

Exploring key spatial determinants for mobility hub placement based on micromobility ridership

Daniela Arias-Molinares^{a,*}, Yihan Xu^b, Benjamin Büttner^b, David Duran-Rodas^b

^a rGIS Research Group, Department of Geography, Complutense University Madrid, Spain

^b Technical University of Munich, Chair of Urban Structure and Transport Planning, Germany

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ABSTRACT

Over the past decade, cities have witnessed a surge in micromobility services that offer flexible mobility options for citizens on an as-needed basis, such as for covering the first/last mile connection of their trips. Although these services have known benefits, including reduced CO₂ emissions and less public space required for parking, there is still insufficient understanding of their common dynamics and usage, which can support decision-making in the quest for allocating new mobility infrastructure, like mobility hubs. In this paper, we propose a methodology to identify potential mobility hub locations based on the common associated spatial factors with the ridership of different micromobility services (station-based bike-sharing, dockless moped-style scooter-sharing and scooter-sharing services) in Madrid, Spain. We identify the common associated spatial factors with micromobility usage (e.g. bike stations' density, commercial land use and cycling infrastructure) and train linear models to explore which dependent variables represents better a “common ridership” of multiple micromobility services while fitting better that data. Subsequently, we test our models in a different area to identify potential hotspots for suggested locations. Findings show that considering micromobility ridership altogether using principal component analysis provides better ridership estimations in the test areas. The methodology has the potential to be replicable in other cities and guide decision-making processes for searching potential mobility hub locations.

1. Introduction

The recent shared mobility services introduced in many cities are intended to tackle the current climate crisis while improving citizens' mobility. These services offer an alternative to the private automobile, especially when covering the first/last mile connection of trips. Micromobility services in particular, are defined as the short-term access to low-speed shared mobility vehicles (Shaheen and Cohen, 2019). Investment and interest have sparked a rapid expansion due to its benefits: low air/noise pollution, avoidance of congestion, reduction of parking space needed and intermodality potential with mass transit (Aguilera-García et al., 2020). Nevertheless, micromobility services still require planning to offer infrastructure for their usage without harming other's circulation (i.e. pedestrians) (Henderson, 2019). In addition, by having more travel options available now, passengers may begin to increase their trip's transfers, making the concept of intermodality and multi-modal travel a key concern (Brand et al., 2017).

Mobility hubs aim to provide a more attractive connection between various sustainable modes of transport and to organise them in a

designated area (Aono, 2019; Aydin et al., 2022; Blad et al., 2022). Many definitions are offered for mobility hubs (Blad et al., 2022; Miramontes et al., 2017; Tran and Draeger, 2021), but the concept's central idea is to create a space that integrates public and shared mobility modes to improve the public realm (comoUK, 2021). They are designed to be highly visible, safe and accessible to allocate public, shared and active travel modes while also offering relevant and enhanced community facilities (Bell, 2019).

To implement new mobility infrastructure, especially mobility hubs, decision-makers need to solve multiple planning tasks simultaneously. One of the most important and strategic decisions regards the definition of a location, or in other words, an answer to the question “where to allocate a new mobility hub?”. Proposing methodologies that assess how to prioritise and decide on where to install them are highly relevant for transport authorities, as it could be a tool to inform public policy. Previous studies have delved into this topic and proposed methodologies that consider three different approaches: 1) accessibility measurement oriented to maximise access to points of interest (POIs) and jobs (Ben-Elia and Benenson, 2019; Duran-Rodas et al., 2022; Guan et al., 2020;

* Corresponding author.

E-mail address: daniar02@ucm.es (D. Arias-Molinares).

Hernandez, 2018), 2) mathematical optimisation methods oriented to find the best locations based on the operators' perspectives (maximise profit or demand) (Nair and Miller-Hooks, 2016; Petrovic et al., 2019; Steiner and Irnich, 2020), or 3) a combination of both (Frank et al., 2021).

Few studies include micromobility ridership analysis in their modelling approaches, primarily because of its recent inception. We intend to contribute to this line of research by considering both, public transport infrastructure in the form of intermodal stations where most transfers occur, and micromobility usage. If mobility hubs are the integration of both public transport and micromobility services, then we argue it's necessary to understand micromobility services in location-planning.

This study aims to first explore the common determinants of the ridership of multiple micromobility modes and based on these findings, showcase potential hotspots for the allocation of mobility hubs. To that end, our main research question is: what are the common determinants associated with the ridership of multiple micromobility options? Since this approach has not been considered in the previous literature, our second research question is: how to estimate the common determinants of the usage of multiple transport modes?

Our study uses GPS records of trip arrivals for three different micromobility services (shared bikes, mopeds, and scooters). The study data is collected for the city centre of Madrid (Spain) which has been known as one of Europe's living labs for shared mobility (Arias-Molinares and García-Palomares, 2020). We build regression models of each micromobility service to associate the trip arrivals with spatial factors. Additionally, we explore a second approach by merging the trip arrivals of different micromobility services as "one variable" using Principal Component Analysis (PCA) and then associating it with the built environment. These two approaches and resulting models are compared to identify the one that fits better the dataset (historical ridership data). Finally, the predicted usage helps to build kernel density maps and, thus, find the hot spot areas for potential locations for new mobility infrastructure. The rest of the paper is structured in four sections. Section 2 explores the background literature. The study case, data and methods are explained in section 3. Section 4 describes the main results. Discussions are offered in section 5 and, finally, section 6 includes the conclusions and limitations of the study.

2. Background

2.1. Current research on micromobility demand

The literature on micromobility services has increased in the last decade, particularly for bike-share programs as these were the first systems to be deployed. Some studies explore the integration of public transport and micromobility services, as well as its determinants. For example, (Oeschger et al., 2020) conducted a systematic literature review of studies that focus specifically on the integration of micromobility and public transport systems. They delved into the exploration of how the topic has been studied, the factors and aspects considered and some of the determinants of the intermodality. In (Reck et al., 2022) the authors proposed a model to estimate the first modal choice between eight transport modes. They found that trip distance, precipitation and access distance were fundamental for choosing a micromobility service. In the study done by (Cheng et al., 2022) the authors focused on the relationship between the built environment and the integration of dockless shared bikes with the rail system. Their insights show that those rail stations with higher population density, bike parking facilities and road connectivity presented more bike-rail integration.

Moreover, quantitative studies related to micromobility service usage and demand have only recently been taken up, leaving much to be explored. For example, (Corcoran et al., 2014) used GPS data to explore the effects of weather and calendar events on spatio-temporal patterns of bike-sharing using multivariate regression models. Another similar

study conducted by (Purnama, 2018) analyses GPS records from the public bike-sharing system in London and New York and used Pearson's correlation coefficient to observe the association of external factors with daily usage. Similarly, (Nickkar et al., 2019) used GPS records to study the influence of socio-demographic factors on travel patterns in Baltimore and evaluated the relationship between gender and land use in terms of the trip's origin and destination locations. While spatial factors are studied within a city, (Duran-Rodas et al., 2019) identified associated factors with bike-sharing usage in different cities. Moreover, in the study (Duran-Rodas et al., 2021) potential demand for bike sharing is estimated using structural equation models via the built and social environment.

More recently, with the introduction of new shared micromobility modes like mopeds and scooters, studies have analysed factors associated with usage between existing bike-sharing, moped and scooter systems. One of these studies, conducted by (Zhu et al., 2020) compares dockless bike-sharing and station-based scooter-sharing services using GPS records (of bikes) and a scraping tool (for scooters) to estimate redistribution trips. They also found that fleet sizes as well as other descriptive characteristics can help understand the differences of the two services. Moreover, (Younes et al., 2020) studies six dockless scooter-sharing services and historical trip data for the city's public bike-sharing service (Capital Bikeshare in Washington DC) to estimate two variables: hourly number of trips and hourly median duration of trips. This estimation was based on a negative-binomial regression model including environmental and economic variables such as weather-related data, gasoline prices, local events or disturbances, day of the week, and time of day. Regarding moped-style scooter sharing services (also known as moto-sharing), two recent studies are found. (Pérez-Fernández and García-Palomares, 2021) uses GPS datasets and proposes a methodology to locate parking places based on the varying distribution of demand over the day. Additionally, (S. Bai and Jiao, 2020) applied univariate LISA to identify areas of high demand (hot spots) in the use of shared e-scooters, as a preliminary step before applying regression models.

2.2. Current research on mobility hub allocation

The literature on mobility hubs is as recent as the nature of the concept itself (2000s) (comoUK, 2021). Moreover, the mobility hub allocation is a topic in need of new contributions. While some authors argue that the term "mobility hub" is relatively new, the ideas behind it are not (Rongen et al., 2022). Transit-Oriented Development (TOD) and Park and Ride (P + R) policies are two clear examples of urban planning strategies aimed at reducing resistance to transfers between public transport and micromobility services. It is argued that mobility hub allocation could also take into consideration the criterion that TODs and P + R's measures considered, as well as other studies that delved into the methodologies to allocate different infrastructures like clinics (Páez et al., 2013) or bike-sharing stations (Bahadori et al., 2021). For example, placing them where travellers find important destinations (POIs and jobs) or designing them differently according to their particular objective.

(Blad et al., 2022) developed and tested a methodology to determine suitable areas for mobility hubs in Rotterdam, incorporating government, end-user and operator perspectives. The authors focused on what they called the "regional" mobility hub located outside city centres to act as an intermodal point of transfer. Their methodology considered five criteria that measured location suitability: potential demand at a certain location, hub implementation costs, generalised travel costs to and from the hub, link to surrounding areas, and societal impact. Another study by (Aydin et al., 2022) applied a weighted multicriteria methodology considering a different criterion (public interest, structural suitability, demographic patterns, and accessibility) to select new mobility hub locations in Istanbul. Their results supported a hub location within the city centre near transport facilities to increase intermodality.

