used to improve commercial services' locations, optimize impact on visitors, and for strengthening Wi-Fi network connectivity in areas of higher device density.

It is important to highlight that Wi-Fi infrastructure data can be obtained for both closed and open spaces [3]. However, it is primarily in these open spaces where this data source achieves remarkable importance for urban planning. In this sense, pedestrian-counting technology based on Wi-Fi networks has been identified as a cost-effective infrastructure to collect pedestrian mobility data [4]. In addition, under smart destination deployments, the use of Wi-Fi networks to identify and classify visitors' behavior has been explored preliminarily in recent work [5].

Most mobility studies that have used Wi-Fi networks obtained mobile devices' locations by analyzing data generated by wireless communication protocols based on the IEEE 802.11 standard. During the network discovery phase, a search mechanism at nearby connection points (Wi-Fi access points) operates via pings. The data accessed during the standard discovery mechanism is registered by the network controller for technical purposes. However, it also contains valuable information that can be used to detect the presence of a device, discover how long it has been connected, or quantify the number of times it has been detected [1–3,5,6]. Coverage area is generally limited to the space where an event is performed (e.g., a conference or a music show) or the area where a certain company or public service (e.g., a library) runs its activities. This limited coverage area is considered a limiting factor [4], and can be solved by combining different data sources or different technologies, such as video tracking systems or GPS (Global Positioning System) tracking devices. Obviously, this increases the cost when applied to large pedestrian facilities [7]. Additionally, combining tracking data from different areas (train stations, airports, shopping malls, etc.) is an option to extend the limited data coverage attained from just one Wi-Fi network. However, this can become a challenging task when different infrastructures collect data in non-uniform formats. Other previous works [5] required a city SSID (service set identifier) database to be created, or the preferred SSIDs were collected from devices and this data analyzed to estimate mobility patterns. In our opinion, the SSID database has certain limitations including the requirement of continuously revision to update the database; and furthermore that collection of preferred SSIDs from devices could include personal information like personal Wi-Fi SSIDs, which raises privacy concerns. Therefore, this work proposes the use of data anonymously available in public Wi-Fi networks.

Beyond the analysis of pedestrian flows, there is a growing literature that uses advanced techniques to solve alternative problems. In this vein, researchers tried to solve the last-mile delivery distribution of agricultural products using vehicles and a multi-objective VRP algorithm [8]. Similar solutions could be applied focusing on pedestrian mobility, when high-frequency mobility data is available. The use of hyperspectral image classification methods has been explored [9], but its application in Smart City areas increases equipment costs. In fact, cameras are not usually used for monitoring pedestrian mobility, due to costs of image computation and rules about individual privacy in European countries. Other solutions based on unmanned aerial vehicles (UAVs) [10] do not require camera installation, but the management of UAVs in crowded areas is challenging for security reasons. Of course, these kinds of solutions can be used by public administrations, but the required image technologies are not available and associated equipment costs are restrictive in small or medium-sized communities. Moreover, application of these methods is problematic for pedestrian urban management. This paper focuses on Wi-Fi network capabilities because these kinds of infrastructures are often deployed in small and medium-sized communities in Spain, and aims to demonstrate which infrastructures and which methods could be easily adopted and applied for urban management. In addition, when data from the Wi-Fi networks is collected and organized into a relational database, it is possible to apply novel mathematical solutions [11] to obtain useful information for urban mobility managers.

The contributions of this work are summarized; see also Table 1.

- This study explored the technological issues of using a unique urban public Wi-Fi infrastructure deployed in Palma City, covering a much larger outdoor space than previous analysis.

- Two algorithms are proposed to classify the detected devices, considering two relevant dimensions: First, between static or mobile users considering geographic patterns; second, between usual or sporadic users considering temporal patterns.
- A Level of Service indicator is defined to monitor the fulfilment of COVID-19 restrictions. In addition, a transformation factor is derived to obtain an estimation of the number of pedestrians, according to the monitored devices inside the calibrated areas (devices/m^2).
- The paper defines a public Wi-Fi networks methodology, and discusses the technological infrastructure that can be used to generate a set of useful urban mobility indicators, and implement real-time monitoring and analysis in complex urban spaces.

Table 1. Comparison of contributions of different analysis of pedestrian research works.

Feature	[1]	[2]	[3]	[4]	[5]	[6]	[7]	This Work
Pedestrian-oriented	-	✓	✓	✓	✓	✓	✓	✓
Outdoor pedestrian flow monitoring	-	✓	✓	✓	✓	✓	-	✓
Results with high volume of users	-	-	✓	-	-	-	✓	✓
Using additional components	✓	✓	✓	✓	-	✓	-	-
Using passive probe requests	-	✓	✓	-	✓	✓	✓	✓
Geolocation	✓	-	✓	✓	-	✓	✓	✓
Device classification	-	-	✓	✓	✓	-	✓	✓
Counting devices	✓	✓	✓	✓	✓	✓	✓	✓
Density estimation	-	-	-	✓	-	✓	✓	✓
Obtaining level of service in urban space	-	-	-	✓	-	-	-	✓

In Table 1, the contribution of this paper is compared with previous works. The application of our proposal should strengthen the use of public Wi-Fi infrastructures data. Specifically, we proved how it is possible to transform the data's space and time components into usable knowledge that can be efficiently integrated in urban mobility planning and management. This work reports the level of service of analyzed areas using a high volume of users in a crowded touristic city.

In general, urban mobility models assume that congestion occurs when a high number of individuals coincide in the same space and time. Therefore, monitoring the number of people is not sufficient to determine the congestion level. Congestion depends on the available space at a precise moment in time, e.g., ten people walking across an open square are not the same as ten people on the sidewalk of a street. In this light, this study describes a methodology that combines monitoring data from public Wi-Fi networks and detailed urban information, to estimate congestion density and social distance at near-real-time observability.

We tested this proposal in the city of Palma (Balearic Islands, Spain) using Wi-Fi networks covering the main touristic areas. The application demonstrated that our proposal provided useful urban mobility data regarding two specific challenges, i.e., monitoring pedestrian flows in an urban tourism destination, and controlling social distancing measures associated with the COVID-19 pandemic.

