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► **To cite this version:**

Rania Swessi, Zeineb El Khalfi. Shared Micro-mobility: Technologies, Challenges and Prospects of Using Collected Data. International Workshop on Distributed Computing for Emerging Smart Networks, May 2023, Bizerte, Tunisia. pp.41-55, 10.1007/978-3-031-52823-1_3. hal-04534773

HAL Id: hal-04534773

<https://hal.science/hal-04534773>

Submitted on 5 Apr 2024

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Shared Micro-mobility: Technologies, Challenges and Prospects of Using Collected Data

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Abstract. Electric micro-vehicles including scooters, bicycles, and mopeds are gaining popularity as a preferred shared mode of transportation due to their environmental sustainability and cost-effectiveness. However, despite their numerous benefits, these micro-mobility services face several challenges that may limit their adoption. In this paper, we provide a comprehensive discussion of shared micro-mobility services as well as the associated challenges, including maintenance difficulties, infrastructure regulation, safety concerns, and imbalance issues. We also explore the potential solutions that have been implemented to address these challenges and the available datasets that can be used to optimize micro-mobility services.

Keywords: Micro-mobility devices · Connected micro-mobility · Micro-mobility datasets · Challenges · Service optimization

1 Introduction

Shared micro-mobility services have become increasingly popular in recent years as a flexible and sustainable alternative to traditional transportation options [39, 14, 25]. Companies like Bird, Lime, and Voi offer electric bikes, scooters, and other small vehicles for short trips in urban areas. These services are particularly useful for tourists, workers, and anyone seeking a quick and convenient transportation mode for their daily needs [13]. In addition to being cost-effective and affordable with low rental fees, micro-mobility services are eco-friendly, requiring significantly less energy to operate than traditional cars. Furthermore, they help alleviate traffic congestion and parking demand in urban areas, making them a more practical and efficient transportation option [39]. However, the reliability of these services is often challenged by various issues, such as maintenance difficulties, infrastructure regulation, safety, and imbalance problems [38, 26, 40, 23]. These issues can severely impact user satisfaction and company revenue. Therefore, it is crucial for micro-mobility operators to implement effective strategies to enhance the services and the overall user experience. Fortunately, researchers have shown that collected data from shared micro-mobility systems, such as trips, locations, and traffic data, can help solve these problems. For example, trip data or location can be utilized to optimize fleet placement and

reduce maintenance costs [37]; while vehicle sensor data or traffic data can be used to identify collision risks and improve user safety [26, 22].

This paper offers a comprehensive analysis of micro-mobility services, with a particular focus on the devices and technologies used for communication between them. It presents a detailed overview of the challenges facing these services, with the existing datasets that can be leveraged to address them. By synthesizing the latest research and insights, it offers practical guidance for researchers and practitioners in this field. In addition, we perform an analysis of a real-world dataset obtained from the Bird company’s micro-vehicle fleet usage in Bordeaux to determine the key factors that can enhance the services and improve the overall user experience.

The remainder of this paper is organized as follows: In Section 2, we introduce the micro-mobility service, including the different modes that are commonly used and the technologies that enable their communication. Section 3 provides an overview of the challenges faced by micro-mobility services, while Section 4 outlines how collected data from micro-mobility services can be used to solve these problems and optimize the services.

2 Overview of shared micro-mobility services and technologies

As the demand for urban transportation solutions has increased, shared micro-mobility services have emerged as a viable and sustainable option for short-distance trips. To support the efficient operation of these services, various communication methods are used to enable real-time tracking, monitoring, and management of the micro-mobility devices. This ensures that users have access to accurate and up-to-date information on vehicle availability, location, and route planning. Additionally, it enables operators to effectively manage and maintain their fleets, optimize vehicle allocation and charging, and respond quickly to any issues or incidents. This section will cover the characteristics of the commonly used devices in shared micro-mobility services, as well as the communication technologies that enable their effective deployment and operation.

2.1 Micro-mobility devices

In recent years, the availability of shared micro-mobility services has greatly expanded, covering a variety of frequently used modes like bicycles and e-scooters [11, 1]. These modes of transportation differ in terms of design, cost, and operation mode. Figure 1 shows an example of micro-mobility devices, including e-scooters, e-bikes, e-mopeds, and segways.

Bikes are typically the most affordable and widely available mode of shared micro-mobility transportation. They are simple to use and provide a low-impact workout. Electric bikes, or pedelecs, on the other hand, offer a smoother ride thanks to a pedal assist feature that makes it easier for users to travel further and faster. A speed-pedelec (S-pedelec) is a type of electric bike that is designed

to provide assistance up to higher speeds, typically up to 45 km/h, and may have different legal requirements than traditional e-bikes. Electric scooters are also common and practical to use, with their straightforward design making it simple for users to park them anywhere in free-floating systems. Although more expensive and requiring a valid driver's license to operate, electric mopeds offer a more powerful and effective form of transportation. Finally, electric skateboards and segways are the newer additions to the micro-mobility market, offering unique and fun transportation modes that are popular among young adults; however, they are not yet widely available for shared use. In the end, a person's choice of transportation depends on their preference, budget, and intended use.