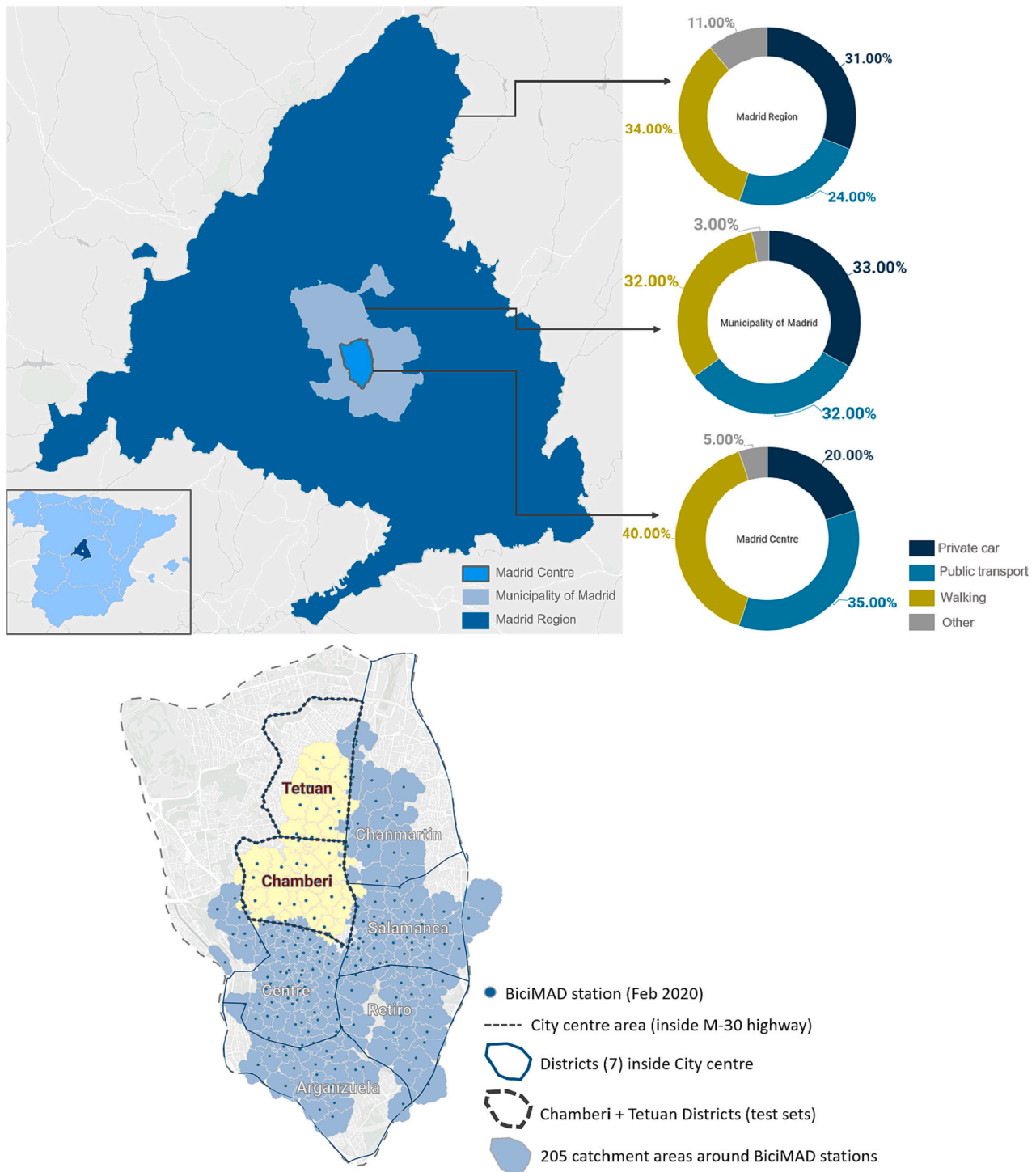


Fig. 1. Madrid's city centre as study case. Source: own elaboration.

Similarly, (Tran and Draeger, 2021) proposes a methodology that integrates network science and urban data analytics to spatially locate hubs and calculate performance metrics. These metrics include hub location, capacity, multimodal availability, travel times, and equity based on differential access to hubs by household income. The authors offer a tool for city planners to select urban hubs based on weights that reflect policy priorities and scenarios. The study by (Frank et al., 2021) develops a decision-support tool for rural decision-makers to locate mobility hubs, combining accessibility (access to important points of interest POIs and jobs) and optimisation-based modelling criteria. Their

model sought to improve accessibility planning to POIs by maximising the average share of POI categories that inhabitants may reach within a certain travel time threshold. Additionally, workplaces are considered by maximising the average ratio of travel time by car and the travel time of (intermodal) travel itineraries for rural commuters. (Nair and Miller-Hooks, 2016) presented a bilevel network design model to minimise total travel time as well as costs for implementing mobility hubs. Their model includes decisions on shared mobility service locations and considers vehicle inventories and hub capacity. (Petrovic et al., 2019) proposed a methodology for allocating mobility hubs along a public rail

transport route in a two-step methodology. First, they use a GIS-based approach to determine the best set of potential locations with consideration for population and catchment areas (population covered in a certain area). Second, they propose an optimisation algorithm to provide decisions on potential locations given a predefined number of final locations.

From these previously mentioned studies, we can highlight the use of new sources of data and methodologies to process massive amounts of mobility data. On the topic of micromobility study, efforts have been oriented to understand the spatio-temporal demand patterns. Regarding studies on mobility hub allocation, contributions have been focusing on the proposal of different ways to assess the location problem, which is needed for public and transport planners to allocate resources in an efficient way (where demand is). Even though this is a topic of growing interest, we still do not know enough about it. Therefore, the research gap addressed with our study is oriented to contribute at the same time in two lines of research, by doing both, understanding demand and proposing a method for allocating mobility hubs. Additionally, our paper is relevant at two different levels. First, it analyses more than two different shared modes of transport, leveraging from the most usual “1-vs-1-comparison-style” seen in literature (docked bike vs dockless bikes, bikes vs scooters, etc) as we specifically analysed three modes: bikes, mopeds and scooters. Covering more shared modes is highly relevant when trying to capture the whole mobility dynamics and understating demand. Secondly, when trying to allocate mobility hubs, many of the referenced studies considered only public transport system data, with the exception of (Tran and Draeger, 2021), which considered micromobility parking areas. Our study aims to include variables related to the built environment as well (including public transport infrastructure), but also variables related to micromobility trip arrivals in the modelling process (see list of variables in Table 2).

3. Study case, data, and methods

3.1. Study case

The study area takes place in the city centre of Madrid known as one of Europe's living labs for shared mobility, allowing its residents to be familiar with the emerging transport options, especially micromobility services (Aguilera-García et al., 2020). This area is also known as “Almendra Central” which is the urban area inside the M-30 highway and the core centre of the city. The last mobility survey conducted for Madrid (Comunidad de Madrid, 2018) showed that in the city centre, people move in a more sustainable way compared to the regional modal share (see Fig. 1). The Almendra Central is composed of seven inner districts (Tetuan, Chamberi, Chamartin, Salamanca, Centre, Retiro and Arganzuela) which agglomerate around one million residents. The multiple and varied shared mobility supply, along with a solid public transport system, a great land-use diversity and high population/employment densities has made Madrid an appropriate area for these new services to thrive (Arias-Molinares and García-Palomares, 2020; Fluctuo, 2022; Granda and Sobrino, 2019). In 2019, the shared mobility fleet was estimated to be more than 20.000 vehicles (Arias-Molinares and García-Palomares, 2020; Granda & Sobrino, 2019). These services are usually supported by mobile applications where their clients register and locate vehicles and in the case of Madrid, the whole micromobility fleet is electric.

For our study, we considered three micromobility operators: *BiciMAD*, *Movo*, and *Moving*. *BiciMAD* is Madrid's public bike-share system, in operation since 2014, currently managed by the Municipal Transport Company (EMT) with around 75,000 subscribers (Ayuntamiento de Madrid, 2019). Since its launch in 2014, four expansions have taken place with a total of 264 stations and 2900 bikes. All vehicles in *BiciMAD*'s fleet are equipped with GPS trackers and pedal assistance up to 25 km/h. The second service is called *Movo*, a moped-style scooter-sharing and scooter-sharing service launched in 2018, operating 500

mopeds and 1400 scooters (Polo and González, 2019). Finally, *Moving* is also a moped-style scooter-sharing operator that manages 755 mopeds. The company was operative in Madrid from 2018 to 2020 but is no longer operating in Madrid (Arias-Molinares and García-Palomares, 2020). *BiciMAD* has designated locations where users pick and leave the bicycles at, while dockless services, like *Movo* and *Moving*, offer more flexibility as the vehicles can be picked/returned at any location within a geographic area (also known as geo-fence).

3.2. Data

This research used a dataset composed of information collected from six main different groups of variables (see Table 2):

- **Micromobility trip arrivals:** trip datasets were provided by micromobility operators through established collaboration agreements with *Movo* and *Moving* to access anonymised trip data. *BiciMAD*'s data is publicly shared through an open data portal.¹ For each service, we obtain information related to the trips' origin and destination. The datasets cover the timeframe from June to December 2019 (last semester of 2019). We decided to conduct our analyses considering only trip destinations as previous studies have recommended (Duran-Rodas et al., 2021). The reason behind this choice is that trip arrivals are more closely correlated with the trip purpose than departures.
- **Cycling infrastructure and intermodal stations:** Madrid's cycling infrastructure is collected from the City Hall's open data website² which offers a layer of cycling infrastructure updated until 2014. They categorise cycling infrastructure into two categories according to the level of segregation with respect to traffic flow: 1) partly or fully segregated (“Vías de uso exclusivo o preferente”), and 2) non-segregated (“Vías de uso compartido”). Additionally, in order to consider the location of the main intermodal stations, we added information containing the average number of travellers entering these stations per day. This information was provided through a collaboration agreement with the transport authority of the city (Consorcio Regional de Transportes de Madrid) which manages intermodal stations. Intermodal stations in Madrid are pre-defined by the transport authorities as those transport infrastructures designated to facilitate intermodality (interchange connections) between different modes of public transport. Inside the city centre we can find the following ten intermodal stations: Chamartín, Plaza Castilla, Moncloa, Atocha, Príncipe Pío, Avenida de América, Estación Sur, Nuevos Ministerios, Plaza Elíptica y Sol.

Table 1
Network Centrality measure- closeness normalised.

Measure	Definition	Normalisation
Reach	$Reach [i]^r = \sum_{j \in G - \{i\}, d(i,j) \leq r} W[j]$	$Reach [i]^r norm = \frac{Reach [i]^r}{\sum_{j \in G - \{i\}} W[j]}$
Closeness	$Closeness [i]^r = \frac{1}{\sum_{j \in G - \{i\}, d(i,j) \leq r} (d(i,j) * W[j])}$	$Closeness [i]^r norm = \frac{Closeness [i]^r * Reach [i]^r}{Reach [i]^r}$

Source: Own elaboration based on (Sevtsuk et al., 2016).