Considering the further replicability and generalization of our proposal, we recommend using public Wi-Fi infrastructures as monitoring tools in smart cities, as a cost-effective solution to cover as many city areas as possible. Hence, our technical proposal is based on the proposed architecture's capacity to manage three specific challenges from the network data; high volumes of geolocation data; real-time reception; and recording. The method involves transforming this information into useful indicators for urban management and health risk monitoring.

The rest of the paper is structured as follows: Section 2 discusses proposals for using Wi-Fi networks to study urban mobility. Section 3 introduces the proposed monitoring system architecture connected to Palma's Wi-Fi network. Section 4 describes the data analysis implemented to transform the technical information into usable urban mobility information. Specifically, the city's areas are characterized through a set of indicators combining geospatial information and real-time monitoring data. Section 5 describes two applications that illustrate the usefulness of these indicators. In particular, we employ dynamic urban flows and social distancing as examples. Finally, Section 6 contains the conclusions and recommendations.

2. Using Wi-Fi to Analyze Device Mobility

Developing public Wi-Fi infrastructure is one of the main policies included in the smart city's strategy [12]. In this sense, allowing city users to connect their devices to the internet in public spaces has become a priority for many public administrations. This has been accompanied by even more general use of mobile devices, for work and leisure activities. In tourist destinations, the infrastructure is deemed an opportunity to offer digital services to visitors.

Similarly, these public infrastructures have, in recent years, become a tool for monitoring urban mobility by providing useful data for city administrators. These new uses take advantage of the increasing number of mobile devices owned by the general population. Devices come equipped with a Wi-Fi transmitter that periodically sends out probe requests to identify available Wi-Fi networks in the surrounding area [1–3,6]. The periodicity of the probe request can be considered random because it depends on different features, including the operating system, the apps that are installed and running, the device status (running, screen turned on or off, executing apps in the second plane, making a phone call), etc. Based on these probe requests, Wi-Fi networks can estimate the location of the mobile device if it remains in the coverage area. It is relevant to emphasize that the identification of the device does not require that it is logged into the Wi-Fi network, but only that it has the transmitter antenna turned on.

Detecting people in an area by using Wi-Fi networks is a cost-effective option with advantages over other alternatives, such as the GSM (Global System for Mobile Communications) network, which provides too much imprecise data to be used at a pedestrian scale; or Bluetooth; or image-based analysis, which requires the installation of specific scanners and cameras. Thus, where GPS is not available, for example indoors, location through Wi-Fi is a highly effective alternative [13–16]. In fact, its use in outdoor spaces is gaining greater attention due to its potential for providing mobility data in large areas. In this regard, we focused on urban public Wi-Fi infrastructures available to public administrations, and how they can be used to monitor levels of service throughout the city. As far as the authors are aware, there have been few studies that propose feasible methodologies to transform automatic Wi-Fi-based device-detection data in extended urban areas into useful and interpretable indicators, for incorporation in urban planning and management systems or to provide real-time warnings in smart-city decision-support systems, to prevent security risks and unhealthy congestion.

3. Public Wi-Fi as Monitoring Systems

Locating the presence of a mobile device near an access point is performed by detecting the probe requests that are sent by the devices with connectivity based on the 802.11 protocol family. Two simple methodologies can be used to detect the presence of the device, using an activated Wi-Fi antenna. The first is based on knowing the exact geographic location of every access point in the network. Then, we need to assume that each access point creates an isolated network outside the radio range of another access point. Thus, when a mobile device is detected, its location can be approximated to the position of the access point (generally, this distance is calculated at 200 m in all directions in an obstacle-free area). The second method sees the network as a set of access points that collaborate and exchange information. The position of the mobile device is linked to the distance between the device and the access point, based on the quality of the communication channel according to the received signal strength (RSS). The RSS parameter indicates the signal strength received by the access point antenna during its probe requests; the signal strength is generally inversely proportional to the distance. Therefore, the estimated distances between the mobile device and each access point enable high spatial resolution if the number of access points is high [17].

Probe requests are periodically sent by mobile devices, whether they are connected to a Wi-Fi network or not. Indeed, these requests are the device's procedure to detect nearby Wi-Fi infrastructures and are essential for detecting the access points that offer the best service quality. Wi-Fi access points can detect discovery request frames that include the MAC address identifier (media access control). Therefore, if the location of the access points is known, it is possible to geolocate and identify the presence of a specific mobile device in a service area. The time intervals used to generate probe request frames depend on several factors [18], including the mobile model, the operating system, the number of open applications, types of applications using the communication channel, etc. For example, Cisco Meraki published the technical information shown in [19], based on empirical tests performed at its networks.

A more in-depth study [18] that analyzed requests from four mobile models in different circumstances reached similar conclusions. Probe request frequency is an issue to bear in mind when implementing monitoring methodologies. In our research, we considered that although the number of probe frames per minute may increase according to each specific situation, both studies indicated that at least one request per minute was made when the device was asleep. Therefore, counting devices for periods under a minute would likely lead to underestimationg of numbers. Due to this and to account for reasonable urban pedestrian mobility, we set a minimum five-minute interval period when performing the monitoring exercises.

Additionally, it is important to consider that devices were detected regardless of whether they were associated with the Wi-Fi network. In this sense, it is relevant to remember that probe requests are inherently a discovery mechanism seeking nearby networks, and are therefore constantly generated at intervals as it is explained in [19]. Thus, devices were detected whenever they were in the coverage area of at least one access point, when they had their Wi-Fi transmitter activated. Therefore, we want to emphasize that whether or not the device was connected to mobile networks for internet connection (4G or 5G), its probe request packets could be sniffed by APs, and were included in the analysis.

Currently, there are commercial products available that provide precise geolocation data based on these working principles. In this sense, public Wi-Fi infrastructures with device geolocation capacities are a reality that is generating high expectations regarding their potential for smart cities. One of these commercial products is provided by Cisco Meraki; the system combines devices' raw location data and the physical location of each access point. With this data, it provides real-time location estimations for all devices with active Wi-Fi or Bluetooth (BLE) transmitters.