Fig. 1. Example of micro-mobility devices

These shared micro-vehicles allow users to rent vehicles for a limited time at an affordable cost. Most shared micro-mobility services are accessed through a mobile app that lets users find nearby vehicles, unlock them with their phones, and pay for their use. Shared micro-mobility services can be classified into two main categories: fleet services (where the vehicles are managed and provided by a company) and peer-to-peer services (where individual vehicle owners make their vehicles available to other users for a fee) [9, 32]. Fleet services can be both docked and dockless, with or without charging stations, depending on the type of vehicle.

Table 1 represents a comparison of micro-mobility devices, their features, and specifications like average weight, power supply, range (the distance that the device can travel in a single charge), legal requirements, etc. The values presented in the table are indicative averages and may not accurately represent the precise specifications of each micro-mobility device.

Table 1. Micro-mobility devices and their features

Device \ Feature	E-scooter	E-bike	S-pedelec	E-moped	Segway
Average weight (kg)	10-25	15-25	30-35	30-70	50-60
Max speed (km/h)	25	25	45	45	20
Operable pedal	no	possible	yes	possible	no
Power supply (watts)	250-500	250-750	500-750	500-2000	400-800
Range (km/h)	40-100	40-80	50-100	50-100	20-30
Average charging time	4-8h	3-6h	3-6h	4-8h	4-8h
Occupants	single rider	single rider	single rider	multiple riders	single rider
Legal requirements	none	none	license/helmet	license/helmet	possible
Age requirements	14-16	14-16	>16	>16	14-16

2.2 Micro-mobility Companies

There are several shared micro-mobility companies that have gained popularity around the world, with some of the most well-known being:

1. **Bird** provides electric scooters and bikes and operates in around 50 metropolitan areas across the United States, 14 cities in Europe, and 3 cities in the Middle East. Their micro-vehicles are available for short-term rentals through the Bird mobile app and are designed to be a sustainable transportation option. Bird’s electric scooters and bikes are designed to be lightweight and easy to use, with a top speed of 32 km/h and a range of up to 50 km/h on a single charge [3].
2. **Lime** provides electric bikes, scooters, and mopeds in over 100 cities worldwide. Lime’s electric vehicles are designed to be easy to use and are equipped with safety features such as lights and brakes [13, 17].
3. **Voi** is a Swedish shared micro-mobility company that provides a variety of electric vehicles, including bikes, scooters, and mopeds. Voi’s mobile app is also designed with sustainability in mind, with features such as a carbon footprint calculator that shows users how much CO2 is saved [34].
4. **Spin** is a popular shared micro-mobility company that provides electric scooters, bikes, and e-assist bikes. It operates in over 70 cities worldwide, including Europe, Canada, and the United States. Spin’s micro-vehicles are designed to be reliable, with a focus on safety and durability. Spin’s mobile application is also user-friendly, with clear instructions on where to locate and how to unlock the fleet, as well as helpful riding safety tips [31].

Various systems are used by micro-mobility companies to handle their fleets. Docking is a common system in which vehicles are picked up and dropped off at designated stations. These stations can be fixed physical stations or virtual stations. Virtual stations refer to well-defined zones without physical boundaries, with an obligation to park the fleet inside these zones. Alternatively, the dock-less system allows users to park vehicles anywhere within a specific operating zone. Some companies use a hybrid system that offers both docked and undocked parking options. The choice of a system depends on several factors, such as the city’s size and metropolis, user demand, and regulatory requirements. Each system has its own advantages and disadvantages, making it essential for companies to assess their needs before deciding on the most suitable option.

Micro-mobility companies also adapt to the specific needs and expectations of their customers and focus on specific purposes such as Bird for leisure, Lime for work, and Voi for tourism [4, 21]. However, this choice can also depend on various factors, including personal needs, distances, available transportation options, traffic conditions, and individual preferences.

2.3 Technologies used in connected micro-mobility devices

Shared micro-mobility vehicles, such as e-scooters, e-bikes, and e-mopeds, are typically equipped with wireless communication systems, such as embedded SIM cards, Global Positioning System (GPS) receivers, and sensors [24, 6, 8]. These technologies not only allow companies to track the vehicles’ location and condition, but they also enable direct communication between the vehicles using short-range or low-power technologies such as Bluetooth, Zigbee, LoRa, or Wi-Fi [5, 33, 36]. Some shared micro-mobility vehicles can also be equipped with Vehicle-to-Vehicle (V2V) technology for short-range and direct communication. It enables the exchange of information between vehicles and can be used for collision avoidance, traffic optimization, and platooning. This technology can be especially useful in densely populated areas where there is a high demand for short-distance transportation.

To connect micro-mobility vehicles to the internet or to the central control system, cellular communication technologies such as 4G and 5G can be used for long-range communication [28]. 4G allows for high-speed remote communication, enabling operators to monitor in real-time the status of vehicles, such as their battery level, speed, track status, and other key components. With the arrival of 5G, the infrastructure is expected to further improve road safety with a comprehensive vision of traffic and roads in real-time, allowing for more advanced safety features [28]. Additionally, 5G will enable faster and more reliable communication for monitoring, control, and management of micro-mobility fleets, which can lead to more efficient operations and better overall user experience. Some other technologies including Near Field Communication (NFC), or QR codes can also be used to connect the device to the user’s mobile phone or unlock the fleet [8]. Table 2 represents a comparison of communication technologies used in shared micro-mobility systems.