¹ BiciMAD's Open Data Portal: [https://opendata.emtmadrid.es/Datos-estaticos/Datos-generales-\(1\)](https://opendata.emtmadrid.es/Datos-estaticos/Datos-generales-(1))

² Madrid City Hall Open Data Portal: <https://datos.madrid.es/portal/site/egob/menuitem.c05c1f754a33a9f4b2e4b284f1a5a0/?vgnextoid=325e827b864f4410VgnVCM2000000c205a0aRCRD&vgnextchannel=374512b9ace9f310VgnVCM10000171f5a0aRCRD&vgnextfmt=default>

Table 2
Variables used for the study.

Variable	Description	Group	Unit	Mean	Standard deviation	Min	Max
Trips_bike_arrivals	Average daily arrivals using BiciMAD bikes inside each 400 m-catchment area			44	25	0	130
Trips_moped_arrivals	Average daily arrivals using mopeds inside each 400 m-catchment area		arrivals	10	6	1	33
Trips_scooter_arrivals	Average daily arrivals using scooters inside each 400 m-catchment area	Mobility		2	1	0	5
Intercity_train	Average daily number of travellers entering a intercity train station		travellers	847	5.606	0	52.950
Intercity_bus	Average daily number of travellers entering a intercity bus station			990	8.275	0	79.713
Closeness_norm	No distance defined = total network considered	Network centrality measures	degree	0,000336	0,000064	0,000191	0,000451
pop_20_49	Total residents between 20 and 49 years old covered inside each 400 m-catchment area	Socio-demographics	inhabitants	1.999	1.565	0	8.825
income	2018 Average annual household income		euros/year	54.388	17.162	26.743	91.933
cycling_infra	Proximity to cycling infrastructure	Proximity to cycling	m	1.101,29	783,11	0,00	3.826,72
seg_cycling_infra	Proximity to segregated cycling infrastructure			150,03	326,50	0,00	2.345,22
nonseg_cycling_infra	Proximity to non-segregated cycling infrastructure	infrastructure		951,27	741,50	0,00	3.645,78
employment	Number of employees covered inside each 400 m-catchment area			3.588	2.668	276	16.559
Employ_edu	Number of employees in the educational sector covered inside each 400 m-catchment area			193	194	0	1.060
Employ_health	Number of employees in the health sector covered inside each 400 m-catchment area			180	182	0	992
Employ_hotel	Number of employees in the hospitality sector covered inside each 400 m-catchment area	Employment	employees	417	385	18	2.950
Employ_leisure_entertain	Number of employees in the leisure/entertainment sector covered inside each 400 m-catchment area			94	118	0	663
Employ_office	Number of employees in offices covered inside each 400 m-catchment area			1.232	1.361	48	9.264
Employ_retail	Number of employees in the retail sector covered inside each 400 m-catchment area			422	403	0	2.526
LU_greenareas	Parks and green areas			19.760,47	36.975,39	0,00	246.786,49
LU_industrial	Industrial			7.086,96	14.954,41	0,00	86.453,98
LU_entertain	Leisure and hotels			8.933,26	15.669,80	0,00	95.197,10
LU_office	Offices	Land use	m2	44.659,56	48.507,00	1.293,43	290.493,99
LU_Residential	Residential			245.886,12	156.453,19	0,00	872.932,70
LU_Retail	Retail/commerce			33.596,89	23.046,01	224,99	128.040,71
LU_sport	Sport areas			2.462,85	7.985,61	0,00	68.743,69
cat_accommodation	Accommodation = lodgings			0	0	0	1
cat_admin	Administration and public institutions = police, city hall, courthouse, embassy and local government office			1	1	0	9
cat_atm	ATM			1	2	0	10
cat_bar_rest	Bars and restaurants = bar, café, night club and restaurants			4	4	0	18
cat_cul_lei	Culture and leisure = amusement park, aquarium, art gallery, bowling alley, casino, library, movie theatre, museum and stadium			1	1	0	4
cat_education	Education = School, secondary school and university			0	0	0	2
cat_health_well_beu	Health, wellness and beauty = Beauty salon, dentist, doctor, drugstore, hair care, hospital, pharmacy, physiotherapist, veterinary care, gym and spa	Points of interest (18 specific categories)	Number of POIs	8	7	0	40
cat_home_service	Home service = Electrician, locksmith, moving company, painter, plumber and roofing contractor			0	0	0	2
cat_home_food_deli	Home service- food delivery = meal delivery			1	1	0	8
cat_open_air	Open air = Park and cemetery			0	1	0	4
cat_open_air_acco	Open air accommodation = campground			0	0	0	1
cat_religious	Religious = Church and mosque			0	1	0	3
cat_shop_basi	Shopping basic = Insurance agency, bakery, bank, clothing store, convenience store, furniture store, hardware store, home goods store, laundry, pet store, post office, real estate agency, shoe store, supermarket and lawyer			8	7	0	33
cat_shop_mall	Shopping department store mall = department store and shopping mall			0	0	0	3
cat_shop_optional	Shopping optional = accounting, travel agency, bicycle store, bookstore, car dealer, car rental, car repair, car wash, electronics store, florist, jewellery			6	5	0	30

(continued on next page)

Table 2 (continued)

Variable	Description	Group	Unit	Mean	Standard deviation	Min	Max
cat_tour_attrac	store, liquor store, meal takeaway, movie rental, storage and store						
cat_transp_private	Touristic attractions = touristic attraction			0	1	0	3
cat_transp_public	Transport-private = parking and gas station Transport-public = bus station, subway station, train station and transit station			0	0	0	3
cat_Dining	Dining = Bar, café, restaurant and meal delivery Entertainment = night club, amusement park, bowling alley, casino, movie theatre, stadium and spa			0	1	0	10
cat_Entertainment	Dining = Bar, café, restaurant and meal delivery Entertainment = night club, amusement park, bowling alley, casino, movie theatre, stadium and spa			5	4	0	22
cat_Public_facilities	Public facilities = Police, city hall, courthouse, embassy, local government office, library, school, secondary school, university, hospital, cemetery, church, mosque, airport, bus station, subway station, train station, transit station			1	1	0	7
cat_Shopping	Shopping = beauty salon, drugstore, hair care, pharmacy, physiotherapist, electrician, locksmith, moving company, painter, plumber, roofing contractor, insurance agency, bakery, clothing store, convenience store, furniture store, hardware store, home goods store, laundry, pet store, post office, real estate agency, shoe store, supermarket, accounting, travel agency, bicycle store, book store, car dealer, car rental, car repair, car wash, department store, electronics store, florist, jewellery store, liquor store, meal takeaway, movie rental, storage, store, lawyer, shopping mall and gas station	Points of interest (5 general categories)	Number of POIs	19	14	0	77
cat_tour_attrac	Touristic attractions = aquarium, art gallery, museum, park, tourist attraction			1	1	0	6

Source: own elaboration.

- Land use and employment: Land use data is provided by the Directorate General for Cadastre in Spain (Cadastre) with built entities of the study area (buildings). The databases define the surface area [m²] of each type of land use in the year 2020.
- Points of interest (POIs): A layer of more than 30.000 POIs is obtained from Google Places API (updated up until 2020). We grouped them according to two categories: 1) 18 specific categories, and 2) five general categories. The aggrupation was done considering similar activities (see Table 2).
- Socio-demographic: Census data is obtained from the National Institute of Statistics (INE) which includes the population count for 2019. Additionally, income data is provided by the City of Madrid's open data website, containing the average annual home income by census section of Madrid for 2018.
- Centrality measures: We calculate a network centrality measure called "closeness" in its normalised form. It indicates how close a node *i* is to all other nodes in the network. It is calculated using the following formulas (See Table 1):

4. Methods

The proposed method aims to estimate potential micromobility ridership in new areas of the city and use this finding to allocate new mobility infrastructure. To that end, we start with the data collection and cleaning process and then follow a two-stage process: (1) stage-identification of common spatial factors associated with micromobility usage, and (2) stage- estimation of micromobility usage (see Fig. 2).

4.1.1. Data collection and cleaning

First, we processed, cleaned and prepared the datasets. For all services, the initial cleaning process involved keeping only trips with distances between 100 m and 70 km and travelled time between 60 s and 2

h as recommended in previous studies (Jaafar, 2022; McKenzie, 2019). This was necessary in order to eliminate erratic data, unrealistically long-distance trips (probably GPS errors), and redistribution trips (as only BiciMAD tagged them). As we had the total arrivals of the last semester of 2019, we divided the total amount of arrivals in the six-month period by 180 days (30 days * 6 months = 180 days/semester) in order to obtain the average daily arrivals per mode. Once the data is cleaned, we created 400 m-network-based catchment areas around each of the 205 BiciMAD stations that were operative until February 2020.

As a result, we obtained 205 catchment areas from the bike sharing stations (our spatial unit of analysis). These service areas are calculated around a 400 m walking distance in the transport network and do not overlap each other. The choice of 400 m was determined based on previous studies that stated that it is an acceptable walking distance (Aguilera-García et al., 2020; Tran and Draeger, 2021; Zhao et al., 2021). The 205 catchment areas are used to aggregate trip arrival information and the rest of the variables. Any shared bike, moped, or scooters' arrival point that falls within each of the 205 catchment areas is counted. As the catchment area sizes are smaller in the city centre where the density of BiciMAD stations is higher, the aggregation of the different variables is affected by the area of the catchment area. In order to make a comparable analysis between the different modes, we calculated each variable density per square metre (variable/m²). In other words, we divided all the variables that are area-related (with the exception of income and closeness), by the catchment area obtaining the unit of the variable per square metre (m²).

4.1.2. First stage: Identification of common spatial factors associated with micromobility usage

Following data preparation, we used the methodology synthesised in Fig. 3. In this stage, we follow two approaches. The first approach identifies the common spatial factors associated with micromobility usage by each micromobility mode individually, and in a second approach, we develop a combined variable that represents the three shared services together. Variables are preselected using Pearson's

correlation coefficient threshold of 0.7 between all variables studied as done in (Zhao et al., 2021). In the first approach, variables with the highest correlation with trips arrivals were initial inputs for the stepwise OLS regression models for each shared service (bike, moped and scooter). The dependent variable was the count of trip arrivals per m2 (bike, moped and scooter arrivals) and the independent variable considered were the built environment variables collected for each catchment area.

As a second approach, we used PCA to identify a component that represents the usage of the three modes together (combined model). PCA is an econometric measure that would serve for dimensionality reduction and for combining multiple ridership data of multiple modes, since usually, the different services present a relative high multi-correlation among them. The data distribution of the dependent variables in each model and their relationship to each other can be seen in Fig. 4. Addressing multiple micromobility services would require the creation of a new latent variable called “micromobility usage” based on the first component of the PCA (PC1). The resulting PC1 intends to combine most of the variance (in this case, 74,12%) of trip arrivals of the three micromobility services. It is worth highlighting that the first component does not include the entire variance but the biggest proportion of it in a single variable. Furthermore, our main goal is not to capture the whole variance in the first principal component but to identify common factors with the majority of the variance and further estimate “hot or cold spots” (for decision making on potential location of mobility hubs) rather than the exact or precise estimation.

