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On the adoption of e-moped sharing systems

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Abstract

Recent years have witnessed the emerging of novel shared mobility solutions that provide diffused on-demand access to transportation. The widespread adoption of these solutions, particularly electric mopeds (e-mopeds), is expected to bring important benefits such as the reduction of noise and atmospheric pollution, and road congestion, with extensive repercussions on liveability and quality of life in urban areas. Currently, almost no effort has been devoted to exploring the adoption patterns of e-moped sharing services, therefore, optimal management and allocation of vehicles appears to be a problem for service managers. In this study, we tried to demonstrate the validity of the hypothesis that the adoption of electric mopeds depends on the built environment and demographic aspects of each neighbourhood. In detail, we singled out three features concerning the area characteristics (distance from centre, walkability, concentration of places) and one about the population (education index). The results obtained on a real world case study show the strong impact these factors have in determining the adoption of e-moped sharing services. Finally, an analysis was conducted on the possible role that the electric moped sharing can play in social equalization by studying the interactions between rich and poor neighbourhoods. The results of the analyses conducted indicate that communities within a city tend to aggregate by wealth and isolate themselves from one another (social isolation): very few interactions, in terms of trajectories, have been observed between the richest and poorest areas of the city under study.

Keywords: Features identification; E-moped sharing; Urban mobility; Social isolation

1 Introduction

Understanding urban mobility patterns is becoming increasingly important for planners, administrators, and transport providers. Indeed, the growing concern for the environment, demographic changes, citizen lifestyle, and economic issues are constantly redefining urban mobility. Urban transport has a significant impact on the quality of life of most people, and this is especially true today as more than 50% of the world population lives in urban areas, with Europe reaching 75%.[1] Furthermore, by 2050, almost 68%[2] of the world

[1]https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

[2]https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html/

population is predicted to live in urbanized areas, exacerbating human mobility and freight transport problems, which are crucial drivers for economic development and liveability in the city [1]. As pointed out in [2], another important issue concerns air pollution, which entails great environmental risks for citizens. To overcome these challenges, institutions are enacting air quality plans and mobility strategies, in which transport alternatives to traditional mobility plays a key role. In this sense, electric shared mobility can represent an opportunity for local administrations to rethink urban transport in terms of sustainability by disincentivizing bulky private motor vehicles, which often cruise the city with only the driver. The resulting reduction in traffic and air pollution would result in health benefits and cost savings for the citizen and a reduction in environmental impact on the community [3, 4].

In the field of shared vehicles, e-moped sharing is increasingly assuming a prominent position in Europe cities:[3] currently 15 of the 22 countries, that have introduced the use of mopeds, are located in Europe and represent 54% of the total fleet deployed (in 2019 it was 58%). Germany (26), Poland (23), the Netherlands (19) and Spain (9) have the highest number of cities with moped sharing services, with the Netherlands experiencing a very strong growth over the past year. In the current situation, where many governments have signed the Paris Agreement[4] on climate change, electric mopeds can be a valid instrument to mitigate the pollution problem: on the one hand, city pollution can be directly reduced by the adoption of electric vehicles, and on the other, compact conveyances have a positive effect on the problem of road congestion, which is also a cause of pollution. In this sense, the authors of [5] show that the introduction of an adequate fleet of shared e-mopeds can replace a relevant percentage (up to 23%) of car trips. Therefore, e-moped represent a major enabler to build up a sustainable urban transport system and to improve city liveability. Nonetheless, although several research contributions can be found in the field of shared mobility, mainly addressing car, bike, and e-scooter sharing services, almost no effort has been dedicated to study the adoption of shared electric moped, despite its significant growth in recent years.

Given a tessellation of the area of interest (i.e., the city) in regularly-shaped squares, called regions (equivalently, markers), the problem of adopting e-moped sharing, defined as the problem of predicting the shared use of e-mopeds and studying users' behaviour within each region, has been little explored in literature. The few studies published on this subject contemplate the use of simulation [5], information directly linked to users (surveys) and mobility data [6, 7], but this knowledge is not always available and easy to access. For these reasons, in this study we focus on assessing the hypothesis that the adoption of electric mopeds depends on the landscape and demographic aspects of each marker, information that is more easily accessible. In particular, this research proposes a study that uses mobility data to investigate the determinants of e-moped adoption through the analysis of specific factors that, although not directly related to users, allow us to predict and effectively explain the adoption of shared mopeds. In particular, four variables have been considered: distance from the centre, walkability, concentration of places, and education index.

[3] https://mopedsharing.com/moped-sharing-report

[4] https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

As recent studies have shown that the building environment and land use have a strong influence on the adoption of bike sharing [8], we are interested in analyzing whether the effect is also evident for the case of shared e-mopeds. To carry out this analysis, we use walkability and concentration of places to capture the structural characteristics of the city. Walkability allows us to identify areas of the city with a high concentration of physical activity [9], that is areas where people are more likely to walk than to drive. While, concentration of places is considered a useful indicator for analyzing the heterogeneity of points of interest (POI) and it can be used as a proxy for the presence of different services in an area. In addition, distance from the city center is leveraged to study the effect of locations within the city. For example, in [10], it is shown at the country level that those who live in less economically developed areas have a larger radius of travel in order to reach the central areas of the country with the greatest economic development (e.g., the capital). Therefore, in a similar way, we use this index to capture the importance of the spatial position with respect to the central place of a city, its center. Finally, we use the education index as a proxy for the average socio-economic status [11–13] of the residents of an area. This variable is taken into consideration in the study as we are also interested in verifying whether the sharing of electric mopeds acts as a social equalizer or, to the contrary, it increases social isolation, i.e., the tendency of highly disadvantaged and highly advantaged neighborhoods to have few interactions with each other [14].

This paper is organized as follows. After this introductory chapter, the relevant literature is reviewed in Sect. 2. In Sect. 3, we present the variables used in the study with the related analysis methodology, while in Sect. 4 we describe the case study. In Sect. 5 we present and discuss the main results of the study. Finally, Sect. 6 concludes the paper and outlines future research.

2 Related work

Over the past few years, the attention towards shared mobility services has grown steadily, generating worldwide interest. This has led to considering shared mobility as one of the three revolutions of urban transport along with electrification and automation of vehicles [15]. The meaning of the phrase *shared mobility* is twofold; on the one hand, it refers to a service that provides vehicles to be shared between different users with a pay-per-use billing model. Examples of those services are: car sharing, bike sharing, or scooter sharing (both mopeds and kick-style). On the other hand, it may refer as well to scenarios in which a single ride is shared [16]. In this paper, we consider the first characterization, where the user is provided with *as-a-service* short-term access to a mean of transport.