Nonetheless, the technical architecture required to process the enormous amount of geolocated data is a challenge for the creation of real solutions for wide Wi-Fi networks. When commissioning a computing architecture, it is important that the product possesses sufficient processing capabilities to be able to collect the huge volume of geolocation data generated by urban Wi-Fi environments. The following section describes the architecture and computing services that are required for our urban monitoring applications.

3.1. Network Connections and Computer Services Architecture

Obviously, an initial requirement for implementing an urban mobility modelling service based on Wi-Fi data is to install the corresponding network that can geolocate devices. There are commercial products that provide suitable solutions for installation in urban spaces. These products are equipped with a cloud platform that has configuration and management capabilities for the access points. Geolocation data is also provided by this cloud platform, although due to the large volumes involved, data is aggregated for storage on the platform. Aggregation may be based on different dimensions: time (only the final value is saved for each given interval, i.e., one per hour), space (defining geographic areas and saving their aggregate information), or other device categorizations, such as detected devices, connected devices, habitual devices, etc. All these aggregations enable a reduction in data size, although they also decrease the precision of any further analyses.

One alternative that maintains data precision is to provide a data collection protocol able to process all the records as they are produced. Note that the data is generated at a non-fixed rate depending on the number of network access points and detected devices at each moment. The main challenge associated with this massive real-time recording is the infrastructure required to avoid any data loss. Figure 1 shows the implementation in Palma, with services based on a producer–consumer strategy.

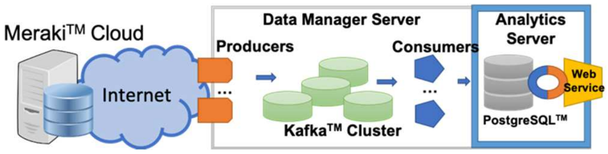


Figure 1. The connection architecture of the Wi-Fi network and computing services for data processing.

An initial logical division of the Wi-Fi network into three subnetworks is performed in this setup, to reduce the number of access points comprising each subset. The objective is to decrease the number of detections in each service coverage area. To capture the data flow, we implemented a cluster based on an Apache Kafka server (Kafka.apache.org). This is an open-source server for distributed management of data flows. Using this server, up to three producers or input channels are created, and each channel is associated with each of the subnetworks. The data received by the producer channels are stored in a queue, waiting for the consumer to read the format of the received data, process them, and order them in relational tables. We used the PostgreSQL database engine as the relational tables' manager.

Once the data is organized into a relational database, analytics can be performed following different methodological approaches depending on final application requirements.

This design enabled over four million average daily detections to be processed from over 250,000 unique daily devices in the Wi-Fi service areas in Palma.

4. Proposed Urban Monitoring Methodologies

Urban mobility monitoring is attracting increasing interest in terms of city management and to optimize resources and services offered to visitors and residents. However, automated monitoring of this mobility remains uncommon.

Mobility data from public Wi-Fi infrastructures are not currently used at the same levels as in shopping centers and other private spaces. This fact may partly be due to the lack of methodologies to transfer raw data into easily understandable indicators. If those indicators are available, they can be subsequently used to inform public decision-making. In this sense, this study defines different indicators focusing on their transferability as knowledge to be incorporated in real solutions:

- The first proposed methodology identifies and classifies the devices discovered by the Wi-Fi network. The classification method is based on reducing the data sources and obtaining the maximum useful information from the data collected from Wi-Fi networks. The methodology classifies the devices considering their geographical mobility and according to temporal patterns.

- The second proposal describes how to define a level-of-service indicator based on Wi-Fi network data. Using well-known definitions, a novel level-of-service indicator is defined and applied to consider COVID-19 social distance restrictions.
- The finally proposed methodology focuses on real-time observability of the Wi-Fi network data. For pedestrian mobility management, the number of devices is not relevant; it is necessary to transform the observations from the network to estimated pedestrian data. So, this last methodology computes a transformation factor, and defines the method to estimate or calibrate this factor, for use in city mobility applications.

The main aim of this paper is to promote the general application of these strategies in all cities where public Wi-Fi coverage exists.

4.1. Identifying Devices in Smart Cities

Identification of devices has been used in previous research to determine common routes based on the device observations.

The usefulness of detected devices for urban monitoring is enriched if they are classified into different groups. Three main reasons justify some level of aggregation; first, not all detected devices are of interest; second, different groups are likely to present different behaviors, and disentangling their particularities improves the overall understanding of mobility. Finally, different policies might be more appropriate for different groups. In the following paragraphs, we describe the analysis performed for our research.

4.1.1. Device Classification by Type

Using Wi-Fi infrastructure data implies the detection of any device that is performing probe requests. Thus, printers, routers, personal, and work computers, as well as many other devices with Wi-Fi connectivity, were detected and located. Generally, to enhance the traceability of mobile devices of interest, these other devices should be identified and removed. However, their impact is generally low and represents a somewhat deterministic factor in the results.

We differentiated between mobile and static devices, taking advantage of the temporal and spatial characteristics of the data. If a device always appeared in the same location or with small variations attributable to location error—regardless of the hours of the day—we can determine that it was not a mobile device and, therefore, not relevant for urban mobility studies. The proposed Algorithm 1 differentiates mobile devices from other devices.

Algorithm 1. Process to differentiate mobile and static devices with a Wi-Fi connection.

```
define range_monitor = 5 min
define error_position = X meters (value obtained by calibration)
define table_MACS_pos = empty table
Run the SQL sentence "Select DISTINCT MAC_address in new range_monitor"
for each new MAC_address do
  if MAC_address in table_MACS_pos Then
    if MAC_address is device Then
      if |present_position–previous_position| > error_position Then
        MAC_address is defined as mobile
      else
        MAC_address remains classified as device
          update previous_position to present_position
      else
        MAC_address remains mobile
    else
      previous_position = position of new MAC_address
      Run the SQL sentence "Insert new MAC_address and previous_position in tabla_MACS_pos"
      Identify the MAC_address as device
```

This algorithm enables the device type to be continuously assessed in configurable periods, five minutes in our case. If a device is mobile, then there are detection records with location distances above the positioning error offered by the Wi-Fi infrastructure. The "error_position" parameter largely depends on the number of infrastructure antennas and the calculation methodology used. Nevertheless, it is possible to observe different positioning errors for each urban service area due to the geometry and placement of the Wi-Fi antennas. Therefore, the "error_position" values may vary from one place to another in the same city. A good position error value calibration is required, considering a mean value for the entire coverage area or a different value for each monitoring area. In this work, the "error_position" was considered equal to 20 m as a mean value for all areas, considering the error value estimated by Cisco Meraki network location analytics.