PCA aims to reduce dimensionality and weigh all observations based on a composite index variable (X. Bai et al., 2022; Patil and Sharma, 2022). In most scenarios, PCA is applied to transform a high-dimensional dataset into a lower-dimensional dataset by using only the first few PCs, so that dimensionality is reduced with minimal loss of information. Its central idea is creating an index variable, in our case *micromobility usage*, from a set of correlated variables. It is commonly used to convert collinear variables into several, linearly uncorrelated variables named principal components (PCs). This is done by finding a new coordinate system, so that the information of the data is mainly concentrated on the new axes. In this conversion, each PC is a linear combination of the original variables, as shown in Eq. (1). After listing the eigenvalues of the correlation matrix of the original dataset in descending order, then the *i*th PC is associated with the *i*th eigenvalue, and the corresponding eigenvector $(\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{ip})$ is used to summarise the original variables. The PC associated with the largest eigenvalue, that is, the first PC, captures the most information.

$$PC_i = \alpha_{i1}X_1 + \alpha_{i2}X_2 + \dots + \alpha_{ip}X_p \tag{1}$$

If *n* PCs are retained, they need to be weighted to obtain a total score, which, in our case, is going to be the approximation of *micromobility usage*. The weight of the *k*th PC is given by Eq. (2), and the final total score is given by Eq. (3):

$$W_k = \lambda_k / (\lambda_1 + \dots + \lambda_n) \tag{2}$$

$$Total\ score = \sum_{k=1}^n PC_k W_k \tag{3}$$

Where λ_k represents the associated eigenvalue of the *k*th PC.

Once we conducted the PCA and obtained the scores, we used these scores as the dependent variable for a new model as representative of micromobility usage. Consequently, this first part of the methodology results in three independent models (bike, moped and scooter model) and one combined model, allowing us to identify the common associated spatial factors in each particular mode and spatial factors associated with micromobility usage in general.

4.1.3. Second stage: Estimation of micromobility usage

The second stage involves testing the resulting models and comparing which one offered a better fit in comparison with historical data. We started by selecting two districts of the Almendra Central as test set (Chamberi and Tetuan). We decided to not select the centre district as it functions in a very particular way: it concentrates the highest amount of cultural, touristic and entertainment facilities and it is gentrified (very few living here with very high incomes) (Comunidad de Madrid, 2018). We selected Chamberi district because it is a central residential area of Madrid characterised by mixed land use, middle-high income population and where most of the available cycling infrastructure is located. We also selected Tetuan as it is a middle-low-income area, with diverse foreign population (Latin, Asian, etc.), high mixed land uses and scarce cycling infrastructure. For both districts, we divided the complete dataset (205 stations) into two separate ones: 1) train set: 88% and 95% of the stations and 2) test set: 12% and 5% of the stations corresponding to the Chamberi and Tetuan Districts respectively (see Fig. 5).

Choosing complete districts as test sets, allowed us to test our model in a controlled areas without doing the selection randomly. We applied the resulting equations from the previous stage to the training sets and mapped results using kernel density to identify hot spot areas where the mobility hub could be located. We compared the five resulting maps: 1) estimated bike arrivals, 2) estimated moped arrivals, 3) estimated scooter arrivals, 4) sum of estimated arrivals (3 modes), and 5) estimated PCA micromobility usage scores. We contrasted these resulting maps with the historical data of arrivals to identify the best fitting

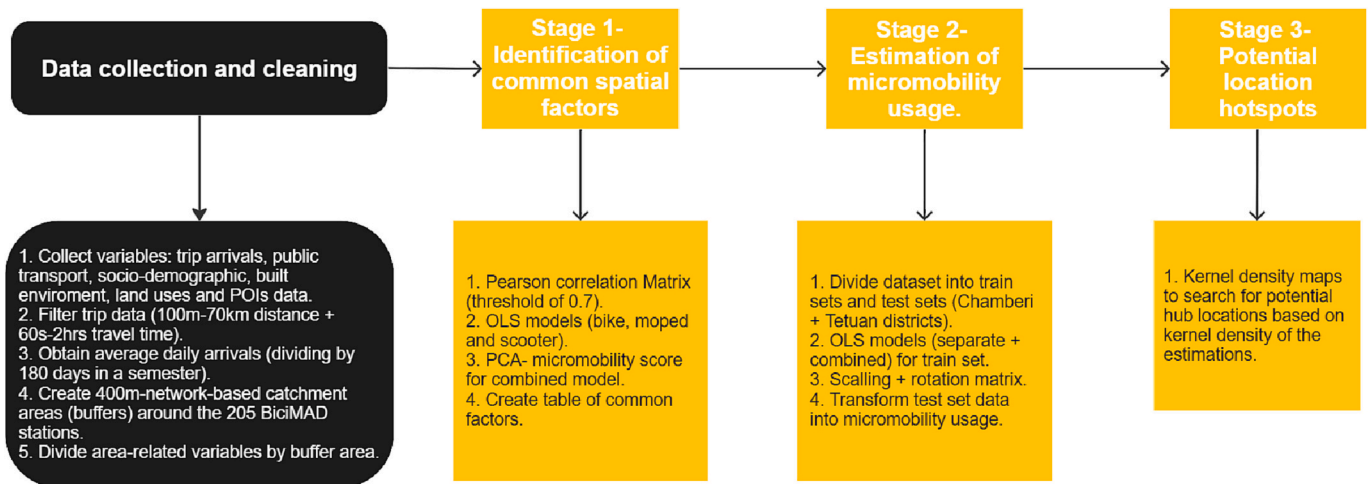


Fig. 2. General methodology. Source: own elaboration.

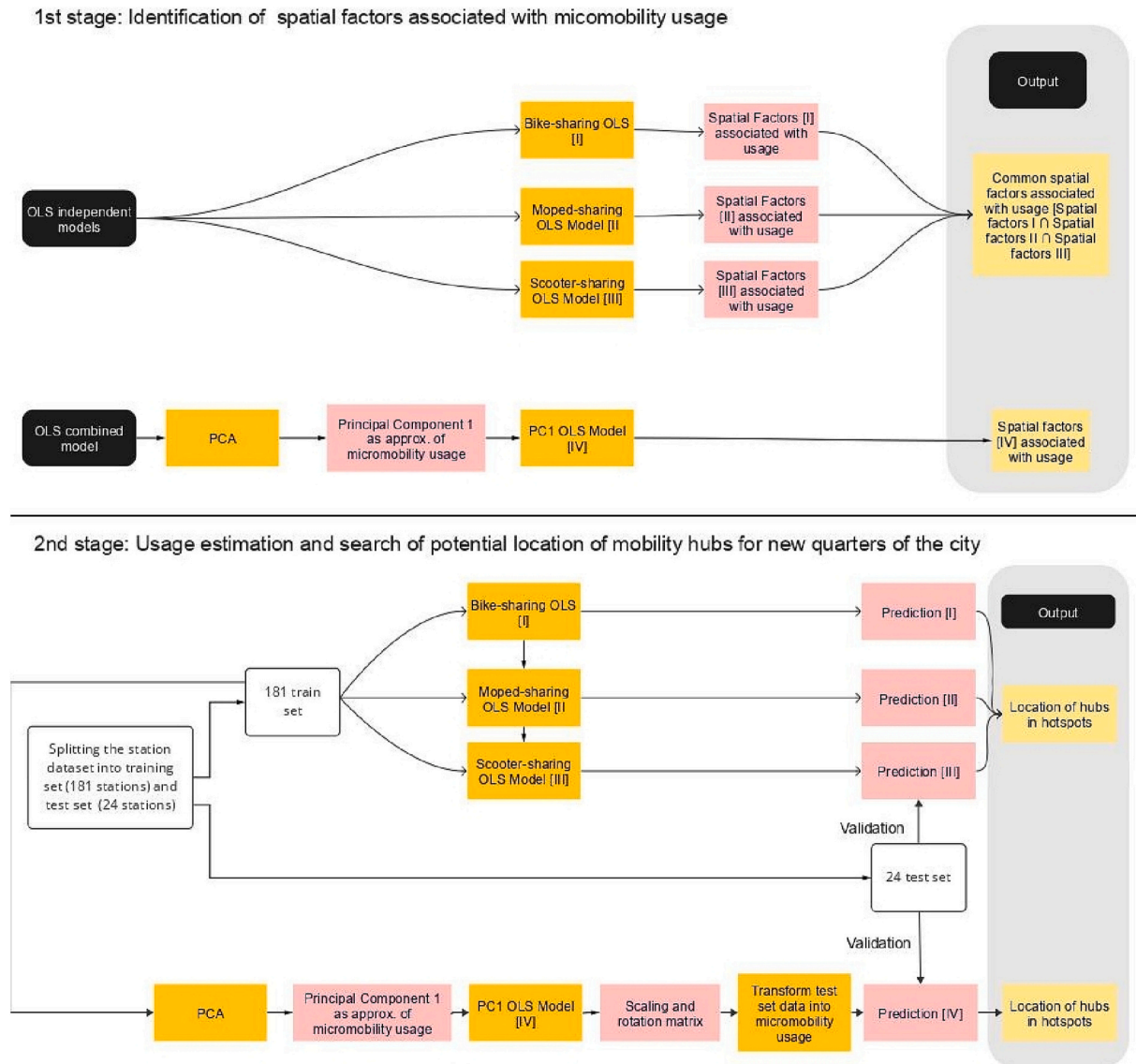


Fig. 3. Proposed methodology for micromobility usage analysis. Source: own elaboration.

model.

Finally, we applied all the models to the test sets in Chamberi (24 stations) and Tetuan (11 stations) and contrasted the results with historical data. To compare the micromobility usage scores estimated by the combined model with those of the test sets, the score for the arrival data of the test sets is calculated by projecting them onto the same space as the training data. For this, we scaled the test sets data using scaling information of the training sets and then used the rotation matrix of the PCA from the training sets. Once the validation of the model is observed, we could map hot spot areas for potential mobility hub locations.