Shared mobility has a strong impact on urban areas as it is often considered a valid instrument to address the problems of traffic congestion and air pollution. Among the benefits of shared-use vehicle systems, in [17] the authors highlighted four main advantages with important consequences on the quality of life: *(i)* provision of mobility alternatives that are more flexible than public transport and cheaper than the private vehicle, *(ii)* potential to lower human transport costs and reduce the need for city parking areas, *(iii)* improvement of air quality since most solutions are based on electric or hybrid-electric vehicles and *(iv)* access to and encouragement of the use of more efficient and environmentally friendly modes of transport.

The early forms of alternative mobility came in the shape of bike sharing services, followed by car sharing schemes. Later, moped sharing has established itself as an innovative mobility model in urban areas, with some peculiarities that make it an attractive option especially for short distances in the central areas of the city. Finally, in recent years, electric scooters have also been introduced with great success. Existing literature on shared mobility focuses mainly on car sharing or bike sharing. Regarding car sharing, previous studies have widely analysed the typical profile of users [16] or its impact on modality competition [18]. While, in the bike sharing field, many authors have extensively explored the main factors for and barriers to the adoption of bike sharing systems [19], as well as its effect on urban congestion [20]. Finally, in the last few years, research focused on the benefits and use of electric scooters has also been growing [21, 22].

To the best of our knowledge, e-moped adoption is poorly understood, despite its significant growth in recent years. There are only a handful of works dealing specifically with mopeds, also due to the limited data available. In fact, [6] and [7] grounds their analyses solely on an online survey conducted in Spain, [23] and [24] use actual mobility data; lastly, [5] uses a simulator to generate synthetic mobility data. More in detail, in [23] a first approach was tested for the clustering of users of mopeds. The authors developed a cluster analysis to study moped sharing users and identify customer segmentation based on scooter sharing usage data. Users are profiled according to four variables: *(i)* age, *(ii)* time between rides, *(iii)* distance driven, and *(iv)* revenue per customer. In [6] the authors focused on identifying the characteristics that most influence the use of electric moped sharing. They adopted a generalized ordered logit model to explore the key factors determining the use of shared e-mopeds. In [24] the authors used GIS and GPS data to identify optimal locations for moped sharing parking spaces in central Madrid. A first overview of the moped sharing demand by exploring the usage and views towards this new mobility alternative is provided in [7]. To this end, they conducted Kruskal–Wallis tests to identify the segment of the urban population that is most likely to adopt moped sharing, and further statistical mean differences were made in specific variables related to moped sharing. Finally, [5] investigates the capacity of a shared platform of electric mopeds to replace the transport by passenger cars in Berlin by developing a simulation-based analysis. Based on the data generated by a simulator, the authors also provide holistic environmental and economic views through an analysis of the impact on the life cycle of the fleet.

In conclusion, the literature analysis suggests that the study presented in this paper is the first to analyze in detail socio-economic and structural factors behind the utilization patterns of e-mopeds in a city. In addition, we explored the interplay between e-moped use and social isolation of the more and less affluent social classes within the city.

3 Methodology

Our primary goal is to study the adoption of e-moped sharing services within the urban context by correlating utilization patterns to socio-economic and structural factors. Secondly, the study aims at finding evidence of the social isolation phenomenon by identifying meaningful social categories based on the economic status and calculating the rate of interaction among them. In what follows, the methodology implemented is outlined.

The study began with the definition of the target variables, which act as proxies for the adoption of e-moped sharing services. Once this first part was completed, we identified the dependent variables trying to meet two driving requirements: *(i)* they must be easily accessible, and *(ii)* they must show a close relationship with built environment and demographic aspects of the city. Finally, after applying a feature selection method, a linear regression was performed with the selected covariates. The results obtained were evaluated both in terms of the adjusted R-square and the importance of the independent variables.

It is worth pointing out that while mobility is characterized by well-known temporal dependencies (e-mopeds data presents trends and seasonality which depend on the day of the week and the time of day [25, 26]), the socio-economic and structural characteristics of the city are represented by covariates that can be considered almost constant in the medium term. Correlating those factors temporally is therefore impossible. To overcome this issue, we have identified in the literature mobility indicators that are also measures of a central tendency [27]. A detailed description of the dependent and independent variables used in this study is given below.

3.1 Dependent and independent variables

In this paper, the adoption of shared e-moped is evaluated through two different variables: the travel radius, which provides a sensible proxy for how much the service is being used, and the average daily flow, which focuses on how it is being used.

Travel radius (r_g). It is the average distance (in meters) travelled by the e-mopeds of the region under study i towards all the other markers to which the e-mopeds are directed [27]. The radius is calculated using Equation (1):

$$R_i = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[2g \times \sin^{-1}\left(\sqrt{\sin^2\left(\frac{\varphi_t - \varphi_i}{2}\right) + \cos\varphi_i \cos\varphi_t \sin^2\left(\frac{\phi_t - \phi_i}{2}\right)}\right)\right]^2}, \tag{1}$$

where n is the total number of regions reached by e-mopeds starting from i, t identify a marker visited by e-mopeds starting from i, ϕ_t (ϕ_i) is the latitude, φ_t (φ_i) is the longitude of the marker t (i, respectively) and g is the radius of the earth in meters.

Average daily flow (a_f). It is the total e-moped flow measured in a region divided by the number of considered days, as shown in Equation (2):

$$AF_i = \frac{\sum_{n=1}^{N}(\iota_{n,i} + \omega_{n,i})}{N}, \tag{2}$$

where N is the total number of analysed days, $\iota_{n,i}$ is the total flow of day n entered marker i and $\omega_{n,i}$ is the total flow of day n leaving marker i.

As mentioned before, three independent variables were selected that carry information about the characteristics of the region (distance from centre, walkability and concentration of places), and one feature to characterize the population (education index).

Distance from centre (x_d). It is the distance in meters between the center of a marker and the point considered the geographic centre of the city (it accounts for decentralization). It is measured by applying the Haversine formula [28], which determines the shortest distance between two points on the surface of a sphere (in this case the earth).

Education index (x_g). It is the indicator that measures the share of graduates, i.e., the ratio between the number of graduates and the total number of residents, in each region of the city. It is used as a proxy for the average socio-economic status of an area as in [11–13] it was highlighted how higher education is related to higher wages and greater economic and social well-being. Specifically, in [12], the authors point out that higher education includes higher lifetime earnings, a more satisfying work environment, better health, longer life, more informed shopping, and a lower likelihood of unemployment.

The choice of selecting this indicator was made due to the lack of detailed salary information (for the case study presented in Sect. 4) for privacy reasons. The education index is calculated considering the population group aged between 25 and 70. The choice of this demographic cohort should shield the analysis from possible bias due to the tendency of off-site students to live near universities and colleges; nonetheless, any information about young people domiciled but not residing in the city analyzed in this study was removed.

