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Spatio-temporal Analysis of Micromobility Sharing in the City of Rome

Giovanni Tuveri[a,*], Eleonora Sottile[a], Francesco Piras[a], Italo Meloni[a]

[a]*University of Cagliari, Via San Giorgio 12, Cagliari 09124, Italy*

Abstract

This study examines the demand for shared micromobility in Rome, focusing on free-floating bike and e-scooter sharing services, using a dataset that overcomes the limitations of GBFS data. Unlike GBFS, which is typically used for station-based systems and presents challenges for free-floating services (due to frequent vehicle ID rotations and difficulties in tracking trips), this dataset is provided by *Roma Mobilità* and includes over 9 million trips recorded between 2022 and 2023 from seven service providers. The analysis reveals how usage patterns are influenced by seasonal variations, weather conditions, and tourist flow, with a clear preference for e-scooters in warmer months and more consistent bicycle usage in milder conditions. The highest trip volumes occur in summer, with peaks in July for e-scooters and October for bicycles. Spatially, areas with restaurants, residential buildings, and public transport connections generate the most trips. By applying a Zero-Inflated Poisson regression, the study identifies key factors influencing trip generation and attraction, providing actionable insights for urban planning. These results offer valuable guidance to optimize the deployment of shared micromobility services, enhance infrastructure, and improve user experience, ultimately making shared mobility solutions more efficient and effective for users, service providers, and the community.

Keywords: micromobility sharing; zero-inflated regression; free-floating

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* Corresponding author. Tel.: +39-070-675-5268.
E-mail address: giovanni.tuveri@unica.it

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1. Introduction

Shared Mobility is a mobility model that includes services such as car sharing, scooter sharing, bike sharing, and other forms of shared transportation, whose benefits are now well-known: it helps reduce the number of vehicles on the road, thus reducing traffic congestion and its related externalities; it promotes a more efficient use of resources, as more people can share the same vehicle for their trips, optimizing the use of available space and vehicles; contributes to improving the accessibility of public transport by providing a solution for the first and last mile in integration with macro-mobility.

In this context, short-term bike and scooter rental services, known as bike and scooter sharing, are included. These services are designed to meet the needs of users who need to travel short distances, generally less than 2 km. Despite the numerous advantages of shared micro-mobility, some critical issues still prevent widespread use, with only 118,000 trips out of approximately 97 million daily trips[1]: for example, the lack of adequate bike lanes, the limited vehicle availability, a lack of knowledge about the services, high usage costs, and the generally low acceptance of these vehicles by other road users. Unfortunately, user demand for shared micro-mobility services is still not well known, due to the unavailability of usage data, which service providers tend to not make readily available.

Shared mobility, and particularly micromobility sharing, has been a topic of interest in the literature for several years already (Frade and Ribeiro, 2014; Laporte et al., 2015). Several studies tried to understand different aspects of the phenomenon underlying the acceptance and spread of shared mobility services. For example, (Médard de Chardon et al. (2017) tried explaining the success of bike-sharing using data from city from all over the world, while Lee et al. (2021) tried identifying the factors affecting the willingness to use e-scooter sharing services in Korea, and Baek et al. (2021) investigated the value of shared e-scooters as a last-mile means of transport. Li et al. (2022) preformed a comparison of shared e-scooter services in 30 European cities, while Carrese et al. (2021) focused more on the situation in Italy, with a focus on the city of Rome. Jobe and Griffin (2021) tried understating the effects of the spread of COVID-19 on the bike sharing system in the city of San Antonio, Texas (US).

Some researchers also tried to get a better understanding of the phenomena of shared mobility by using different modeling techniques. Degele et al. (2018) used clustering to identify four different e-scooter customer segments, in order to propose solutions for the improvement of the business models. Singhvi et al. (2015) used regression models to predict the use of New York City's bike sharing services. Noland et al. (2019) used a Zero-Inflated Poisson (ZIP) regression to study bike sharing patterns for station-based data from the city of New York.

Some of these studies used data originating from specific user surveys built by the research teams (Baek et al., 2021; Jobe and Griffin, 2021; Lee et al., 2021), but most large scale studies are based on datasets which are either provided by the service operator, or publicly available readily or through APIs or other feed services like GBFS (Generalized Bikeshare Feed Specification), which provides a common system for sharing services providers to give information on their services (https://gbfs.org/). GBFS data usually includes the number of trips starting and ending at sharing stations, in a chosen time interval, number of vehicles available, position and battery levels for each shared vehicle, and more. Additional data can then be associated to each station/vehicle position by using other sources (*e.g.*, transport network, land-use information).