4.1.4. Third stage: Identifying potential locations

After estimating ridership, kernel density maps show potential hot spots where new hubs can potentially be established. Kernel density maps calculate a magnitude-per-unit area from point or polyline features using a kernel function to fit a smoothly tapered surface to each point or polyline. In this case we have used as layer the service area (point layer) and the magnitude is the micromobility usage score results. The main idea is that “hot areas” represent the areas where ridership is expected to be highest for the various modes of transportation. Typically, hubs cannot be placed where the highest ridership is expected due to

insufficient available space and conflicts with other services or infrastructure. Therefore, we present “hot areas” that can be selected by decision makers to find a suitable point to build the hub.

5. Results

5.1. Identifying common key determinants on micromobility usage

Our main results for the first stage of the study are described and summarised in Table 3. We have found that for all modes, the common associated determinants are essentially three: 1) station's density (closeness), 2) the presence of cycling infrastructure, and 3) variables related to commercial land uses (employment in retail and points of interest of shopping). Hence, our results yield that people are attracted to travel to places where more Bicimad stations are offered (near the city centre) and where there is abundant mixed land use and diverse activities available. We also highlight the importance of the presence of cycling infrastructure as, according to current legislation, this is the space where scooters can circulate while mopeds' flow is assigned to the road. Therefore, the presence of cycling infrastructure and the offer of commercial sites like restaurants, stores, etc., make an area highly

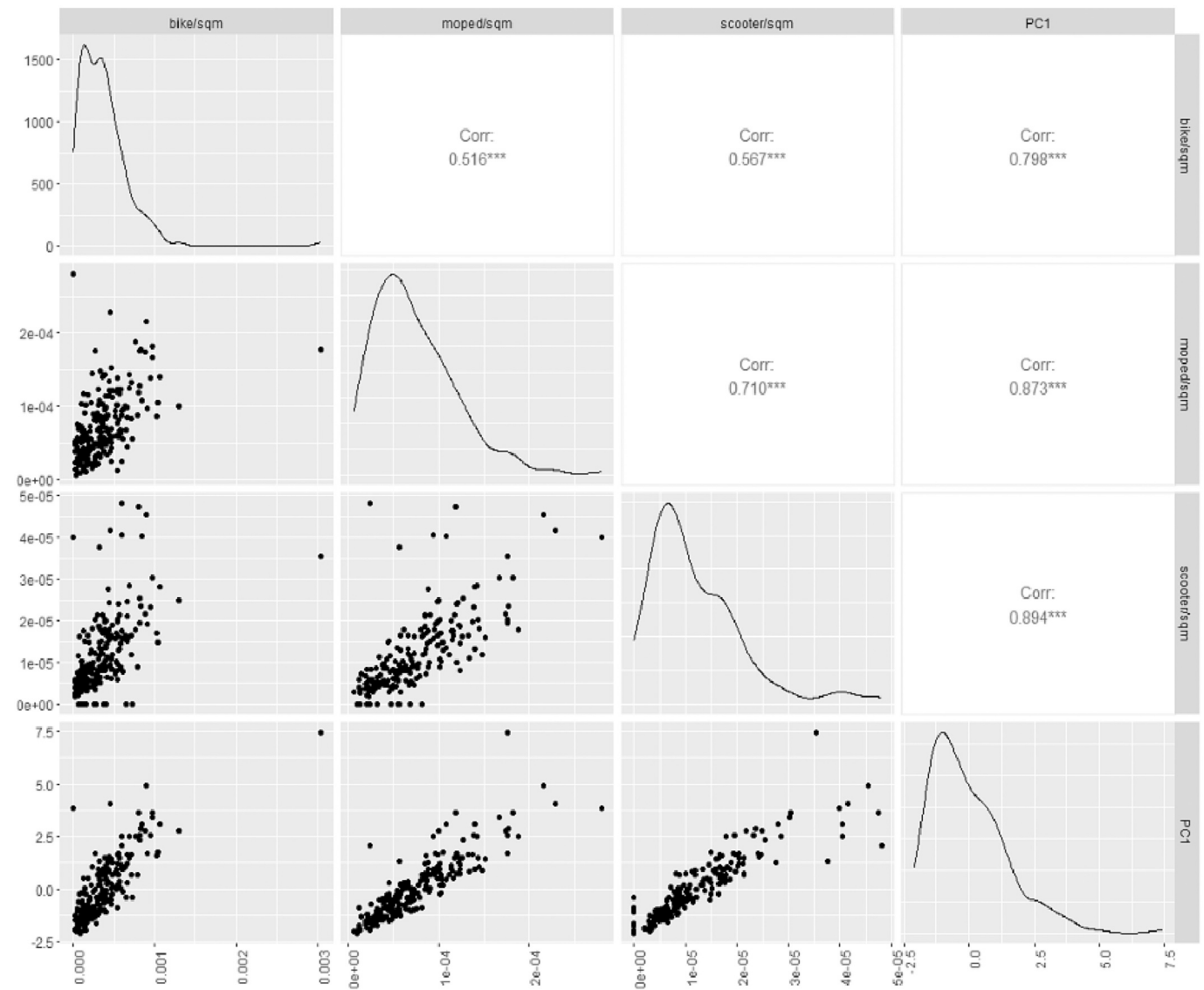


Fig. 4. Distribution of the dependent variables. Source: own elaboration.

attractive to arrive with micromobility services. All the models and their coefficients are shown in Table 3, and the combined model (PC1) offers the best fit ($R^2 = 0,66$).

In the case of bikes, the presence of a population between the ages of 20 and 49 years old is significant as well as culture, leisure, and entertainment points of interests. In the case of mopeds, other variables that are associated with their usage are office land use and employees in the hospitality sector. In the case of scooters, we observe that variables associated with their usage are related to intermodal train stations and employees in the hospitality and entertainment sector. Last, in the combined model, we obtained significant variables from the presence of a population between the ages of 20–49 years old, the employment in the hospitality and office sector and culture and leisure points of interest, especially in areas near the city centre.

After comparing common determinants between the three separate models, we continue by comparing these with the significant ones from the combined model. In Table 3, we have highlighted the common variables repeated in each of the four models and we have assigned similar colours to the ones that relate to the same land use or point of interest. From our results, we can infer commercial and office land use are highly relevant attractors of micromobility trips. Additionally,

entertainment, cultural sites, and hotels are also important. Thus, we can state that bikes, mopeds and scooters are used for both commuting and recreational activities. The higher the mix of land uses and the more central a point of interest is, the higher the probability that someone will arrive using a micromobility service.

5.2. Identifying the best-fitting model to allocate new mobility hubs

Once we identified the associated determinants of micromobility's usage, we now focus on finding the best location for mobility hubs. Fig. 6 shows the resulting predictions when applying the different models to the 181 training stations without Chamberi district. Based on these models, similarities arise between predictions. Bike and scooter predictions are similar by estimating the best locations in the city centre, while moped predictions highlight northern areas where many working sites are located. In the bottom maps (Fig. 6.d, 6.e and 6.f), we can see that estimated arrivals (Fig. 6.d) and the real arrivals (Fig. 6.f) give more priority to the city centre with the latter prioritising the locations more to the north of the centre district. Based on the associated factors, Fig. 6.e offers the best location according to the micromobility usage score which prioritises the city centre. Additionally, Fig. 7 shows the resulted

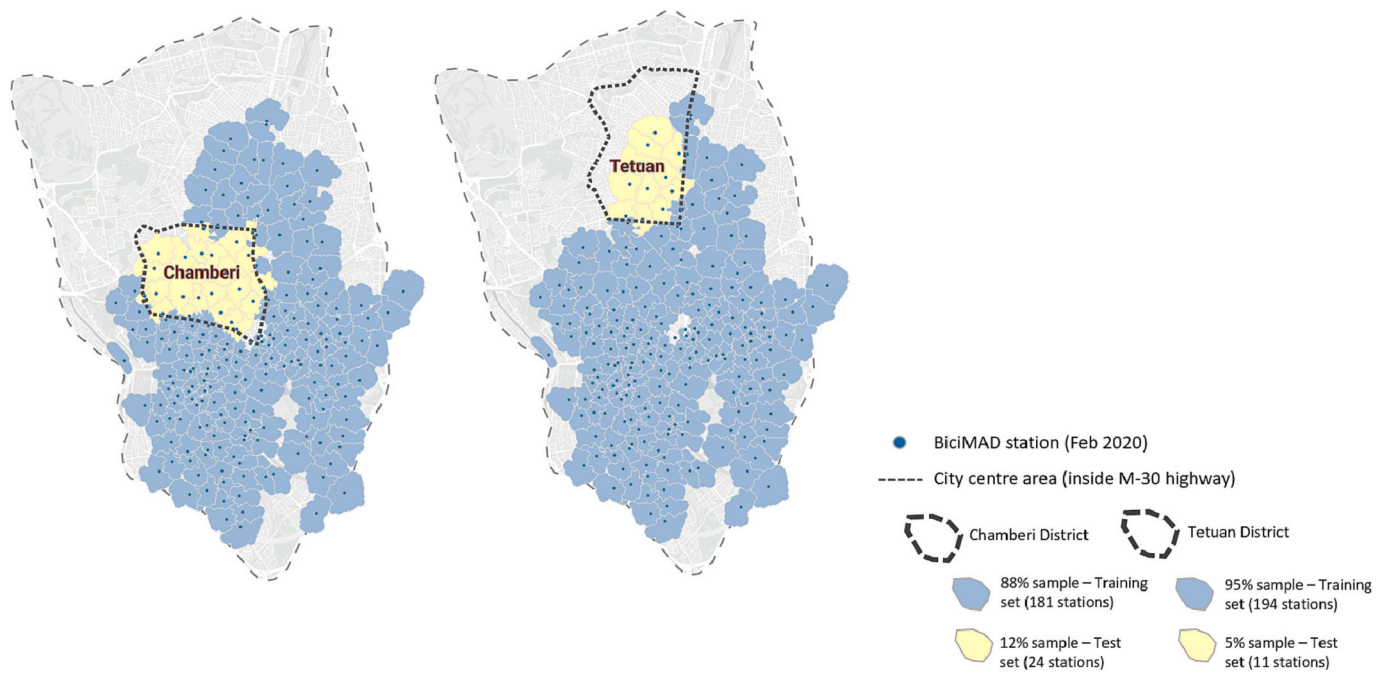


Fig. 5. Map of the 205 stations divided in training and test sets for both Chamberi and Tetuan districts. Source: own elaboration.

Table 3 Key determinants influencing micromobility services.