Walkability (x_s). It was proposed in [29] and is the index that measures the city's street network orientations distribution. In particular, streets' orientation is the angle that the vector, joining its start to end coordinates, makes with North. In other words, the streets' orientation entropy measures the variability in their respective azimuths. It is calculated as shown in Equation (3):

$$H_i = -\sum_{k=1}^{n} P(o_k) \log P(o_k), \tag{3}$$

where n represents the total number of bins, k indexes the bins, and $P(o_k)$ represents the proportion of orientations that fall in the kth bin. In more detail, Boeing [29] proposes a measure for disorder in city street orientation (H_i), whereas, two follow-up studies [9, 30] have used measure H_i to link it to walkability and physical activity. Specifically, [30] operationalized the measure from [29] using the entropy to capture city imageability/legibility, and [9] used the same entropy measure to show that street entropy is strongly associated with physical activity. Based on these studies, a high value of H_i corresponds to a disordered region in terms of the road graph, which encourages walking. On the other hand, a low value of H_i indicates that the region has more orderly road networks, which are less conducive to walking and require more driving or transportation.

Concentration of places (x_p). It measures the diversification of Points of Interest (POIs), P_i, through the calculation of entropy with respect to the different classes of POIs present in the macro-categories of services and buildings, such as entertainment, commercial, transport and healthcare. Concentration of places is calculated following Equation (4):

$$P_i = \frac{-\sum_u p_{u,i} \log(p_{u,i})}{\log(|P_i|)}, \tag{4}$$

where $p_{u,i}$ is the proportion of the POI category u in zone i and P_i is the set of POI categories in i. The numerator in this expression is the Shannon entropy [31] associated with the different categories of POI in i, normalized by the log of the number of categories of POIs present in i.

Regions that have an elevated diversification of POIs with equal propensity have a high entropy, while areas that tend to have a large number of POIs of few categories are considered to have low entropy.

3.2 Linear regression model

To predict the adoption of electric mopeds and measure the effect of the different covariates, inspired by the approach presented in [32], a regression model was used as it is a reliable method to quantify the impact of each variable on a topic of interest [33]. Therefore, given the feature vectors $x_d \in R^n$ and the target value $y_d \in R$, we aimed at predicting

$\hat{y}_d$ using an Ordinary Least Squares regression model of the form:

$$\hat{y}_d = w_o + w_1 x_d^1 + \cdots + w_n x_d^n, \quad d = 1, \ldots, N, \tag{5}$$

where the coefficients w_j are learned by the model, n is the number of predictors and N is the total number of observations.

The results of the regression model were evaluated with the Adjusted R-squared, which is a modified version of R-squared that is adjusted for the number of predictors in the model. It is used to determine how reliable the correlation is and how much it is determined by adding independent variables. In terms of values, it increases when a new term improves the model more than would be expected by chance, while it decreases when a predictor improves the model less than expected [34].

Finally, a feature selection was applied to remove non-informative or redundant predictors from the model [35]. In detail, the best combination of independent variables was identified in terms of Adjusted R-squared.

3.3 Well-off groups and interaction ratio

In order to divide the different markers into well-off bands, we used the education index as a proxy for a socio-economic indicator. More in detail, we calculated the quartiles of the education index distribution and split the markers into four different groups, viz., *very deprecated* (VD), *deprecated* (D), *well-off* (W) and *very well-off* (VW). Let $\mathcal{C} = \{VD, D, W, VW\}$ be the set of the four classes, the interaction ratio $Ir_{CC'}$ between two classes C, C' can be calculated following Equation (6):

$$Ir_{CC'} = \frac{\sum_{w\in C}\sum_{d\in C'} x_{wd}}{\sum_{P\in\mathcal{C}}\sum_{w\in C}\sum_{d\in P} x_{wd}} \quad \forall\left(C, C'\right) \in \mathcal{C}^2, \tag{6}$$

where x_{wd} is the number of interactions (trips) observed between marker w and marker d. Therefore, the interaction ratio represents the percentage of observed interactions between markers belonging to two socio-economic classes and approximates the probability of a trip beginning in the markers of one class and ending in those of the other.

4 Case study

A real word case study was considered for the experimental analysis: *E-Moped Sharing Dataset* contains records of vehicle pick-ups and drop-offs over one week (December 2–8, 2019) for the city of Milan, Italy. The coordinates of each vehicle, the sampling time, and the reference marker, i.e., the one the vehicle falls within, are provided. Sampling has been performed at regular intervals of 15 minutes. By analysing the dataset, it is possible to trace the trips made by the vehicles and construct the transition matrix containing the probabilities of displacement. In this case, the central section of Milan has been divided into 223 regular markers with sides of 400 meters, as shown in Fig. 1. The marker size, set in the original dataset, is comparable with those used in other studies [5, 6, 36]; it can reasonably be considered adequate as corresponds to a distance easily walkable to reach a vehicle. The dataset was provided to us by FLUCTUO,[5] a European leading aggregator of data on shared mobility services, for research purposes.

[5] https://fluctuo.com/

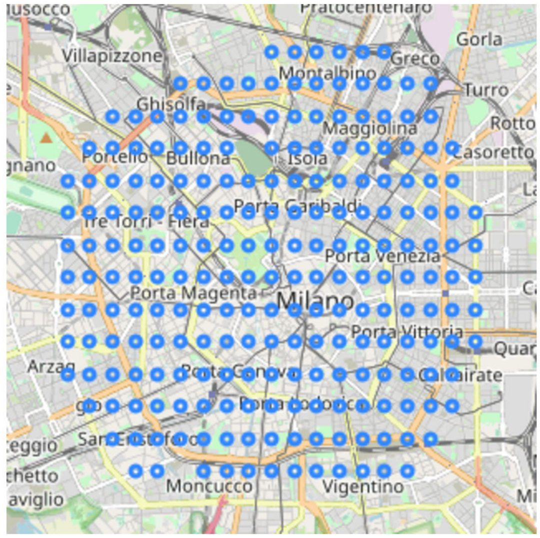


Figure 1 Area of analysis

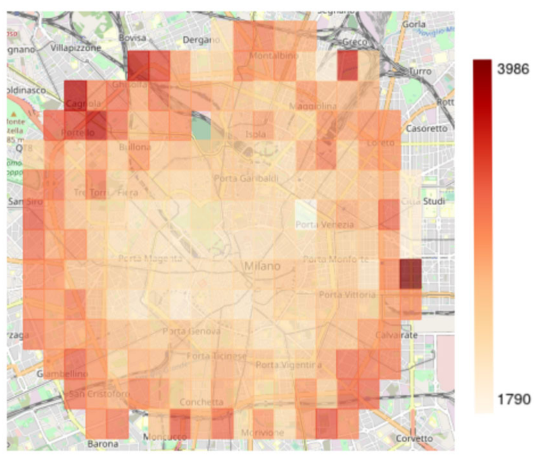


Figure 2 Travel Radius

4.1 Dependent and independent variables

In this subsection, the target variables and covariates specifically related to the Italian city of Milan are explored.