4.1.2. Devices' Classification as a Resident or Visitor

From an urban analysis standpoint, it is useful to differentiate between mobile devices that were repeatedly detected over the weeks and those that were only detected in a given period of time. The first group of devices, which we labeled as "usual," belonged to people who often move around the city and are likely to be residents. Sporadic devices more likely belong to visitors or tourists.

Urban mobility studies require analyzing all city users (residents and visitors) identified as mobile. However, it is also true that considering different groups is useful for understand underlying mobility patterns and can provide additional insights into causes of congestion. In this vein, and from the perspective of an urban tourist destination such as Palma, a usual device should be understood as one that is classified as mobile and has been detected on different days over a 'long' period of time. Meanwhile, a sporadic mobile device would be detected only in what we call a 'short' period. We established the duration of these 'short' and 'long' periods considering the usefulness of identifying sporadic devices that were most likely to belong to a visitor or tourist profile. Considering official statistics (INE, 2019), the average length of stay in July, August, and September 2019 was between 5.1 and 5.45 days in the islands' major destinations (Calvià and Palma), and between 6 and 6.3 days for Majorca as a whole.

The above features and data were used to develop the identification protocol shown in Algorithm 2. Devices classified as mobile that were only detected within a seven-day period were deemed sporadic, while those identified for longer periods of time were considered usual. This is a recursive algorithm that updates the classification results as new data is collected by the network. In this sense, all devices were initially classified as sporadic; however, if the device was seen again at a date that exceeds the seven-day period, it was classified as usual. The classification algorithm shown below includes the definition of the parameters that we applied to the data. Note that considering three months of data, we established a maximum long period of 92 days in the current application.

It is important to emphasize that the proposed data classification requires additional information to supplement that provided by the network. In other words, data analyses require contextualization for transformation into usable knowledge. For example, in our case, the definition of the time periods was based on visitors' lengths of stay. Such contextualization relies on adapting data to the unique nature of the study areas, and to the requirements of the different decision-making agents.

Algorithm 2. Process of classifying mobile devices into usual or sporadic, depending on the on the Wi-Fi connection detection period.

```
define range_monitor = 5 min
define short_period = 7 days (defined by touristic statistics)
define long_period = 92 days (maximum period analysed)
define table_MACS_mode = empty
Run the SQL sentence "Select DISTINCT MAC_address in new range_monitor"
for each new MAC_address do
    if each MAC_address in table_MACS_mode then
        if MAC_address is "sporadic" then
            if short_period < (current_time-DATE) < long_period then
                MAC_address is "usual"
            else
                MAC_address remains "sporadic"
                update field DATE at current_time
        else
            MAC_address remains "usual"
            update field DATE at current_time
    else
        DATE = current_time
        Run the SQL sentence "Insert new MAC_address and DATE in tabla_MACS_mode"
        MAC_address is "sporadic"
```

4.2. Defining the Level of Service as an Effective Indicator for COVID-19 Management

Due to the current COVID-19 pandemic, urban congestion has become a particular area of concern. Consequently, the terms social distance and physical distance have suddenly appeared as an emerging indicator for public and private managers. In this regard, detection of crowdedness based on communication infrastructures is drawing considerable attention in the context of pedestrian flow management [4,20,21], especially regarding Wi-Fi or Bluetooth-based technologies [2,13,14].

However, detecting the number of devices in a period only provides a partial pedestrian congestion indicator. Detecting 100 devices in a wide, open square is not the same as detecting them on a shopping street with traffic lanes between them. Therefore, we must incorporate further urban information to transform network data into usable high-frequency indicators. Only then can the raw data become detailed spatial data for improving pedestrian flow management.

In this sense, we use the concept of level of service (LoS) [22]. This framework has traditionally been used for modeling transport capacity where pedestrians interact with street traffic. LoS measures the number of services that a given infrastructure provides to its users, considering its carrying capacity and the level of use. This conceptual approach has also been applied for controlling pedestrian infrastructures considering walking speed [23]. Analyzing walkability in an urban space is challenging because it presents high spatial and temporal fluctuations. Therefore, it is not desirable to assume uniform density or speed. Consequently, high-frequency data combined with detailed walkability analysis are gaining attention for their potential to provide LoS indicators. LoS conceptualization regards considerations such as being able to walk at the desired speed, stopping, changing direction, crossing the space, etc.

Henson's study [22] defines six LoS indicators based on the available square meters (m^2) per person in a specific city area. Henson's classification is an easily understandable mobility indicator based on m^2 available per person (resources approach) or the number of people per available m^2 (congestion approach).

Considering previous studies and considering the new needs for high-frequency indicators, we define a new social distance indicator that can be used in monitoring and managing public spaces (parks, gardens, commercial streets, tourism spots, beaches, transport nodes, etc.) that have available public Wi-Fi infrastructures.

Additionally, we extend our analysis to consider the challenges imposed by COVID-19. To guarantee pedestrians' social distancing, each of them should have a minimum available space. Our proposal defines a hypothetical circle around the individual with a radius corresponding to half of the social distance set by health authorities. Following conventional health authorities' recommendations of maintaining social distancing above 1.5 m [24], a minimum area per pedestrian of 1.767 m^2 must be allowed for safe walkability. Based on the aforementioned LoS concept, we calculated that this minimum area corresponds to 0.566 pedestrians per available m^2. Any higher value implies a lower social distance, and therefore reduces safety. Following the same logic, we considered it an acceptable level of safety walkability if there was enough walkable area to maintain a pedestrian distance between 1.5 m and 2.5 m. This corresponds to a density approach set between 0.566 and 0.204 pedestrians per available m^2. Finally, the urban space can be categorized as very safe when the number of pedestrians per square meter is below 0.204.