Dependent variable		Independent variable	Coefficient	StdError	t-Statistic	Probability	Robust SE	Robust t	Robust Pr	VIF
Bike arrivals per day		Intercept	-0.000383	0.000	-4.048	0.000*	0,000	-5,277	0,000*	-----
Akaike's Information Criterion (AICc)	-2838,538	Closeness	1,526718	0,280	5,449	0,000*	0,318	4,798	0,000*	1,236
Adjusted R-Squared	0,445	Population (20-49 years old)	0,008778	0,002	4,105	0,000*	0,002	4,308	0,000*	1,058
Joint F-Statistic	28,233	Segregated cycling infrastructure	0,023240	0,010	2,363	0,019*	0,009	2,669	0,008*	1,129
Joint Wald Statistic	194,078	Employment- retail	0,008595	0,003	2,811	0,005*	0,004	2,049	0,042*	1,403
Koenker (BP) Statistic	58,398	Culture & Leisure (cat19)	7,744891	1,847	4,194	0,000*	3,512	2,205	0,029*	1,294
Jarque-Bera Statistic	886,289	Entertainment (cat6)	5,262237	2,006	2,623	0,009*	4,647	1,132	0,259	1,246
Moped arrivals per day		Intercept	-0.000011	0.000	-0.703	0.483	0.000	-0.887	0.376	-----
Akaike's Information Criterion (AICc)	-3647,437	Closeness	0,203398	0,046	4,378	0,000*	0,041	4,967	0,000*	1,758
Adjusted R-Squared	0,499	Income	0	0.000	-2.356	0.019*	0.000	-2.341	0.020*	1.298
Joint F-Statistic	34,927	Land use- Office	0,000032	0,000	4,684	0,000*	0,000	3,144	0,002*	1,412
Joint Wald Statistic	168,793	Cycling infrastructure	0,001439	0,001	2,758	0,006*	0,001	2,628	0,009*	1,202
Koenker (BP) Statistic	47,097	Employment- hotels	0,001523	0,001	2,198	0,029*	0,001	1,800	0,073	1,949
Jarque-Bera Statistic	116,267	Shopping (cat6)	0,112776	0,027	4,185	0,000*	0,035	3,268	0,001*	1,195
Scooter arrivals per day		Intercept	-0.000011	0.000	-4.323	0.000*	0.000	-4.869	0.000*	-----
Akaike's Information Criterion (AICc)	-4346,117	Closeness	0,047324	0,008	5,796	0,000*	0,008	6,114	0,000*	1,640
Adjusted R-Squared	0,604	Train departures	0,000020	0,000	4,113	0,000*	0,000	9,222	0,000*	1,041
Joint F-Statistic	52,777	Cycling infrastructure	0,000212	0,000	2,264	0,024*	0,000	2,266	0,024*	1,168
Joint Wald Statistic	1229,486	Employment- hotels	0,000629	0,000	5,107	0,000*	0,000	3,789	0,000*	1,860
Koenker (BP) Statistic	32,982	Employment- entertainment	0,001074	0,000	2,737	0,006*	0,001	2,135	0,034*	1,342
Jarque-Bera Statistic	162,877	Shopping (cat6)	0,012895	0,005	2,646	0,008*	0,006	2,203	0,029*	1,181
PC1		Intercept	-3,825945	0,365	-10,484	0,000*	0,295	-12,991	0,000*	-----
Akaike's Information Criterion (AICc)	521,030	Closeness	6566,644912	1172,004	5,603	0,000*	1179,102	5,569	0,000*	1,660
Adjusted R-Squared	0,663	Population (20-49 years old)	41,689360	8,119	5,135	0,000*	8,767	4,755	0,000*	1,171
Joint F-Statistic	58,359	Cycling infrastructure	46,739071	13,689	3,414	0,001*	12,253	3,814	0,000*	1,228
Joint Wald Statistic	419,389	Employment- retail	41,762304	11,932	3,500	0,000*	14,567	2,867	0,005*	1,640
Koenker (BP) Statistic	30,375	Employment- hotels	90,067239	17,679	5,095	0,000*	23,514	3,830	0,000*	1,883
Jarque-Bera Statistic	116,861	Employment -Office	17,358206	6,447	2,693	0,008*	7,054	2,461	0,015*	1,500
		Culture & Leisure (cat19)	13970,452560	6477,110	2,157	0,032*	8655,715	1,614	0,108	1,222

* Statistically significant p-value (p < 0,01).

Source: own elaboration.

kernel density maps elaborated for the test set of Chamberi.

We also calculated the normalised root mean squared error (RMSE) using min-max scaling to compare the models since we work with different scales. To validate our approach, we applied the methodology again with another district, in this case, Tetuan as the test set. Table 4 shows that the most similar model with historical ridership data (better fit) is obtained by the moped OLS model (model 2 for Tetuan), while the best model for overall micromobility usage is model 5 (combined model-

PC1 OLS model). Thus, the combined model, using micromobility data altogether, can be seen as more robust.

6. Discussion

Based on this methodology, we can use micromobility usage scores to identify the best location for a possible mobility hub, using the areas with the highest score (dark purple areas in the kernel maps). Results are

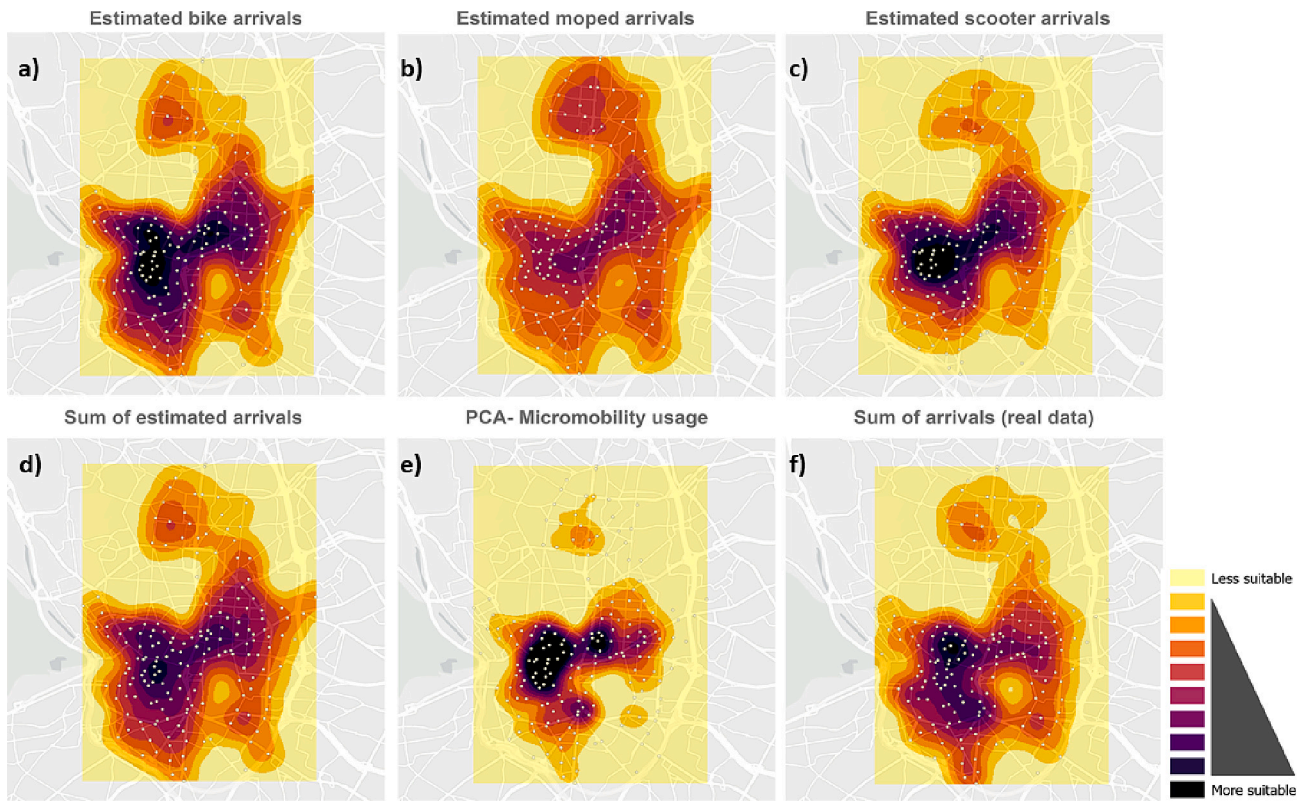


Fig. 6. Results of usage estimates according to the different models (training set of Chamberi-181 stations). Source: own elaboration.

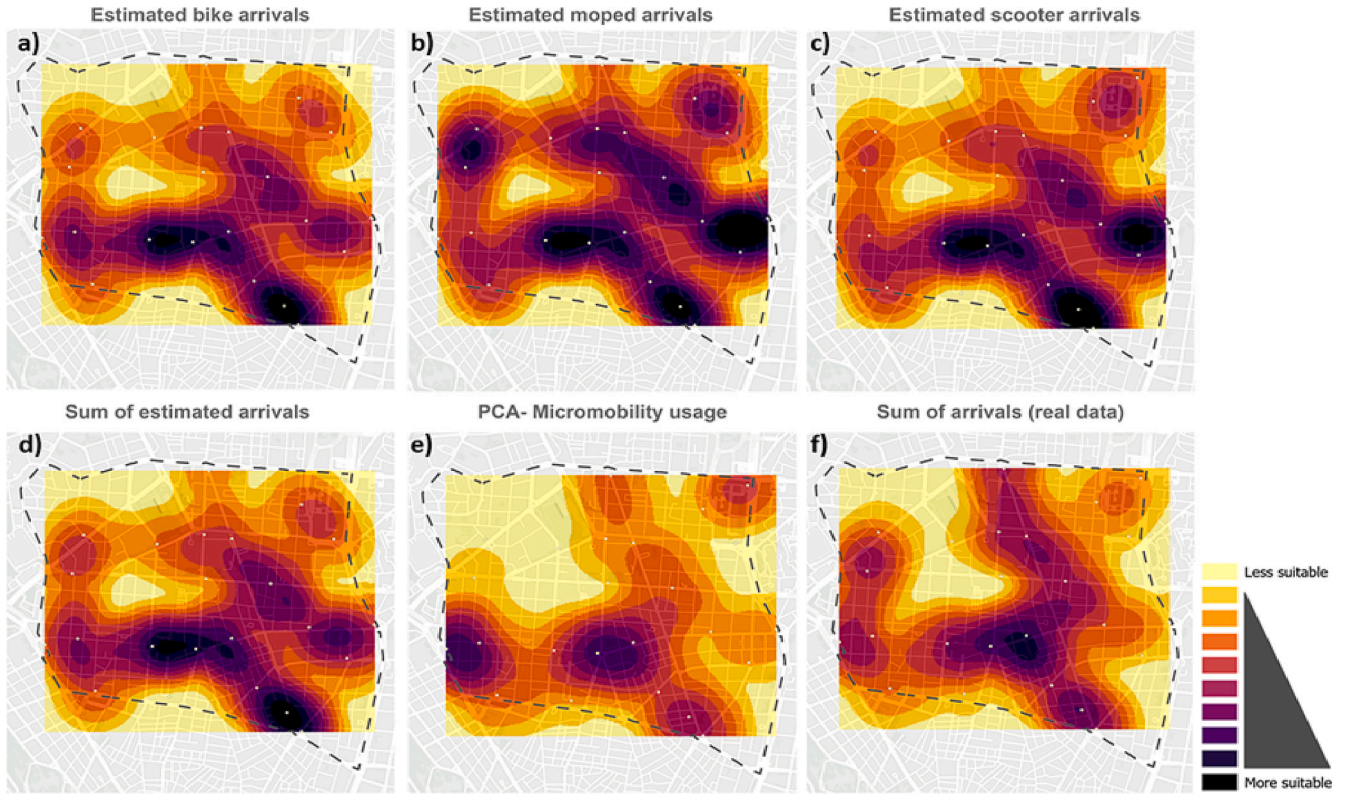


Fig. 7. Results of usage estimates according to the different models (Test set of Chamberi- 24 stations). Source: own elaboration.