Shared mobility services can be categorized into two main schemes: station-based and free-floating. Station-based sharing is a system which involves several docks in different places in a city, where users have to take the vehicles and also return them (Cheng et al., 2020). Free-floating sharing is instead a scheme which allows users to unlock vehicles anywhere they find them (usually by means of a smartphone application) and also leave them anywhere inside a previously specified service area (Cheng et al., 2020). Using GBFS in this case is challenging, since vehicles IDs rotate frequently and it's virtually impossible to track them. Data from free-floating providers is

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[1] Rapporto nazionale sharing mobility 2023: VII-Rapporto-nazionale-sharing-mobility.pdf, Ministero delle Infrastrutture e dei Trasporti REPORT_III trimestre 2023.pdf (mit.gov.it)

also harder to obtain, since in this case the information must be associated with a vehicle instead of a station and poses larger privacy-related issues.

This study can partially overcome the limitations of GBFS data since it is based on a dataset provided by the *Roma Mobilità* observatory: a free-floating sharing micromobility dataset covering all trips performed in the city of Rome, obtained with the collaboration of the several service providers operating in the city. The analysis first involves a detailed statistical analysis of the characteristics of shared micromobility usage, aimed at highlighting inter-period and intra-period variations throughout the year, seasons, months, weeks, and weekdays versus weekends. An analysis of the distances travelled in relation to the type of vehicle used was also conducted. A spatial analysis of the data identified the municipalities and areas with higher trip generation and attraction.

The main goal of this study was to characterize the demand for shared micromobility usage in the city of Rome to identify actions to be taken for proper planning that makes it efficient and effective for the individual user, the community, and the managing company. We wanted thus to identify which elements from the surrounding system of activities (i.e. shops, restaurants, recreational, etc.) and other transport systems (stations and bus stops) influenced the use of shared micro-mobility services, to understand the phenomenon and give the providers some useful tools to improve the level of their services. To this end, a Zero-Inflated Poisson (ZIP) regression was applied to determine the weights of trip attributes and zone attributes in relation to the probability of generating/attracting trips and the number of trips generated/attracted.

The following paper is organized as follows: section 2 gives a complete description of the dataset used both for statistical analysis and in the models; the modelling framework is reported in section 3, along with the results obtained; finally, we give our conclusions in section 4.

2. Data description

The complete dataset included data ranging from August 2020 to October 2023, for a total of 24,613,448 trips recorded by 10 different providers who offered bike-sharing and e-scooter-sharing services in the city of Rome. The reference timeframe used as a focus of this analysis is the most recent 12 months for which complete trip information is available, *i.e.* from October 2022 to September 2023. It was decided to analyze this reference period to avoid the data being influenced by the pandemic in 2020, with significant impacts continuing into 2021.

The data used is summarized in Table 1. It includes only 9,138,283 trips completed with micromobility vehicles, *i.e.* bicycles and e-scooters. Over 37,000 vehicles were available to users for their shared trips, most of which were e-scooters (26,200), but several (3,402) were unidentified due incomplete data, with the remaining (7,594) being bicycles. The analysis revealed a generally higher use of e-scooters compared to bicycles, with roughly 6.8 million trips completed with e-scooters and much fewer with bicycles (1.8 million trips). On average, every vehicle has been used 2.79 times every day in the year analyzed, with slightly higher values for e-scooters (2.98) and lower for bicycles (2.45). Also on average, trips went for a distance of 2.24 km (2.08 for e-scooters and 2.50 for bicycles) and lasted almost 13 minutes (values are similar for all vehicles).

An analysis was also conducted on the usage across different seasons, both due to the exposure of micromobility to weather conditions that could affect its use, and because of the presence of tourists, which is more concentrated during certain times of the year. As expected, the lowest number of trips was recorded during winter. Most trips are instead recorded during summer (2.5 million e-scooters + 0.5 million bicycles), when the weather is mostly favorable, and Rome is interested by higher numbers of tourists visiting the city. It's also interesting to note how the bicycle trips show roughly the same variations (in percentage) compared to e-scooters, to indicate both vehicles are influenced by seasonal phenomena in the same way.