Therefore, we propose a new indicator. The level of social distance (LoSD) set out in Table 2 combines COVID-19 protocols and the LoS concept.

Table 2. Definition of the Level of Social Distance.

LoSD	Resources Approach m^2/Pedestrian	Congestion Approach Pedestrian/m^2	COVID-19 Safety Level
High	$\geq$4.9	$\leq$0.2	Secure
Medium	Between 1.77 and 4.9	Between 0.57 and 0.2	Accepted
Low	$\leq$1.77	$\geq$0.57	Insecure

This new indicator follows the same logic as the mobility studies, but it incorporates social distancing measures required by health authorities' recommendations, at a tim whene everyone has a need of free space. Of course, the specific thresholds can be adjusted to each country's specific requirements or to the conditions of the space. For example, in closed spaces (such as transport hubs), prescriptions can be stricter than in open spaces.

The application of LoSD requires a precise quantification of available urban space for pedestrians. This calculation must consider spaces occupied by street furniture, terraces, trees, or reserved for other methods of transport (cars, bikes, scooters, etc.). In this sense, in a defined geographical area, and only a limited number of pedestrians will be possible to maintain enough minimum available space between them. Monitoring the social distance in a defined area depends on the walkable area available and the number of pedestrians detected inside the area.

Therefore, we applied advanced spatial analysis techniques that considered cities' uses. Specifically, we used geographical information systems (GISs) to characterize the urban space of the areas under study. As seen in the results section, these techniques enabled us to estimate the available square meters for pedestrians in each of the areas.

To provide usable information for decision making relating to pedestrian mobility, it is necessary to obtain a high-frequency quantification of the number of pedestrians that are using the space. As described, we propose measuring this through the number of devices detected by a public Wi-Fi infrastructure. However, it remains necessary to determine the number of pedestrians based on the number of devices detected by the network. In other words, a homogeneous density value is obtained from heterogeneous available data. This challenge is discussed in the next subsection.

4.3. Estimating near Real-Time Pedestrian Flows

As described in Section 3, Wi-Fi infrastructures passively detect mobile devices within their service area that have their Wi-Fi transmitters activated. This detection does not require that the mobile device is connected to the network; the device's presence is detected from probe request packages that the devices continuously emit to discover nearby Wi-Fi networks. This method can precisely determine the number of mobile devices within the coverage area.

However, we cannot directly assume that this estimated value is equal to the number of pedestrians, since (i) some pedestrians might not be carrying device, or they might have deactivated their Wi-Fi transmitter; (ii) one individual may be carrying several mobile phones (personal and/or for work) or tablets; (iii) although each probe request includes a unique identifier, this identifier may be randomly masked; (iv) the frequency of probe requests emitted by each device is not constant. Therefore, a device may escape detection due to different reasons, such as its position in the service area, variations in radio signal quality, or the speed at which the device is traveling (e.g., the person is on a bicycle).

Due to all the above factors, estimating the number of pedestrians based on the number of communication devices is a challenge. The relation between devices and pedestrians might be affected by factors including the main use of the street (commercial, tourist, transit, leisure, etc.), the time of day, and the temporal aggregation used for analyzing the detected devices.

With all the above considerations in mind, and in line with [25], we propose to define a specific calibrating area for each different typology of urban space use. These categories are based on the factors described in the previous paragraph. In subsequent applications, researchers should evaluate the specific characteristics of the overall spatial context covered by the network.

Previous studies [25] suggested that an accurate formulation for estimating pedestrians should define a people-mobile factor (F_{pm}). This coefficient relates the number of people to the number of devices detected by the network within a given monitoring time period (t_i) and space typology (j). This factor is calculated as per Equation (1). The total number of pedestrians is experimentally obtained and could be appropriately calibrated over time as follows:

$$F_{pm}^{j}(t_i) = \frac{Total\ number\ of\ pedestrians(t_i)}{Detected\ devices(t_i)} \tag{1}$$

There are two main ways to obtain a characterization of the equivalent total number of pedestrians in the sampling zones. The first methodology requires the installation of cameras in strategic areas to apply automatic density estimation [26]. The second strategy consists of traditional empirical sampling in the area. The camera-based solution could, over time, provide an automatic calibration process for the Fpm parameter. However, installing city cameras is not always easy, due to costs or administrative reasons. However, trending smart city strategies [27] may boost their introduction. This stury opted for empirical sampling at the defined zones as a cost-effective solution for the initial Fpm value estimation. The counting campaign was performed at the calibration areas on several days and at different hours during the day.

It is important to note that the Fpm value should be estimated using the time duration included in the classification algorithms described in 1 and 2 (parameter range_monitor). Therefore, the random nature of device detection using discovered packet emissions was included in the F_{pm} estimation methodology, to obtain a level of social distance according to the time period of the Wi-Fi monitoring data. In other words, the calibration factor was dependent on the monitoring period used to count the number of devices.

Regarding the specific calibrating areas, we established that they need to comply with the following criteria: (i) homogeneous size; (ii) space and walkability features that characterize the network's coverage area; (iii) good Wi-Fi coverage; and (iv) representativeness of urban space typologies. Finally, to improve estimation, as many internal sampling zones as necessary could be set per coverage area to obtain an estimate of the number of people.

Figure 2 shows two of these calibrating areas in a major square in Palma. PA1 is an entry and an exit street to the square, with urban furniture and other elements that curtail walkable space. PA2 represents a section of the same square with very few obstacles hindering mobility.

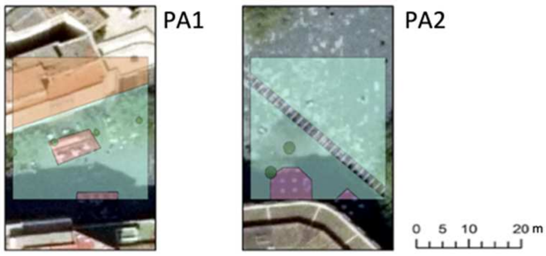


Figure 2. Example of two different calibrated areas in the same area of study in Palma.