Table 4
Normalised RMSE results.

Model	Description	Normalised RMSE (Chamberi)	Normalised RMSE (Tetuan)
1	Bike OLS model	0,297	0,377
2	Moped OLS model	0,267	0,161
3	Scooter OLS model	0,223	0,233
4	Sum of arrivals model	0,271	0,301
5	PC1 OLS model	0,241	0,172

Source: own elaboration.

consistent with previous research that state the need to allocate this infrastructure in areas with mixed use and abundant points of interests (Aono, 2019; Aydin et al., 2022; comoUK, 2021; Tran and Draeger, 2021). In Madrid, we see that the most attractive areas are those that concentrate residential, mixed-residential, commercial, and work-related land uses that are closely linked to an intense usage. This methodology could help planners in other cities to begin exploring areas for future mobility hub locations. The results could vary based on the data available and the local context of the city. Our main contribution relies on offering a methodology applied in Madrid and including different shared modes to explore key determinants of micromobility usage and identify potential locations for mobility hubs. The main idea behind PCA is dimensionality reduction, i.e. to merge the three variables of ridership/usage into one variable based on the high correlation between them. We departed from the hypothesis that PCA (micromobility usage score) might predict better than the three variables separated (bike, moped and scooter arrivals), and we have confirmed this in this paper. We considered the PC1 as a proxy of the different micromobility modes usage altogether. This approach resulted in obtaining the most fitting-model in comparison with the single-mode models.

The resulting maps offer a general area of where a potential mobility hub could be located based on the historical micromobility usage data, rather than a specific location. In other words, our approach highlights potential sites rather than selecting a specific location for the nodes. This approach is based on historical usage which means that micromobility services are recommended to be placed where the current type of user groups perform different activities (e.g., living, working). Because of this, the possibility of offering them to other social groups, such as vulnerable populations, could be hindered (Duran-Rodas et al., 2021).

We would like to highlight that our main goal was to understand the main built environment factors associated with the usage of different micromobility modes. At the same time, we aimed to explore how multiple micromobility modes can be modelled together. For this reason, using other (complex) machine learning techniques is out of the scope of this research, since the focus is not purely on predicting precise numbers but on identifying associated factors and hotspots for potential locations. One of the main challenges in this research was combining station-based micromobility services with free-floating ones. In order to overcome this problem, we transformed the free-floating services into station-based ones. We counted the trips of the free-floating services within a catchment area from the station. The disadvantage of this approach is that it neglects free-floating trips outside the catchment area. However, this method allowed us to combine the two types of datasets together as if the free-floating services were station-based.

7. Conclusions

In this study, we propose a methodology to include micromobility data into the planning process of mobility hubs. We have found that the station's density, commercial, and cycling infrastructure are common factors associated with the use of micromobility, which we recommend as sites for potential mobility hubs. We have modelled each service and

then proposed a combined model that helps us approach associated factors of all services, without differentiating by mode. Finally, we have applied our models to two test sets of stations in Madrid to contrast resulting predictions with real data available. The micromobility usage score model is the one that showed a better fit with real data and considers these common associated factors.

This methodology could help policy planners and transport authorities in mobility hub location planning, making the investment of resources more efficient. In this case, we tested our models in the Chamberi and Tetuan districts, both which are central areas, where we had arrival data and demonstrated that the micromobility usage score was a good fit for determining the hub location. In future studies in which no trip data is available, planners could use this micromobility usage score tool and the variables of built environment available to estimate potential usage of micromobility services. Although they may not operate in those areas yet, they can offer guidance in the start-up process. The methodology is applicable to similar cities as Madrid as it has not been tested in other kind of city and is therefore a limitation. For transferring the model into other areas, we recommend using our methodology, the city's trip data and its variables to estimate its own combined model. Another limitation of the study is that we consider the average daily arrivals of the aggregated data for the last semester of 2019. Future studies could differentiate between weekdays and weekends and between different time bands along the course of a day.

Additionally, we have adopted a 400 m catchment area as we had the built environment collected for this distance only, but further sensitivity analyses could be conducted with different service area's sizes. Moreover, our initial OLS models were oriented to explore some of the influential factors on micromobility, and hence this part of the research constituted a start point to investigate the topic. But when tested for residual spatial autocorrelation, only the bike-sharing model resulted in residuals not being clustered, while dockless services did have residual spatial autocorrelation. Thus, further research could include other mathematical programming, multicriteria decision techniques or conduct a Geographically Weighted Regression (GWR) to overcome this issue. Future studies could also include other sources of data, such as phone data, in order to delve further into different dynamics that occur throughout the day. Finally, further research could explore our data-driven methodology in different contexts to evaluate its suitability and compare the different determinants of usage.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that may appear to influence the work reported in this paper. The authors do not have permission to share the data.

Data availability

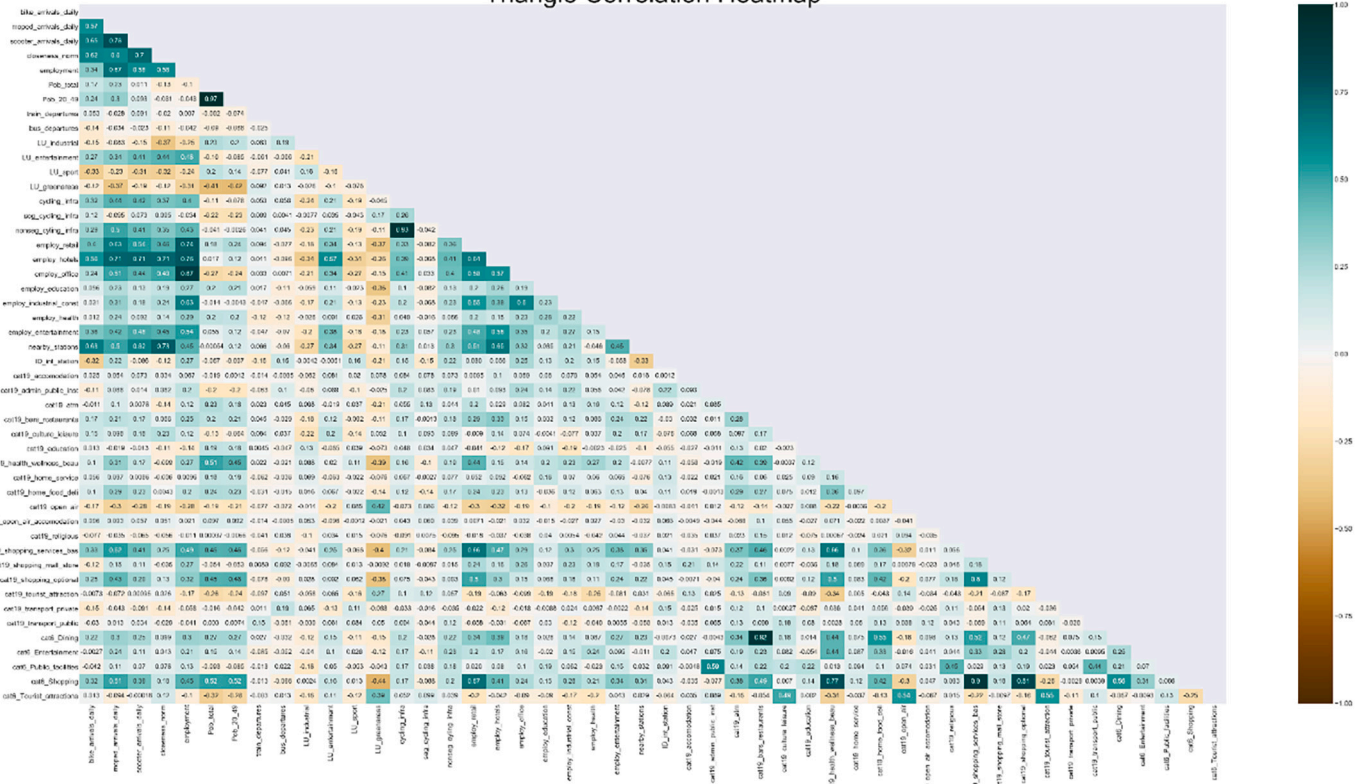
The authors do not have permission to share data.

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Appendix 1. Correlation Matrix (Pearson's coefficient) of the studied variables

Triangle Correlation Heatmap



Source: own elaboration.

References

Aguilera-García, Á., Gomez, J., Sobrino, N., 2020. Exploring the adoption of moped scooter-sharing systems in Spanish urban areas. *Cities* 96 (July 2019), 102424. <https://doi.org/10.1016/j.cities.2019.102424>.

Aono, S., 2019. Identifying Best Practices for Mobility Hubs. https://sustain.ubc.ca/sites/default/files/2018-71%20Identifying%20Best%20Practices%20for%20Mobility%20Hubs_Aono.pdf.

Arias-Molinares, D., García-Palomares, J.C., 2020. Shared mobility development as key for prompting mobility as a service (MaaS) in urban areas: the case of Madrid. *Case Studies on Transport Policy* 8 (3), 846–859. <https://doi.org/10.1016/j.cstp.2020.05.017>.