The more detailed monthly level analysis highlights that the most trips for e-scooters were recorded in July (859,837), while for bicycles the peak is in October (222,445). Instead, both saw the lowest use in January. When analysing the weekly pattern of bicycle trips in the four seasons, autumn is the one with less variations, with a slight peak on Friday, while winter shows a dip on Monday. Spring and summer are very similar, with a growth during the week and a peak use in the day of Wednesday/Thursday, and lower values during the weekend. In the case of e-scooters, the behaviour looks similar during all the seasons, with higher values during weekends, but the difference from start to end of the week is more prominent for winter and autumn. Instead, observing the bicycles trips during different times of day, while there are some seasonal differences, the general daily pattern stays the same all year long. We can identify a morning peak at 9:00 and an evening peak at 18:00, with most trips being in-between. There is also a considerable number of trips during the night up to 1:00, and almost no trips from 3:00 to 6:00. For e-scooter trips, while the generic trend is similar to the one shown by bicycles, the morning peak seems to be absent, with an almost constant growth rate of the number of trips from 7:00 to 18:00/19:00, and a more relevant use of these vehicles during the night.

Table 1. Summary of the dataset

Indicator	Value
Service providers	7
Unique vehicles	37,196
Bicycle	7,594
E-scooter	26,200
Unidentified	3,402
Total trips	9,138,283
Bicycle	1,798,242
E-scooter	6,798,834
Unidentified	541,207
Average daily trips per vehicle	2.79
Bicycle	2.45
E-scooter	2.98
Unidentified	2.10
Average distance per trip [km]	2.24
Bicycle	2.50
E-scooter	2.08
Unidentified	3.29
Average trip duration [min]	12.84
Bicycle	12.98
E-scooter	12.74
Unidentified	13.61

3. Methodology and results

The data was also analyzed by considering a division in zones of homogeneous size, using a hexagonal grid. The total area considered is limited to the area where the use of the sharing services was allowed (based on the available geofences), while also being included inside the "*Grande Raccordo Anulare*" of Rome, which separates the more urbanized area from the peripheral ones. With this subdivision of the area (7,552 zones in total, as shown in Figure 1) we were able to estimate a series of models to predict the number of trips generated and attracted by each of the zones. Since a lot of the zones produced no trips, a model which allows to account for count data with an excess of zero values was needed. Zero-inflated models are the most appropriate modeling framework to be used in these cases. A study of the available literature revealed that the more commonly used models in these cases were the ZIP regression (Lambert, 1992), and the Zero-Inflated Negative Binomial regression (Greene, 1994). While the latter has been already successfully used by Noland et al. (2019) for a similar case-study, after estimating several different models, the ZIP regression was selected, since it produced overall better results with the data available to us.

This model presents two parts, a Poisson count model and a logit model for the prediction of the zeros. More specifically, in a ZIP regression, the responses $\boldsymbol{Y} = (Y_1, \dots, Y_n)$ are independent and behave according to:

$$\begin{aligned} &Y_i \sim 0 && \mathit{with\,probability} \;\; p_i \\ &Y_i \sim \mathit{Poisson}(\lambda_i) && \mathit{with\,probability} \;\; 1 - p_i \end{aligned}$$

so that:

$$\begin{aligned} &Y_i = 0 && \mathit{with\,probability} \;\; p_i + (1 - p_i)e^{-\lambda_i} \\ &Y_i = k && \mathit{with\,probability} \;\; (1 - p_i)\, e^{-\lambda_i}\lambda_i^k / k! \end{aligned}$$