The LoSD indicator was obtained from the number of devices detected by Wi-Fi infrastructure using Equation (2) as follows:

$$LoSD_j(t_i) = \frac{Devices_j(t_i) \, * \, F^j_{pm}(t_i)}{A_j} \tag{2}$$

where $Devices_j(t_i)$ accounts for the number of unique devices detected in zone j during the monitoring period; A_j is the walkable area of zone j. The people-mobile factor (F_{pm}) was obtained during the empirical measurement of the calibration zones using the same range_period values as Algorithms 1 and 2. A specific value can be used for each zone if there are several differences between city areas, mainly in terms of urban uses or available area.

5. Empirical Applications

The Palma City Council promoted a public–private partnership to commission the SmartWifi network in the city. SmartWifi is the commercial name that was chosen by the city council of Palma to identify the project providing Wi-Fi connectivity in all the most popular tourist areas of the city. This telecommunications infrastructure provides free internet access to the most relevant areas of Palma. The coverage areas are shown in Figure 3, based on the distribution of the 114 available access points highlighted in the figure with yellow markers. The network services urban spaces and areas of the port where passengers and goods disembark.

Figure 3. Distribution of Wi-Fi antennas in Palma.

Device location data obtained through presence detection mechanisms were generated from the built-in capacities of the installed Cisco Meraki infrastructure [19]. This enabled presence to be recorded when devices generated probe requests. The uneven distribution of the antennas in the city partly determined the selection of study areas.

5.1. Areas of Study

In this paper, the specific empirical analysis was tested in two main squares of the city (Plaza de España, ZA; and Plaza Mayor, ZB). For each zone (ZA and ZB), two calibrating areas were defined (PA1 and PA2, PB1 and PB2). Figure 4 shows the geographic location of the large zones and the corresponding calibrating areas, within the map of Palma.

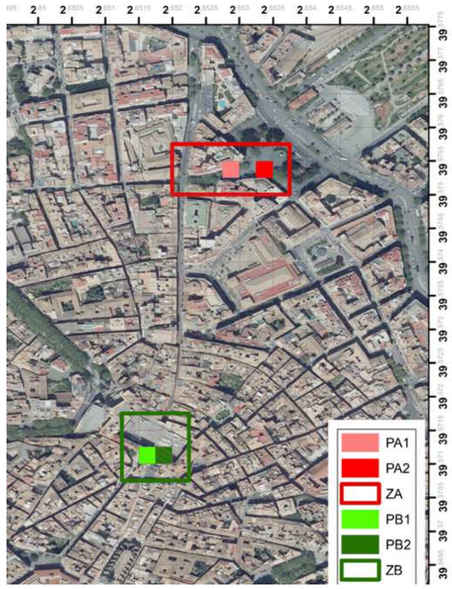


Figure 4. The distribution of studied areas Za with calibration zones PA1 and PA2, ZB with calibration zones PB1 and PB2.

A geographical information system (GIS) was implemented to define the different urban uses of all the areas under study, obtained from the city's information system. These uses included walkable space, buildings, terraces, trees, bicycle lanes, etc. When the areas had been completely mapped, the real available pedestrian surfaces were precisely computed. The m^2 are shown in Table 3.

Table 3. Available Pedestrian Space.

ZONE	Walkable Area m^2
PA1	346.1
PA2	394.8
PB1	318.2
PB2	306.7

The following paragraphs present two examples of the methodology described in the current paper, that can be used to transform WiFi data into information useful for urban planning and management. We use the network data to present an urban monitoring analysis, then describe its application to COVID-19 policies.

5.2. Urban Mobility Monitoring

In this section, we show the technical architecture described in Section 3.1, and the apply data analyses explained in Section 4 to transform raw data into urban information that can be used for urban planning and management. The first application uses all the areas monitored by the network to represent the classification of unique devices between habitual and sporadic, considering a 5 min monitoring interval. Figure 5 illustrates usage during a summer week, from Monday 29 July to Sunday 4 August 2019.

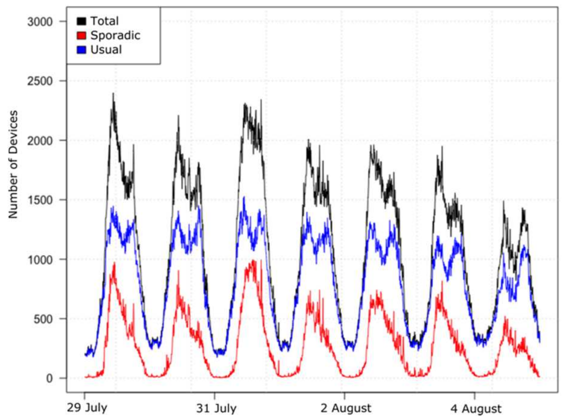
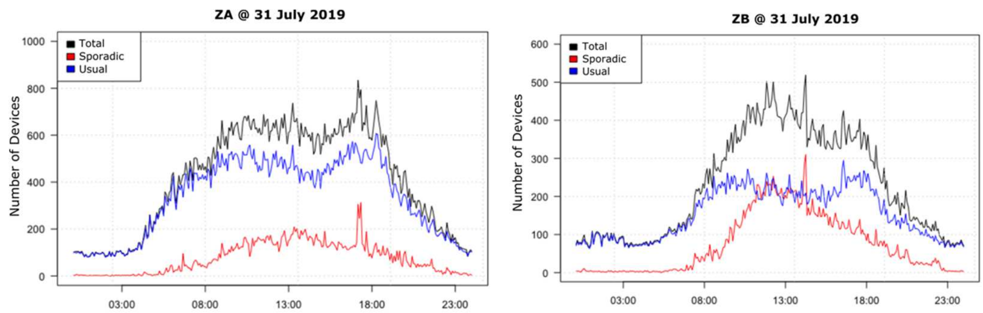


Figure 5. Temporal distribution by device type, from 29 July to 4 August.