Travel radius. Fig. 2 shows the travel radius distribution. As can be seen, the travel radius is directly proportional to the distance from the city centre; indeed, there is a positive correlation (0.57) between r_g and x_d. This means that people from areas further from the city centre tend to travel on average longer than those who start trips from the centre. This is easily explained considering that in the historical centre of the city of Milan are concentrated the main economic, social, and shopping districts.

Average daily flow. This target variable was calculated by applying the Haversine formula [28]; however, it was decided to set a lower bound on the number of trips to be considered. In particular, the connections between regions that registered only one transfer for

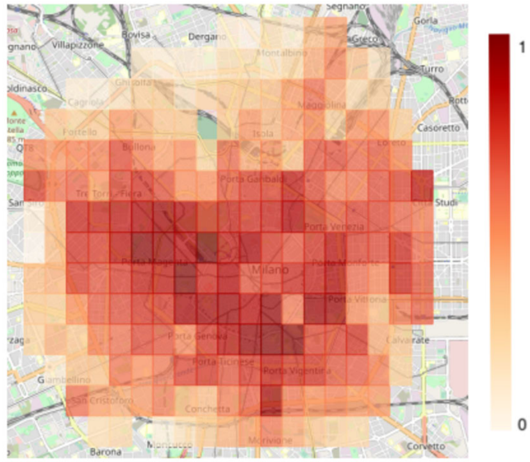


Figure 3 Distribution of the proportion of graduates in the city

the whole week were not taken into consideration. In this way, unusual movements were eliminated.

Distance from centre. The Italian city of Milan has a street network conformed of concentric circles deriving from its medieval legacy. Moreover, as for many European cities, the cathedral (Duomo),[6] with coordinates (45.464211, 9.191383), can still be identified as the geographical (as well as, cultural and economic) centre of the city. Admittedly, the study of this metric requires the prior identification of a point to be considered the city centre, intended as an attraction and aggregation pole such as to have a substantial impact on mobility, and this is not always straightforward as in the case of the city of Milan. In these cases, knowledge of the city and careful data analysis are required. In addition, a modern city might be polycentric with distinct economic and social centres. In these cases, alternative approaches must be considered; for instance, the distance from the closest *center* could be used.

Education index. The data used to construct the education index were obtained from the ISTAT (The Italian National Institute of Statistics) portal[7] relating to the 2011 census. As shown in Fig. 3, the percentage of graduates is higher in the more central areas of the city, while it tends to decrease moving radially towards the suburbs. Furthermore, the strong negative correlation (–0.74) between x_g and x_d highlights an inverse proportionality between the two variables. This result confirms the soundness of considering the percentage of graduates as a proxy feature of the socio-economic status of an area.

Walkability. Fig. 4 shows the distribution of Walkability in Milan. The index values in the image tend to be high especially in the central part of the city and near the green areas. This result can be explained by the highly pedestrian nature of the centre of Milan where several areas are inaccessible to cars.

Concentration of places. The distribution of the variable is asymmetric, pointing towards values between 0.7 and 0.8 with mean 0.75 and standard deviation 0.14. Such a distribution strongly depends on the portion of the city considered in this work, as being the

[6] https://www.duomomilano.it/it/

[7] https://www.istat.it/it/archivio/104317

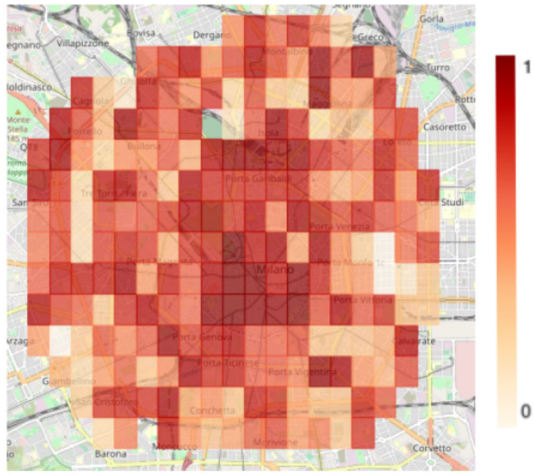


Figure 4 Walkability index in Milan

Table 1 Correlation between the independent variables

Independent variables	Correlation			
	Distance from center x_d	Education index x_g	Concentration of places x_p	Walkability x_s
Distance from center x_d	1	–0.74	0.23	–0.21
Education index x_g	–0.74	1	–0.15	0.20
4Concentration of places x_p	0.23	–0.15	1	–0.18
Walkability x_s	–0.21	0.20	–0.18	1

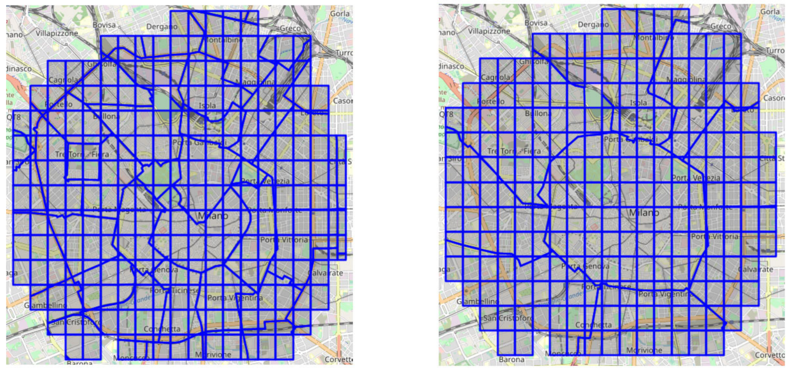
Table 2 Variance Inflation Factor

Variables	VIF
Distance from center x_d	2.25
Education index x_g	2.19
Concentration of places x_p	1.077
Walkability x_s	1.072

central area of the city, the concentration of POI is quite homogeneous with only a subtle difference between the different markers.

Correlation between independent variables. We computed the correlation coefficients between all the independent variables, as shown in Table 1, and found that there is a strong negative correlation (–0.74) between Distance from center and Education index. This could be a sign of collinearity among the predictors.

To further asses this, we calculated the variance inflation factor among the independent variables, and indeed confirmed that the Distance from center and Education index have higher VIF values Table 2. This could be indicative of the fact that higher education may afford people to move to larger sub-urban houses. This phenomenon needs to be accounted for in any further analysis in the form of an interaction variable between education and distance from center.



(a) District subdivision (b) Municipalities subdivision

Figure 5 The two different aggregations of the areas analyzed

5 Validation and discussion

In this section, we initially present the analyses conducted on the dataset for its validation and subsequently we discuss the results obtained from the experiments carried out to predict the two target variables: travel radius and average daily flow.