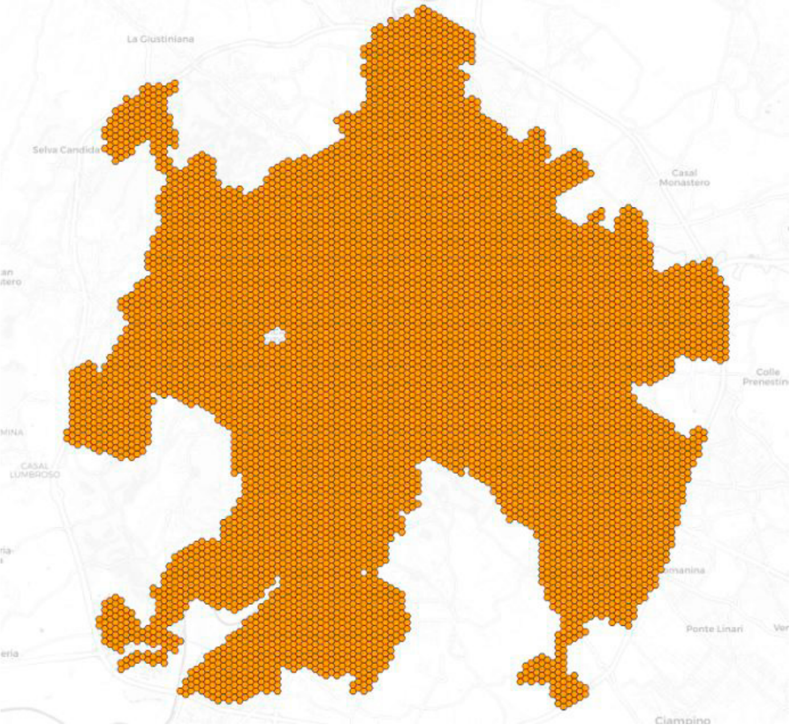

Figure 1. Hexagonal grid used to divide the analysis area

Maximum Likelihood Estimation is used for the estimation of the parameters of the ZIP regression. Further details on the model can be found in Lambert (1992).

Models were estimated for all four seasons, showing comparable results with no noticeable differences between generated and attracted trips, and similar patterns for bicycles and e-scooters. More precisely, autumn, winter and spring were very similar, while some differences can be observed in the results for summer. Considering these observed results, for the sake of the present analysis, only the results for winter (the season with less trips) and summer (the one with most trips) were reported, in Table 2 and Table 3 respectively.

When analyzing the results of the inflated model (which models the probability of zero trips happening), the most statistically significant variable is always the presence of restaurants in the zone, followed by the presence of residential buildings, of cultural/recreational facilities, and bus stops. For the count model, the most statistically significant variable is the number of restaurants in the zone, followed by the number of active workers in the various activities present in the zone, the number of residential buildings, and the number of bus stops. In this case, the model for the e-scooters is slightly different, since in this case the number of metro stations is also significant, much more than what transpires from the bicycle models.

When looking at the differences between seasons, we can notice an increase in significance for the public transport stations and stops, other than for the number workers in the zone, and a loss of significance for the number of hotels and other accommodations when considering bicycle trips, which is probably all connected to the fact that the period of summer sees a considerable increase in tourist presences compared to other seasons.

Table 2. Zero-inflated Poisson regression results for the winter season

		Bicycle				**E-scooter**			
		Generated Trips		**Attracted Trips**		**Generated Trips**		**Attracted Trips**	
		Coeff.	**z-stat**	**Coeff.**	**z-stat**	**Coeff.**	**z-stat**	**Coeff.**	**z-stat**
Inflated model	Intercept	3.924	24.389	3.820	24.443	3.605	27.052	3.575	27.090
	Residential buildings (yes/no)	-1.192	-7.179	-1.165	-7.211	-1.377	-10.037	-1.410	-10.378
	Cycle paths (yes/no)	-0.516	-5.325	-0.476	-4.890	-0.510	-6.157	-0.494	-6.025
	Education facilities (yes/no)	-0.029	-0.122	-0.340	-1.437	0.159	0.889	0.121	0.692
	Supermarkets (yes/no)	-0.543	-5.752	-0.521	-5.462	-0.578	-6.908	-0.498	-5.995
	Restaurants (yes/no)	-1.574	-15.796	-1.584	-15.992	-1.501	-18.401	-1.522	-18.915
	Culture/recreation facilities (yes/no)	-0.663	-7.773	-0.624	-7.248	-0.546	-7.275	-0.575	-7.748
	Metro stations (yes/no)	-0.397	-1.267	-0.676	-2.041	-1.095	-3.283	-0.858	-2.675
	Bus stops (yes/no)	-0.487	-6.186	-0.472	-6.007	-0.576	-8.675	-0.551	-8.389
Count model	Intercept	0.779	19.674	0.707	17.852	1.771	93.555	1.706	90.761
	Residential buildings (count x 10)	-0.351	-12.046	-0.319	-10.842	-0.577	-33.808	-0.508	-31.110
	Education facilities (count)	-0.486	-3.694	-0.463	-3.688	-0.095	-1.670	-0.068	-1.240
	Restaurants (count x 100)	0.930	21.310	0.973	22.583	1.276	61.467	1.259	60.073
	Hotels/Inns/B&Bs (count)	-2.461	-2.364	-2.474	-2.377	-2.584	-4.041	-1.662	-3.734
	Metro stations (count)	0.172	1.842	0.163	1.770	0.435	10.823	0.456	11.100
	Train stations (count)	-0.075	-0.454	0.001	0.007	-0.067	-0.772	-0.083	-0.911
	Bus stops (count)	0.074	6.484	0.064	5.548	0.080	14.226	0.085	14.812
	Workers (count x 1000)	0.421	15.913	0.455	18.066	0.528	40.990	0.538	42.440
	Pseudo R-squared	0.195		0.195		0.285		0.278	
	Log-Likelihood	-5297		-5354		-12106		-12190	