This figure shows that habitual devices appeared in a highly similar pattern on weekdays and their numbers dropped on weekends (3 and 4 August 2019), particularly for Sundays. It is worth mentioning that some habitual devices were systematically detected during the late-night period. Those probably corresponded to static Wi-Fi-based devices located in the coverage area. Additionally, the illustration indicates a reduction in pedestrian movement during the central hours of the day, probably related to lunchtime. In contrast, we see that visitors tended to gather more in the mornings than in the afternoons. Note that the figure corresponds to the last week of July, a hot period for the city of Palma, when afternoons might not be very appealing for city walks.

The coverage of vast city areas also enabled us to focus on specific areas of the city. Figure 6 considers the areas described in the previous section with a more detailed temporal analysis. In this case, we show only one day, 31 July, which was the day in July with the highest number of visitors.



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

Figure 6. Temporal distribution by device type for 31 July, (**a**) Zone A and (**b**) Zone B.

Again, several conclusions can be drawn from the graph. The pattern in the area ZA is strongly linked to the evolution of resident devices. In contrast, area ZB became crowded, basically due to visitors gathering there in the central hours of the day. Interestingly, in both cases, the remarkable sudden increases were related to peaks of visitors.

We present here only the information for short time periods (one week and one day). However, this paper's proposal allows continuous evaluation of the urban space in near real-time. Therefore, it provides an analysis that goes far beyond what can be achieved with other traditional techniques, such as samples or direct observation.

Importantly, we show how raw technical data can be transformed into knowledge that can be incorporated into urban planning and management. Some of the easily observable information derived from this section is as follows: (i) The city's use by residents and visitors presented remarkably different temporal patterns. (ii) High urban overcrowding was mainly due to occasional peaks in the number of visitors. (iii) Different areas present specific patterns of use related to their characteristics.

A corollary of the lessons described above is that distinct urban policies should be designed for specific groups and areas. The technical procedure presented in the paper can be used to inform those specificities.

5.3. Monitoring Urban Congestion: An Application in the Times of COVID-19

In this section, we implement the concepts and parameters explained in Sections 4.2 and 4.3 to analyze urban congestion. More specifically, we used SmartWifi for monitoring near real-time urban congestion related to COVID-19 physical distance measures. The proposed methodology was used to assess compliance with social distancing recommendations. The application of the definition showed in Equation (2) does not requires the estimation of distance between each device, because the indication is based on the density of devices detected in each area of study, see Table 3. Therefore, using the real-time number of devices obtained from Wi-Fi network is sufficient to detect higher densities of persons, where it is not possible to ensure the compliance with social distance. Of course, there might be exceptional cases in which there is a low density of individuals in a given space, who nevertheless decide to gather and do not fulfil safe social distancing.

Additionally, we illustrate the impact on urban mobility of the lockdown imposed in Spain on 14 March 2020. The empirical application compares the evolution of pedestrian flows in 2019 and 2020, a few days before and after the lockdown date. Figure 7 shows the evolution of the number of different devices detected during each period. The effect of the COVID-19 lockdown on pedestrian mobility is evident in all areas.

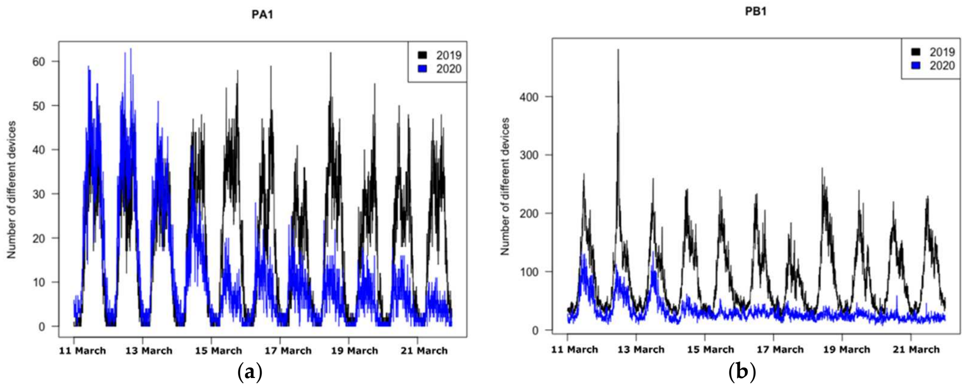


Figure 7. Time evolution of the number of devices, in 2019 and 2020, in sampling zones (**a**) PA1 and (**b**) PB1, during the week that included the start date of the lockdown in Spain (14 March 2020).

The percentage decrease in mobility was between 60% and 80% throughout the city. Figure 8 shows the percentage comparison of March 2020 and March 2019 in the areas described above (ZSA and ZB). We can see that Area ZA, more related to residents' mobility, began the period with a similar number of detected devices. However, area ZB, more related to tourism mobility, was already experiencing a decrease of approximately 20%. It is worth mentioning that COVID-19 had already been impacting tourism flows since late February. After the lockdown, mobility in both areas was consistently reduced by approximately 70%.

Moreover, based on health recommendations and using the zone sampling methodology described in the paper, we applied the level of social distance (LoSD) to generate warnings where appropriate social distancing could not be ensured. This tool used the four areas (PA1, PA1, PB1, PB2) displayed in Figure 4. The near real-time data was aggregated in five minutes and was transformed by the estimated F_{pm}. The available walkable space is indicated in Table 3, and the LoSD limits areedefined in Table 2. With all these considerations, Figure 9 presents the social distance level evaluation obtained by applying Equation (2) for each calibrated area during the week, which includes the beginning of the lockdown in Spain. The limits for each level of social distance defined in Table 2 are highlighted. The effect of the lockdown during the first days is clear as the figure illustrates a transition from detecting risky episodes to a secure spatial mobility after the confinement commenced.