5.1 Dataset validation

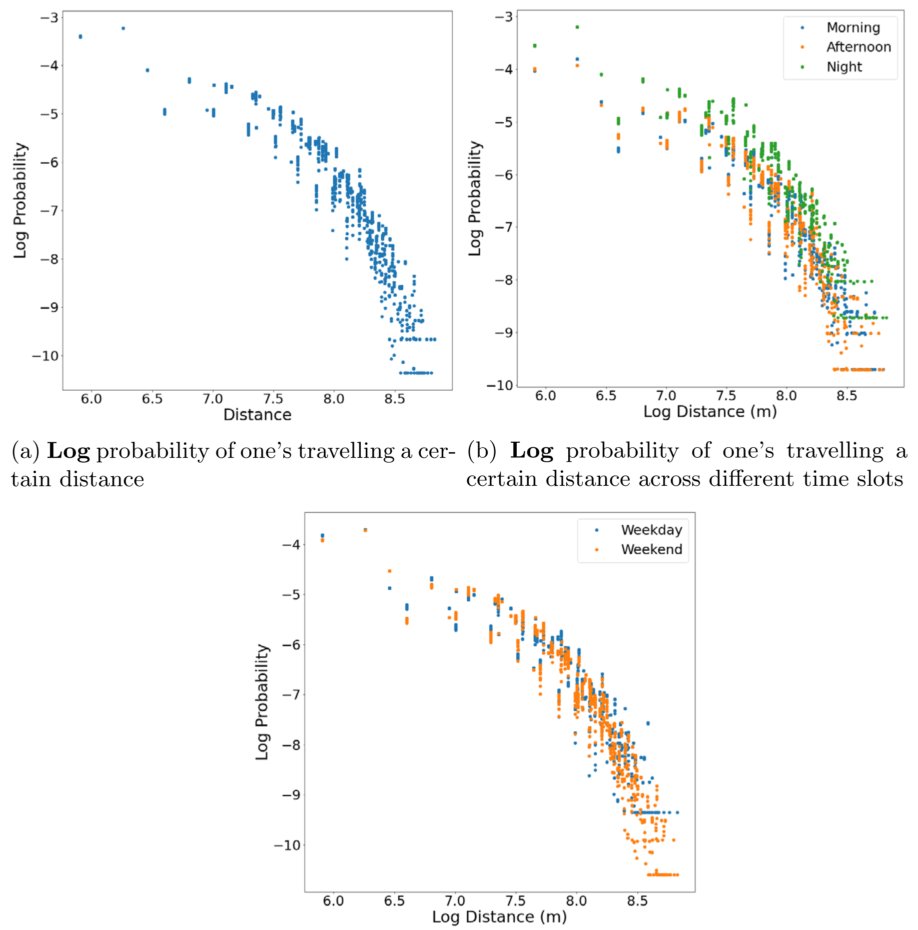
To perform the experiments, the 223 squares were aggregated in *(i)* districts and *(ii)* municipalities. Districts are census areas, which consist of neighbouring blocks (i.e., sections delimited by street segments) grouped based on socio-economic conditions [37], while Municipalities are a different subdivision of the territory decided starting from 1999.[8] The subdivision implies that each Municipality, with the exception of the central area, extends from the semi-central area to the periphery and acquires a partial administrative autonomy.

Therefore, as previously done in [38], each marker was assigned to a specific district. If an area overlapped several districts, as it can be seen in Fig. 5(a), it was assigned to the district with which it had the largest overlap. We performed the same procedure for the assignment of squares to municipalities, since, as shown in Fig. 5(b), a similar scenario occurs. In the end, 46 districts were analysed, about half of the districts in the entire city, and all nine municipalities.

One of the issues that can arise from the aggregation of spatial data is the Modifiable Areal Unit Problem (MAUP), i.e., an effect of statistical bias appearing when samples in a given area are used to estimate aggregated information. For this reason, we decided to perform two different aggregations (namely, at the municipality and district level) and in the analyses we carried out, we compared the behavior of the variables analyzed in both scenarios to check the consistency of the results obtained.

Finally, it was tested whether E-Moped Sharing Dataset verified the hypothesis that the distance frequency distribution is exponentially distributed; this derive by the assumption that people rarely move away from familiar areas, travelling to a limited number of nearby locations, and therefore short-range movements are more frequent than long-range ones.

[8] https://www.comune.milano.it/comune/palazzo-marino/municipi



(a) **Log** probability of one's travelling a certain distance

(b) **Log** probability of one's travelling a certain distance across different time slots

(c) **Log** probability of one's travelling a certain distance across weekdays and weekend

Figure 6 Log probability of one's travelling

The data on e-mopeds in Milan validate the hypothesis: the Fig. 6(a) shows the probability (log) of travelling a certain distance and as can be seen from the image, as the distance increases, the probability of travelling decreases. Furthermore, it was investigated whether the considered dataset remained consistent with the geographic closeness hypothesis when different temporal aggregations are considered. More in detail, the original records were aggregated by daily time slots (morning, afternoon and evening) and by days of the week (Weekdays and Weekends). As shown in Fig. 6(b) and Fig. 6(c), the pattern is also evident at these levels. It can also be seen that trips made at weekends and in the evening have a higher probability of making long distances. This evidence confirms what has been shown in [7], which points out that electric mopeds are widely used for leisure activities, as opposed to free car sharing where the main use is for commuting and airport transfers [39].

It should be noted that in all three graphs, trips over 5 km have a very low probability. This behavior is consistent with what has been observed in the literature: in [5], for instance, the authors observe that the average distance traveled with an electric moped in Berlin is between 3.6 and 4.1 km.

Table 3 Radius prediction

	Radius	
	Districts	Municipalities
Distance from center x_d	1781.75***	–
	(505.21)	
Education index x_g	580.18	–379.25**
	(421.22)	(73.96)
Interaction of x_d and x_g	–1661.34**	–
	(730.81)	
Walkability x_s	–399.83**	–421.22*
	(129.61)	(132.93)
Concentration of places x_p	–	–
Constant	2886.31***	3880.88***
	(496.36)	(344.22)
Observations	42	9
R-squared	0.569	0.922
Adj. R-squared	0.522	0.896

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note: Robust standard errors in parentheses.

5.2 Travel radius prediction

Table 3 shows the results of the two regressions constructed to predict the travel radius. Analysing in detail the regression related to the district aggregation, one can see that three out of the four variables (x_d, interaction of x_d and x_g, and x_s) are significant for the prediction of the radius. The four covariates jointly explain the variance of 56.9% and we get a ${R_{\mathrm{Adj}}}^2$ of 0.522.