Table 3. Zero-inflated Poisson regression results for the summer season

		Bicycle				**E-scooter**			
		Generated Trips		**Attracted Trips**		**Generated Trips**		**Attracted Trips**	
		Coeff.	**z-stat**	**Coeff.**	**z-stat**	**Coeff.**	**z-stat**	**Coeff.**	**z-stat**
Inflated model	Intercept	3.358	27.228	3.613	26.667	3.092	28.846	3.102	28.701
	Residential buildings (yes/no)	-1.152	-8.990	-1.408	-10.122	-1.453	-13.167	-1.533	-13.792
	Cycle paths (yes/no)	-0.451	-5.205	-0.480	-5.497	-0.559	-7.032	-0.478	-6.016
	Education facilities (yes/no)	0.250	1.271	-0.117	-0.589	-0.134	-0.793	-0.153	-0.916
	Supermarkets (yes/no)	-0.548	-6.142	-0.621	-6.906	-0.690	-7.875	-0.647	-7.396
	Restaurants (yes/no)	-1.472	-17.371	-1.379	-16.250	-1.404	-18.692	-1.391	-18.603
	Culture/recreation facilities (yes/no)	-0.521	-6.554	-0.616	-7.717	-0.595	-7.894	-0.623	-8.294
	Metro stations (yes/no)	-1.535	-4.016	-1.595	-3.986	-1.983	-3.913	-1.961	-3.867
	Bus stops (yes/no)	-0.711	-10.294	-0.729	-10.496	-0.857	-13.802	-0.853	-13.798
Count model	Intercept	1.141	42.714	1.181	43.711	2.149	176.585	2.123	175.109
	Residential buildings (count x 10)	-0.439	-20.371	-0.465	-21.351	-0.541	-50.629	-0.510	-48.753
	Education facilities (count)	-0.242	-2.768	-0.394	-4.474	-0.251	-6.477	-0.236	-6.149
	Restaurants (count x 100)	1.156	37.972	1.072	35.083	1.558	119.205	1.532	119.320
	Hotels/Inns/B&Bs (count)	-13.687	-0.065	-9.632	-0.336	-3.091	-3.821	-3.770	-4.578
	Metro stations (count)	0.285	4.870	0.191	3.107	0.526	19.498	0.439	15.641
	Train stations (count)	0.138	1.219	0.051	0.440	0.110	1.905	0.010	0.171
	Bus stops (count)	0.075	9.535	0.071	8.889	0.090	23.979	0.093	24.666
	Workers (count x 1000)	0.474	24.842	0.489	26.348	0.621	76.637	0.640	81.466
	Pseudo R-squared	0.227		0.226		0.351		0.352	
	Log-Likelihood	-8122		-8091		-24212		-23722	

4. Conclusions

In this paper, we tried to understand the phenomenon of shared micromobility in the city of Rome, using data from the service providers and a Zero-Inflated Poisson regression model to find relations between the number of trips and the characteristics of the zone where these trips started or ended.

In summary, the analysis of shared micromobility usage in Rome highlighted how mobility demand varies with seasons, weather, and tourist flow. The findings also revealed a preference for e-scooter usage, especially in warmer months, while bicycles maintain more consistent use in milder conditions. Spatially, areas with restaurants, residential buildings, and public transport connections show the highest trip generation and attraction.

The ZIP regression model offered some insights into key factors shaping the micromobility demand, which could be used to enable more efficient planning for these kinds of services. The models confirmed the significance of the presence of public transport facilities, hinting to the fact that micromobility is often used as a complementary service to connect stations and transport hubs to other points of interest dislocated in the city. These results support the planning of shared mobility services to make them efficient and effective for users, the managing company, and the well-being of the city and its community.