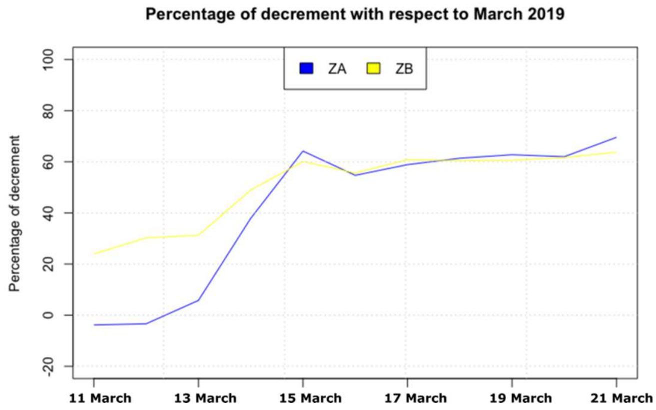


Figure 8. Time evolution of the percentage drop for the number of devices in study areas during the week that includes the start date of the lockdown in Spain (14 March 2020), compared to 2019.

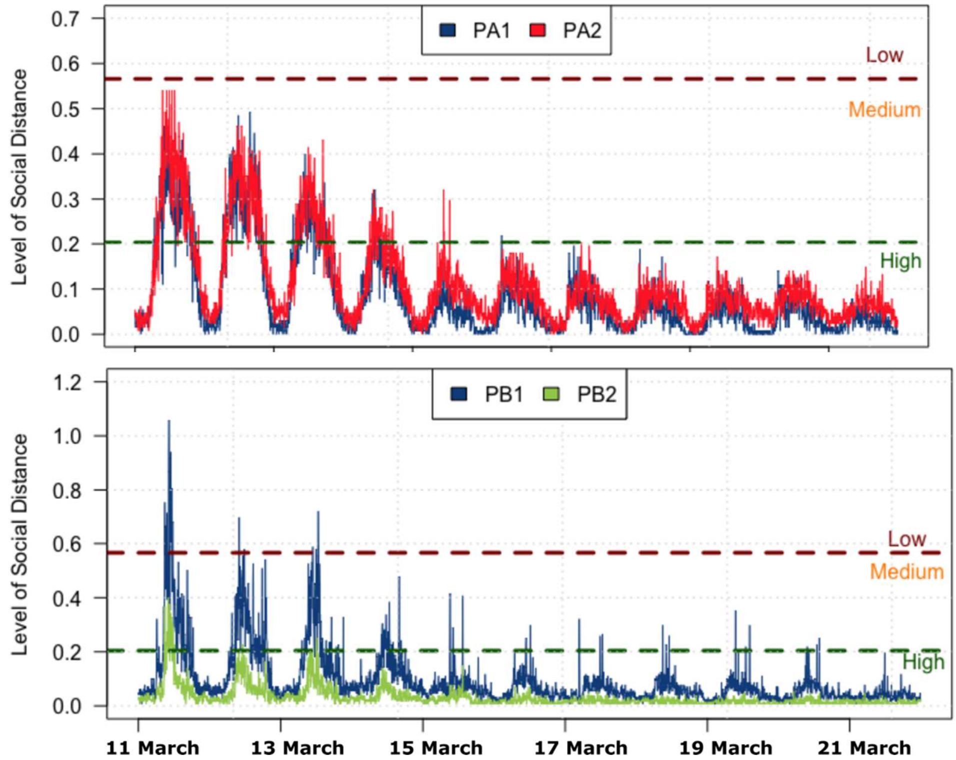


Figure 9. LoSD evolution in study areas during the week that includes the start date of lockdown in Spain (14 March 2020).

Afterwards, the tool continued to be operational and provided information for alerts, as well as being useful for analysis and modelling of urban mobility patterns.

Let us conclude the presentation of the results by summarizing the contribution and significance of the methodology described in the paper. We have proven than the raw technical data generated by public Wi-Fi networks can be transformed into usable information, with public and private applications. In this sense, a technical infrastructure becomes essential to the provision of support for decision-making. Moreover, the proposed architecture is easily replicable, so those smart cities that activate adequate modifications in their Wi-Fi networks become themselves a source of usable information for planning and management. In terms of applicability, the social distance levels can be used to determine thresholds' safety levels. Then, the proposed technical architecture can incorporate automatic alerts to detect when those levels are reached. This information can be supplied to urban mobility administrators or can be directly given to pedestrians so that they can implement self-behavior modifications. Additionally, the monitoring data can be used to forecast numbers of pedestrians in subsequent periods [28].The real-time frequency and the precise geolocation offer the possibility for city councils to activate different policies at specific locations.

6. Conclusions

This study is a response to the need to monitor urban mobility, to contribute to sustainability and improve the quality of information available to urban planners in cities. The main contribution outlines a methodology to define indicators based on the level of service available to pedestrians in urban spaces, including GIS information for the city and obtaining a calibration factor for human presence based on the number of detected devices. The proposal is based on empirical measurements and could be improved further if automated counting systems are available to enhance the precision of the F_{pm} factor.

We defined a new level of social distance indicator (LoSD), which is based on the relationship between health recommendations regarding interpersonal distance, the geophysical capacity of streets for pedestrian use, and the real-time monitoring of the number of devices detected by the SmartWifi network in Palma. We have shown how the proposal is applicable and extremely effective for analyzing risky situations and generating warnings.

The proposed differentiation of habitual and sporadic users of the city enables us to extend the analysis to the field of tourist destination management, and to apply mitigating actions aimed at each user type.

This study was initially based on data recorded during the 2019 summer high tourism season. However, it was applied in near real time (five-minute intervals) during the initial period of the pandemic, which demonstrates that high-frequency city mobility monitoring opens the possibility of substantial applications in the fields of safety, citizen participation, and other city management areas.

The proposed methodology combines high time-frequency and spatial precision to provide accurate characterization of how the analyzed areas of a city are used, with different time frequencies and geographical spread; the study results show its application in Palma. Weekly, daily, and five-minute time aggregations can be performed to extract models of pedestrian behavior. Furthermore, large areas and calibration-based zones were included. These results show notable spatial and temporal patterns in pedestrians' mobility and density in Palma.

In short, the use of public Wi-Fi infrastructures in cities should be seen not as a service but as a tool for urban planning that could contribute to improving urban sustainability, if methodologies such as those set out above are employed to translate detected devices into useful indicators for decision-making by public administrators.

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