The significance of the variable x_d indicates that, as the distance from the city centre of an area increases, the length of the travel radius also increases: the distances that users, who are in more peripheral areas, have to travel to reach different places in the city are greater than those traveled in trips that start in the central area of the city. Therefore, users in areas with vehicle availability but in a less central position use moped sharing to travel longer distances than users in the city centre. This result is in line with what has been observed in studies on bike sharing, where transfer distances are generally longer in suburban areas where public transport services are typically less available [40]. The significance of the variable x_s explains how the use of mopeds is also negatively influenced by the walkability: pedestrian areas have a reduction in the distance traveled. Therefore, these are areas where the environment is suitable for walking and does not encourage the use of e-mopeds.

Regarding the results obtained from the aggregation in municipalities, the value of R^2_{Adj} cannot be trusted due the small sample size (9 observations). Nonetheless, in the following, the behavior of the covariates is discussed and compared against that seen in the districts scenario in order to check the possible presence of MAUP. It emerges how the variable x_s is significant and its behaviour is the same as seen previously. Furthermore, x_g is also negatively related to the target variable: as the education index increases, the travel radius decreases. This behavior is well explained by the fact that the richest zones are in areas of the city where shopping and leisure districts are located. Incidentally, those zones are also better covered by public transportation and feature a higher degree of walkability, making long-distance travels less frequent.

Table 4 Average daily flow regression

	Average daily flow	
	Districts	Municipalities
Distance from center x_d	12.06***	2.32*
	(2.62)	(0.77)
Education index x_g	16.97**	–
	(5.53)	
Interaction of x_d and x_g	−11.60***	–
	(7.97)	
Walkability x_s	–	–
Concentration of places x_p	−1.42	−6.12*
	(1.23)	(2.04)
Constant	−4.01	5.46
	(2.16)	(1.60)
Observations	34	9
R-squared	0.580	0.756
Adj. R-squared	0.522	0.675

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Note: Robust standard errors in parentheses.

5.3 Average daily flow prediction

Table 4 shows the results obtained from the regression regarding the daily adoption of sharing scooters.

Analysing the result obtained with the aggregation in districts, the four covariates explain 58% of the target variable with a ${R_{\mathrm{Adj}}}^2$ of 0.522. The significant predictors are x_d (p-value ≤ 0.001), x_g (p-value < 0.01) and the interaction between x_d and x_g (p-value ≤ 0.001). We set a lower bound, as explained in Sect. 4, and we had a reduction of 19% in the number of observations. Table 4 shows the significance of the variables x_d and x_g. It can be seen with x_d that moving away from the center leads to an increase in daily scooter use. Similarly, an increase in the education index x_g leads to an increase in scooter use. The latter behavior has also been observed in bike sharing, where variables such as *educated*, *working*, *high income* are strongly correlated to the user profile of bike sharing services [8]. Also in the case of car sharing, people with graduate degrees are more likely to use this service; nonetheless, unlike what we see for e-mopeds, living in city center seems to encourage the use of car sharing [39].

Even if the variable is not statistically significant, an increase in x_p leads to a reduction in the daily flow: since as the entropy grows, the diversification of the available POIs increases, this effect is synonymous with a well-supplied area and from which it is not compulsory to move away daily.

Finally, also for this prediction, the regression carried out with the aggregated observations in municipalities cannot be evaluated in terms of R^2_{Adj} for the small number of observations. Again, to check for MAUP, we verify the consistency of results in the municipalities and districts scenarios. It is interesting to note that there are same two covariates, x_d and x_p, remaining after feature selection and both are significant (p-value ≤ 0.05). The first one turns out to be significant also in the district scenario, while the second one is not. Nonetheless, the parameters associated with x_d and x_p have the same signs in both scenarios, suggesting that the presence of MAUP can be ruled out.

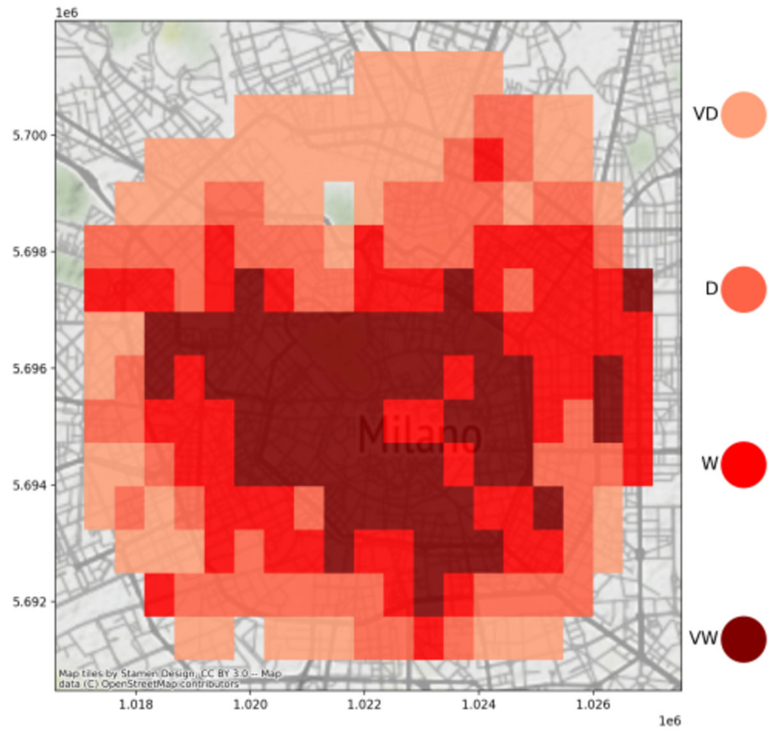


Figure 7 The four different communities based on the well-off indicator shown on the city map

5.4 E-moped sharing is not a social equalizer

In recent years, several researches have focused on social isolation in cities, where it has emerged that social isolation is experienced by residents of highly disadvantaged and highly advantaged neighbourhoods because the two groups spend time in largely non-overlapping parts of the city [14]. Additionally, a surprisingly high consistency was identified between neighbourhoods of different races and income characteristics in average walking distances (in meters) and number of unique neighbourhoods visited in the metropolitan region [41].

We are interested in analysing the phenomenon of social isolation from the point of view of shared moped users. Our goal, in fact, is to verify whether mopeds can be considered vehicles of social equalization. Therefore, we initially identified four different communities, shown in Fig. 7 for the city of Milan, based on the well-off indicator: *(i) very deprecated* (VD), *(ii) deprecated* (D), *(iii) well-off* (W) and *(iv) very well-off* (VW); then, we calculated the interaction ratio reported in Fig. 8 (see Sect. 3.3 for more details). As can be seen from the image, the iteration ratio between areas of the same community is strong, but it is interesting to analyse the behaviour of users of the more affluent and poorer areas: there are few interactions between these two communities. In detail, the interaction ratio of wealthy areas (Community VW) with less well-off areas (Community VD) is 0.08%, while on the other direction is 0.17%. Observing the tendency of the two curves from Fig. 9, an evident trend emerges: the greater the distance in terms of well-being between communities, the lesser the interaction.