While the data used allows for some significant results, there are some limitations in this study. First, we know nothing about the users, and their socio-economics characteristics (e.g., age, gender, occupation, income) could significantly improve the explanatory power of the model. Another important missing factor is the purpose and destination of the trip, which could help explain better the phenomenon. However, gathering this data could be much more costly and time-consuming compared to using the data automatically collected by the service providers.

This aspect could be discussed in the future with the operators, to understand if it would be possible to have users complete a small personal questionnaire, even with just their basic data (age, gender, income, household size, etc.).

For this purpose, another possible analysis could be performed with a much smaller sample, with data gathered from a group of volunteer sharing-users, who would have to agree to inform the analysts about their personal socio-demographic characteristics, and purpose for each trip.

Having more detailed data available would almost certainly improve the prediction capability of the models and the potential for the correct planning of the services.

Also, it would be possible to improve the accuracy of the predictions by using different modeling approaches, either by using different advanced statistical models, or by changing strategy and rely on machine learning algorithms.

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References

Baek, K., Lee, H., Chung, J.-H., Kim, J., 2021. Electric scooter sharing: How do people value it as a last-mile transportation mode? Transportation Research Part D: Transport and Environment 90, 102642. https://doi.org/10.1016/j.trd.2020.102642

Carrese, S., Giacchetti, T., Nigro, M., Algeri, G., Ceccarelli, G., 2021. Analysis and Management of E-scooter Sharing Service in Italy, in: 2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS). Presented at the 2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), pp. 1–7. https://doi.org/10.1109/MT-ITS49943.2021.9529274

Cheng, L., Yang, J., Chen, X., Cao, M., Zhou, H., Sun, Y., 2020. How could the station-based bike sharing system and the free-floating bike sharing system be coordinated? Journal of Transport Geography 89, 102896. https://doi.org/10.1016/j.jtrangeo.2020.102896

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). Presented at the 2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), pp. 1–8. https://doi.org/10.1109/ICE.2018.8436288

Frade, I., Ribeiro, A., 2014. Bicycle Sharing Systems Demand. Procedia - Social and Behavioral Sciences, Transportation: Can we do more with less resources? – 16th Meeting of the Euro Working Group on Transportation – Porto 2013 111, 518–527. https://doi.org/10.1016/j.sbspro.2014.01.085

Greene, W.H., 1994. Accounting for Excess Zeros and Sample Selection in Poisson and Negative Binomial Regression Models.

Jobe, J., Griffin, G.P., 2021. Bike share responses to COVID-19. Transportation Research Interdisciplinary Perspectives 10, 100353. https://doi.org/10.1016/j.trip.2021.100353

Lambert, D., 1992. Zero-Inflated Poisson Regression, With an Application to Defects in Manufacturing. Technometrics 34, 1–14. https://doi.org/10.1080/00401706.1992.10485228

Laporte, G., Meunier, F., Wolfler Calvo, R., 2015. Shared mobility systems. 4OR-Q J Oper Res 13, 341–360. https://doi.org/10.1007/s10288-015-0301-z

Lee, H., Baek, K., Chung, J.-H., Kim, J., 2021. Factors affecting heterogeneity in willingness to use e-scooter sharing services. Transportation Research Part D: Transport and Environment 92, 102751. https://doi.org/10.1016/j.trd.2021.102751

Li, A., Zhao, P., Liu, X., Mansourian, A., Axhausen, K.W., Qu, X., 2022. Comprehensive comparison of e-scooter sharing mobility: Evidence from 30 European cities. Transportation Research Part D: Transport and Environment 105, 103229. https://doi.org/10.1016/j.trd.2022.103229

Médard de Chardon, C., Caruso, G., Thomas, I., 2017. Bicycle sharing system ‘success’ determinants. Transportation Research Part A: Policy and Practice 100, 202–214. https://doi.org/10.1016/j.tra.2017.04.020

Noland, R.B., Smart, M.J., Guo, Z., 2019. Bikesharing Trip Patterns in New York City: Associations with Land Use, Subways, and Bicycle Lanes. International Journal of Sustainable Transportation 13, 664–674. https://doi.org/10.1080/15568318.2018.1501520

Singhvi, D., Singhvi, S., Frazier, P.I., Henderson, S.G., Mahony, E.O., Shmoys, D.B., Woodard, D.B., 2015. Predicting Bike Usage for New York City’s Bike Sharing System.