Aydin, N., Seker, S., Özkan, B., 2022. Planning location of mobility hub for sustainable urban mobility. *Sustain. Cities Soc.* 81 <https://doi.org/10.1016/j.scs.2022.103843>.

Ayuntamiento de Madrid, 2019. Portal de datos abiertos del Ayuntamiento de Madrid. Bicimad.

Bahadori, M.S., Gonçalves, A.B., Moura, F., 2021. A systematic review of station location techniques for bicycle-sharing systems planning and operation. *ISPRS Int. J. Geo Inf.* 10 (8) <https://doi.org/10.3390/ijgi10080554>. MDPI.

Bai, S., Jiao, J., 2020. Dockless E-scooter usage patterns and urban built environments: a comparison study of Austin, TX, and Minneapolis, MN. *Travel Behav. Soc.* 20 (October 2019), 264–272. <https://doi.org/10.1016/j.tbs.2020.04.005>.

Bai, X., Cheng, L., Yang, D., Cai, O., 2022. Does the traffic volume of a port determine connectivity? Revisiting port connectivity measures with high-frequency satellite data. *J. Transp. Geogr.* 102 <https://doi.org/10.1016/j.jtrangeo.2022.103385>.

Bell, D., 2019. Intermodal mobility hubs and user needs. *Soc. Sci. Res.* 8 (2) <https://doi.org/10.3390/socsci8020065>.

Ben-Elia, E., Benenson, I., 2019. A spatially-explicit method for analyzing the equity of transit commuters' accessibility. *Transp. Res. A Policy Pract.* 120, 31–42. <https://doi.org/10.1016/j.tra.2018.11.017>.

Blad, K., de Almeida, Homem, Correia, G., van Nes, R., Anne Annema, J., 2022. A methodology to determine suitable locations for regional shared mobility hubs. *Case Studies on Transport Policy*. <https://doi.org/10.1016/j.cstp.2022.08.005>.

Brand, J., Hoogendoorn, S., Van Oort, N., Schalkwijk, B., 2017. Modelling multimodal transit networks; integration of bus networks with walking and cycling. *MT-ITS Conf.* 750–755 <https://doi.org/10.1109/MTITS.2017.8005612>.

Cheng, L., Wang, K., De Vos, J., Huang, J., Witlox, F., 2022. Exploring non-linear built environment effects on the integration of free-floating bike-share and urban rail transport: a quantile regression approach. *Transp. Res. A Policy Pract.* 162, 175–187. <https://doi.org/10.1016/j.tra.2022.05.022>.

comoUK, 2021. Mobility hubs toolkit. www.como.org.uk/www.como.org.uk.

Comunidad de Madrid, 2018. Documento síntesis: Encuesta domiciliaria de movilidad de la Comunidad de Madrid 2018. <https://www.crtm.es/conocenos/planificacion-e-studios-y-proyectos/encuesta-domiciliaria/edm2018.aspx>.

Corcoran, J., Li, T., Rohde, D., Charles-Edwards, E., Mateo-Babiano, D., 2014. Spatio-temporal patterns of a Public Bicycle Sharing Program: the effect of weather and calendar events. *J. Transp. Geogr.* 41, 292–305. <https://doi.org/10.1016/j.jtrangeo.2014.09.003>.

Duran-Rodas, D., Chaniotakis, E., Antoniou, C., 2019. Built environment factors affecting bike sharing ridership: data-driven approach for multiple cities. *Transp. Res. Rec.* 2673 (12), 55–68. <https://doi.org/10.1177/0361198119849908>.

Duran-Rodas, D., Wright, B., Pereira, F.C., Wulffhorst, G., 2021. Demand And/or Equity (DARE) method for planning bike-sharing. *Transp. Res. Part D: Transp. Environ.* 97 <https://doi.org/10.1016/j.trd.2021.102914>.

Duran-Rodas, D., Navarro-Avalos, F., Hall, J., Nochols, A., Buttner, B., Baguet, J., Susilo, Y., 2022. Deliverable D 3.1 Guidelines for the integration of mobility hubs into the urban space.

Fluctuo. (2022). European Shared mobility index report: Q3 2022.

Frank, L., Dirks, N., Walther, G., 2021. Improving rural accessibility by locating multimodal mobility hubs. *J. Transp. Geogr.* 94 <https://doi.org/10.1016/j.jtrangeo.2021.103111>.

Granda, M., Sobrino, R., Madrid, capital del vehículo compartido con 21.600 unidades. *CincoDías*. https://cincodias.elpais.com/cincodias/2019/06/28/companias/1561742193_436512.html.

Guan, J., Zhang, K., Shen, Q., He, Y., 2020. Dynamic modal accessibility gap: measurement and application using travel routes data. *Transp. Res. Part D: Transp. Environ.* 81 <https://doi.org/10.1016/j.trd.2020.102272>.

Henderson, W., 2019. From Confrontation to Partnership: City Regulation of Micromobility. https://pdxscholar.library.pdx.edu/trec_seminar/182/?utm_source=pdxscholar.library.pdx.edu%2Ftrec_seminar%2F182&utm_medium=PDF&utm_campaign=PDFCoverPages.

- Hernandez, D., 2018. Uneven mobilities, uneven opportunities: social distribution of public transport accessibility to jobs and education in Montevideo. *J. Transp. Geogr.* 67, 119–125. <https://doi.org/10.1016/j.jtrangeo.2017.08.017>.
- Jaafar, S., 2022. Identifying common built environment factors associated with the usage of shared bikes, e-scooters and taxis in Chicago. <https://data.cityofchicago.org/>.
- McKenzie, G., 2019. Urban mobility in the sharing economy: a spatiotemporal comparison of shared mobility services. *Comput. Environ. Urban. Syst.* <https://doi.org/10.1016/j.compenvurbsys.2019.101418>.
- Miramontes, M., Pfertner, M., Rayaprolu, H.S., Schreiner, M., Wulforst, G., 2017. Impacts of a multimodal mobility service on travel behavior and preferences: user insights from Munich's first Mobility Station. *Transportation* 44 (6), 1325–1342. <https://doi.org/10.1007/s11116-017-9806-y>.
- Nair, R., Miller-Hooks, E., 2016. Equilibrium design of bicycle sharing systems: the case of Washington D.C. *EURO J. Transp. Logist.* 5 (3), 321–344. <https://doi.org/10.1007/s13676-014-0055-3>.
- Nickkar, A., Banerjee, S., Chavis, C., Bhuyan, I.A., Barnes, P., 2019. A spatial-temporal gender and land use analysis of bikeshare ridership: the case study of Baltimore City. *City Cult. Soc.* November 2018, 100291. <https://doi.org/10.1016/j.ccs.2019.100291>.
- Oeschger, G., Carroll, P., Caulfield, B., 2020. Micromobility and public transport integration: the current state of knowledge. *Transp. Res. Part D: Transp. Environ.* 89 <https://doi.org/10.1016/j.trd.2020.102628>.
- Páez, A., Esita, J., Newbold, K.B., Heddle, N.M., Blake, J.T., 2013. Exploring resource allocation and alternate clinic accessibility landscapes for improved blood donor turnout. *Appl. Geogr.* 45, 89–97. <https://doi.org/10.1016/j.apgeog.2013.08.008>.
- Patil, G.R., Sharma, G., 2022. Urban quality of life: an assessment and ranking for Indian cities. *Transp. Policy* 124, 183–191. <https://doi.org/10.1016/j.tranpol.2020.11.009>.
- Pérez-Fernández, O., García-Palomares, J.C., 2021. Parking places to moped-style scooter sharing services using GIS location-allocation models and GPS data. *ISPRS Int. J. Geo Inf.* 10 (4) <https://doi.org/10.3390/ijgi10040230>.
- Petrovic, M., Mlinaric, T.J., Semanjski, I., 2019. Location planning approach for intermodal terminals in urban and suburban rail transport. *Intermodal J. Rev.* 31 (1), 101–111.
- Polo, F., González, A., 2019. Cabify integra las motos y los patinetes eléctricos de MOVU en su app. *El Referente*. <https://elreferente.es/tecnologicos/cabify-integra-las-motos-y-los-patinetes-electricos-de-movo-en-su-app/>.
- Purnama, I.B.I., 2018. Spatiotemporal mining of BSS data for characterising seasonal urban mobility dynamics. *Int. J. Adv. Sci. Eng. Inform. Technol.* 8 (4), 1270–1276. <https://doi.org/10.18517/ijaseit.8.4.6510>.
- Reck, D.J., Martin, H., Axhausen, K.W., 2022. Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility. *Transp. Res. Part D: Transp. Environ.* 102 <https://doi.org/10.1016/j.trd.2021.103134>.
- Rongen, T., Tillema, T., Arts, J., Alonso-González, M.J., Witte, J.J., 2022. An analysis of the mobility hub concept in the Netherlands: historical lessons for its implementation. *J. Transp. Geogr.* 104 <https://doi.org/10.1016/j.jtrangeo.2022.103419>.
- Sevtsuk, A., Mekonnen, M., Kalvo, R., 2016. *Urban Network Analysis: Toolbox for ArcGIS 10/10.1/10.2*. doi:10.1.
- Shaheen, S., Cohen, A., 2019. Shared Micromobility Policy Toolkit: Docked and Dockless Bike and Scooter Sharing. <https://doi.org/10.7922/G2TH8JW7>.
- Steiner, K., Irnich, S., 2020. Strategic planning for integrated mobility-on-demand and urban public bus networks. *Transp. Sci.* 54 (6), 1616–1639. <https://doi.org/10.1287/trsc.2020.0987>.
- Tran, M., Draeger, C., 2021. A data-driven complex network approach for planning sustainable and inclusive urban mobility hubs and services. *Environ. Plann. B Urban Analyt. City Sci.* 48 (9), 2726–2742. <https://doi.org/10.1177/2399808320987093>.
- Younes, H., Zou, Z., Wu, J., Baiocchi, G., 2020. Comparing the temporal determinants of dockless scooter-share and station-based bike-share in Washington, D.C. *Transp. Res. A Policy Pract.* 134 (August 2019), 308–320. <https://doi.org/10.1016/j.tra.2020.02.021>.
- Zhao, D., Ong, G.P., Wang, W., Zhou, W., 2021. Estimating public bicycle trip characteristics with consideration of built environment data. *Sustainability (Switzerland)* 13 (2), 1–13. <https://doi.org/10.3390/su13020500>.
- Zhu, R., Zhang, X., Kondor, D., Santi, P., Ratti, C., 2020. Understanding spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility. *Comput. Environ. Urban. Syst.* 81 (March), 101483 <https://doi.org/10.1016/j.compenvurbsys.2020.101483>.