In order to double-check the consistency of the analyses, we observed the behavior of two markers belonging to the city center, an area where the education index is generally

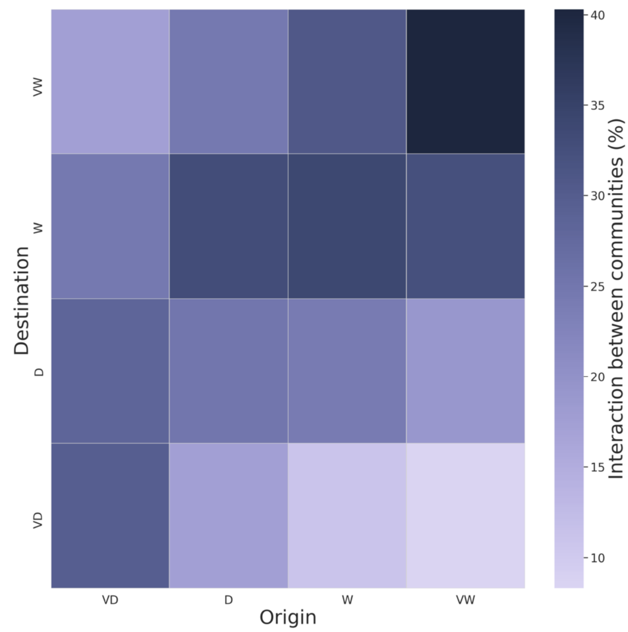


Figure 8 Interaction ratio between communities

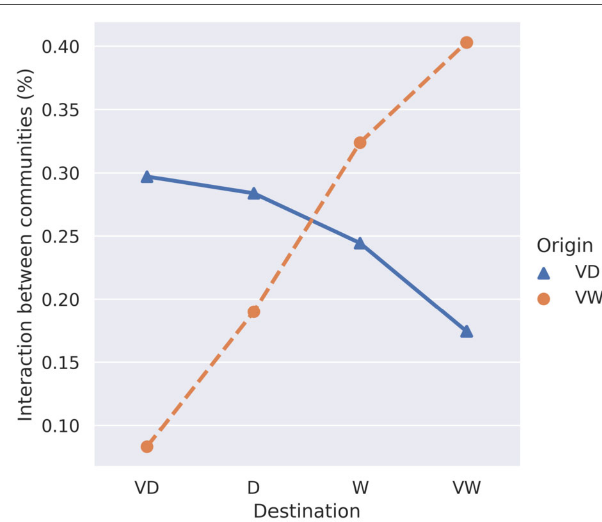


Figure 9 Trend of community VD and community VW interactions

high; both belong to the VW class. For both the ratio of interaction with markers of the same social level is very high (32% and 37%). The interaction ratio decreases dramatically when we consider the movements between these areas and the poorer areas of the city. In this case the interaction ratio falls to 10% and 7% respectively. A similar behavior was observed when we picked two markers with a low value of education index, one from the north of the city and one in the west. Also in this case, the interaction ratio with markers of the same social level is high (31% and 27%, respectively). While, the interaction ratio with markers for the most well-off areas, the ratio decreases to 14% for the first marker and 16% for the second.

The results obtained are consistent with known dynamics of large cities, in which communities tend to be homogeneous in terms of wealth, isolating themselves (even geographically) from one another. In this scenario, even an agile mobility means such as the electric moped does not seem to play an important role in reducing social isolation.

6 Conclusions

The identification of the variables that allow to better explain and understand the adoption of ecological alternative mobility solutions (like shared e-moped) seems to be a topic not yet explored. Besides the relative novelty of these services, it is believed that the main cause of this void in the literature is due to the difficulty of acquiring data to study. The handful of works on this topic in fact make use of surveys administered directly to service users or simulation tools.

This paper presents a study that analyses four different variables related to territorial and population characteristics without using any direct information on users. The analysis allowed us to explore the mobility sharing behaviour of e-moped in the central area of the Italian city of Milan, where users experience limited problems in terms of service delivery. Compared to past studies that limited themselves to highlighting a greater use of e-mopeds in the city centre, our study suggests that, under the assumption that there is no shortage in the supply of vehicles, the use of shared e-mopeds (average daily flow) and the distance travelled (travel radius) is directly proportional to the distance from the city centre. Furthermore, the impact of two of those variables (namely, concentration of places and walkability) on the adoption of the sharing moped seems to suggest that the diversification of the POIs and the organization of the roads play a central role in explaining mobility patterns. Therefore, urban and traffic planners who deploy sharing services could use the outcomes of this work as support for the distribution and allocation of vehicles in cities, especially when available mobility data for the service is limited or missing. Finally, we analysed the possibility that the e-moped sharing service could play a role in social equalization, studying the interaction ratio between neighbourhoods according to their socio-economic status; unfortunately, the results of the analyses conducted indicate that communities within a city tend to aggregate by wealth and isolate themselves from one another. Very few interactions, in terms of trajectories, have been observed between the richest and poorest areas of the city.

Limitations and Future Work. The biggest limitation of this study concerns the limited dimensionality of the dataset both in terms of time horizon (only one week of data) and in terms of space (Milan's suburbs are excluded). Nevertheless, the results obtained are statistically significant and consistent with well-known dynamics in large cities. Future developments will involve studying the impact of the considered variables on other use cases (different sharing services and cities) to uncover similarities and differences with respect to their predictive power on the particular sharing service adoption.

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Abbreviations
POIs, Points of Interest; VD, Very Deprecated; D, Deprecated; W, Well-off; VW, very well-off; MAUP, Modifiable Areal Unit Problem; VIF, Variance Inflation Factor.

Availability of data and materials
Data used in this paper are available at: https://doi.org/10.5281/zenodo.5780444.

Declarations

Competing interests
The authors declare that they have no competing interests.

Author contribution
SF conceptualized the problem, run the analysis and wrote the paper. MC conceptualized the problem and wrote the paper. SJ conceptualized the problem and wrote the paper. SŠ conceptualized the problem and wrote the paper. DQ conceptualized the problem. All authors read and approved the final manuscript.

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References
1. Benevolo C, Dameri RP, D'Auria B (2016) Smart mobility in smart city. In: Empowering organizations. Springer, Berlin, pp 13–28
2. Gosden P, MacGowan A, Bannister G (1998) Importance of air quality and related factors in the prevention of infection in orthopaedic implant surgery. J Hosp Infect 39(3):173–180
3. Shaheen S, Chan N, Bansal A, Cohen A (2015) Shared mobility: a sustainability & technologies workshop: definitions, industry developments. and early understanding
4. Pan S, Fulton LM, Roy A, Jung J, Choi Y, Gao HO (2021) Shared use of electric autonomous vehicles: air quality and health impacts of future mobility in the United States. Renew Sustain Energy Rev 149:111380
5. Wortmann C, Syré AM, Grahle A, Göhlich D (2021) Analysis of electric moped scooter sharing in Berlin: a technical, economic and environmental perspective. World Electr Veh J 12(3):96. https://doi.org/10.3390/wevj12030096
6. Aguilera-García Á, Gomez J, Sobrino N (2020) Exploring the adoption of moped scooter-sharing systems in Spanish urban areas. Cities 96:102424
7. Aguilera-García Á, Gomez J, Sobrino N, Vinagre Díaz JJ (2021) Moped scooter sharing: citizens' perceptions, users' behavior, and implications for urban mobility. Sustainability 13(12):6886
8. Eren E, Uz VE (2020) A review on bike-sharing: the factors affecting bike-sharing demand. Sustain Cities Soc 54:101882
9. Constantinides M, Joglekar S, Šćepanović S, Quercia D (2021) Imagine a walkable city: physical activity and urban imageability across 19 major cities. EPJ Data Sci 10(1):56
10. Šćepanović S, Mishkovski I, Hui P, Nurminen JK, Ylä-Jääski A (2015) Mobile phone call data as a regional socio-economic proxy indicator. PLoS ONE 10(4):0124160
11. Baum S, Ma J, Payea K (2013) Education pays, 2013: the benefits of higher education for individuals and society. Trends in higher education series. College Board
12. Perna LW (2005) The benefits of higher education: sex, racial/ethnic, and socioeconomic group differences. Rev High Ed 29(1):23–52
13. Bowen H (2018) Investment in learning: the individual and social value of American higher education
14. Krivo LJ, Washington HM, Peterson RD, Browning CR, Calder CA, Kwan M-P (2013) Social isolation of disadvantage and advantage: the reproduction of inequality in urban space. Soc Forces 92(1):141–164
15. Fulton LM (2018) Three revolutions in urban passenger travel. Joule 2(4):575–578. https://doi.org/10.1016/j.joule.2018.03.005
16. Sprei F (2018) Disrupting mobility. Energy Res Soc Sci 37:238–242. https://doi.org/10.1016/j.erss.2017.10.029
17. Chapter V (2015) Symbol and Romanticism. Princeton University Press, pp 105–127. https://doi.org/10.1515/9781400867196-006
18. de Luca S, Di Pace R (2015) Modelling users' behaviour in inter-urban carsharing program: a stated preference approach. Transp Res, Part A, Policy Pract 71:59–76. https://doi.org/10.1016/j.tra.2014.11.001
19. de Chardon CM, Caruso G, Thomas I (2017) Bicycle sharing system 'success' determinants. Transp Res, Part A, Policy Pract 100:202–214
20. Wang M, Zhou X (2017) Bike-sharing systems and congestion: evidence from us cities. J Transp Geogr 65:147–154. https://doi.org/10.1016/j.jtrangeo.2017.10.022
21. Bieliński T, Ważna A (2020) Electric scooter sharing and bike sharing user behaviour and characteristics. Sustainability 12(22):9640
22. Baek K, Lee H, Chung J-H, Kim J (2021) Electric scooter sharing: how do people value it as a last-mile transportation mode? Transp Res, Part D, Transp Environ 90:102642
23. Degele J, Gorr A, Haas K, Kormann D, Krauss S, Lipinski P, Tenbih M, Koppenhoefer C, Fauser J, Hertweck D (2018) Identifying e-scooter sharing customer segments using clustering. In: 2018 IEEE international conference on engineering, technology and innovation (ICE/ITMC). IEEE, New York, pp 1–8
24. Pérez-Fernández O, García-Palomares JC (2021) Parking places to moped-style scooter sharing services using gis location-allocation models and gps data. ISPRS Intl J Geo-Inf 10(4):230

25. Fiorini S, Ciavotta M, Maurino A (2021) Listening to the city, attentively: a spatio-temporal attention boosted autoencoder for the short-term flow prediction problem. arXiv preprint arXiv:2103.00983
26. Fiorini S, Pilotti G, Ciavotta M, Maurino A (2020) 3d-clost: a cnn-lstm approach for mobility dynamics prediction in smart cities. In: 2020 IEEE international conference on big data (big data). IEEE, New York, pp 3180–3189
27. Wang Q, Phillips NE, Small ML, Sampson RJ (2018) Urban mobility and neighborhood isolation in America's 50 largest cities. Proc Nat Acad Sci 115(30):7735–7740
28. Robusto CC (1957) The cosine-haversine formula. Am Math Mon 64(1):38–40
29. Boeing G (2019) Urban spatial order: street network orientation, configuration, and entropy. Appl Netw Sci 4(1):1–19
30. Coutrot A, Manley E, Yesiltepe D, Dalton R, Wiener J, Hölscher C, Hornberger M, Spiers H (2020) Cities have a negative impact on navigation ability: evidence from 38 countries
31. Lin J (1991) Divergence measures based on the Shannon entropy. IEEE Trans Inf Theory 37(1):145–151
32. Tran TD, Ovtracht N, d'Arcier BF (2015) Modeling bike sharing system using built environment factors. Proc CIRP 30:293–298.
33. Draper NR, Smith H (1998) Applied regression analysis, vol 326. Wiley, New York
34. Miles J (2005). R-squared, adjusted r-squared. Encyclopedia of statistics in behavioral science
35. Kuhn M, Johnson K et al (2013) Applied predictive modeling, vol 26. Springer, New York
36. Fiorini S, Ciavotta M, Maurino A (2021) A multi-criteria algorithm for automatic detection of city communities. In: 2021 IEEE international intelligent transportation systems conference (ITSC). IEEE, New York, pp 1266–1271
37. Nadai MD, Staiano J, Larcher R, Sebe N, Quercia D, Lepri B (2016) The death and life of great Italian cities: a mobile phone data perspective. In: Proceedings of the 25th international conference on world wide web (WWW), pp 413–423. https://doi.org/10.1145/2872427.2883084
38. Scepanovic S, Joglekar S, Law S, Quercia D (2021) Jane Jacobs in the sky: predicting urban vitality with open satellite data. Proc ACM Hum-Comput Interact 5(CSCW1):48. https://doi.org/10.1145/3449257
39. Becker H, Ciari F, Axhausen KW (2017) Comparing car-sharing schemes in Switzerland: user groups and usage patterns. Transp Res, Part A, Policy Pract 97:17–29
40. Li W, Chen S, Dong J, Wu J (2021) Exploring the spatial variations of transfer distances between dockless bike-sharing systems and metros. J Transp Geogr 92:103032
41. Sampson RJ (2019) Neighbourhood effects and beyond: explaining the paradoxes of inequality in the changing American Metropolis. Urban Stud 56(1):3–32