Table 2. Comparison of communication technologies in micro-mobility

Technology	Range/power consumption	Data transfer rate	Communica- tion mode	Typical use case
Bluetooth	10m / low	1 Mbps	device-to-device	data tracking and control
Wi-Fi	100m / moderate	10 Gbps	device-to-hub/router	data exchange, navigation, and remote management
Zigbee	100m / low	250 kbps	device-to-device/to hub	data exchange, tracking and control
LoRa	10 km / low	50 kbps	device-to-device/gateway	track location and usage /monitoring in real-time
V2V	300m /low	27 Mbps	device-to-device	collision avoidance, traffic optimization, and platooning
4G/5G	6-10 km /high	10 Gbps	device-to-cellular networks	high-speed data transfer, and remote control

Regarding shared micro-mobility companies, Bird and Lime, use a combination of communication technologies including Wi-Fi, Bluetooth, and cellular communication depending on the region’s infrastructure and local conditions [33]. Ultimately, the choice of communication technologies depends on each company’s needs, the availability, and quality of wireless networks in a given region, the transmission range, and local regulatory requirements. Companies may also adopt new technologies as they evolve to meet the changing needs of users and improve the overall experience of shared micro-mobility.

3 Challenges Facing the micro-mobility Industry: An Overview

The field of micro-mobility faces various challenges related to infrastructure, regulation, system imbalance, and safety. One of the major issues is the lack of proper infrastructure for micro-mobility vehicles, such as bike lanes, parking areas, and charging stations [20, 35, 19]. This makes it difficult for users to use and park their vehicles safely and conveniently, which increases the number of improperly parked fleets. Another challenge is the need for regulations that balance the benefits of micro-mobility with issues of public safety, privacy, and property rights. For example, some cities have imposed restrictions on the number of shared micro-vehicles allowed on their streets or required companies to share private data on their operations. Additionally, safety is a concern as accidents involving micro-mobility vehicles have increased. [30]. This requires the implementation of safety measures such as helmets and educational campaigns for both users and drivers.

Micro-mobility vehicles require regular maintenance to remain secure and in excellent operating condition [19]. For example, the batteries in electric micro-vehicles need to be recharged regularly, but their life span can decrease over time, reducing their capacity and performance. Tires on rubber-tired vehicles can suffer damage, punctures, and wear, which also affects their safety and performance. Brakes and brake pads should be checked and replaced if needed. Electrical components may also need maintenance to function properly, and all vehicles experience general wear and tear over time, requiring repair and maintenance. These maintenance issues can be costly and time-consuming, especially for individual owners of micro-mobility vehicles [19].

Regarding the communication technologies in micro-mobility systems, they pose potential security risks. For example, bike and scooter companies utilize a combination of Bluetooth and internet connections to communicate with users' mobile phones and central servers. This can make them vulnerable to hacking and the potential mobilization of numerous vehicles in an urban setting. The authors in [29, 28], propose a wireless communication technology designed to enable long-range communication between devices with low power consumption, namely Low-Power Wide-Area Network (LPWAN). This technology can improve safety and reduce accidents.

Fleet maldistribution and system imbalance are major challenges that affect the availability and accessibility of micro-mobility services and, ultimately, user satisfaction [40, 23, 16, 15]. In the case of dockless systems, fleet maldistribution can result in certain regions or zones being underserved while other areas are oversaturated with vehicles. In physical dock-based systems, system imbalance can lead to empty or full docking stations, which can inconvenience users and undermine the usefulness of the service. When docking stations are completely empty, users are unable to access the service and may be forced to seek alternative transportation methods. On the other hand, when docking stations are completely full, users may have difficulty finding a parking spot, which can result in frustration and discourage further usage of the service. These issues have a negative impact on customer satisfaction, with customers suffering from unfavorable effects like longer wait times, farther travel in finding fleets, and difficulty accessing the service. Furthermore, a decrease in service quality could result in lower customer adoption rates and revenue for the company. To overcome these challenges, micro-mobility providers must develop effective strategies to optimize the distribution of fleets and the management of docking stations while leveraging real-time data and analytics to improve the overall user experience.

4 How can micro-mobility datasets be beneficial?

Data gathering from shared micro-mobility systems can help solve some issues with user satisfaction and safety, while also significantly improving services. For example, trajectory data or location data can be used to optimize fleet placement, reducing imbalance issues and improving user accessibility. Vehicle sensor data or traffic can be used to detect collision risks and potential accidents,

enabling preventive measures to reduce these risks and ensure user safety. In addition, data on users’ usage patterns can be used to improve pricing models, service offerings, and user satisfaction.

4.1 Using data for better problem-solving and services

The use of collected data from shared micro-mobility systems may offer many opportunities to improve the quality and efficiency of services while ensuring a more satisfying and safer user experience. Table 3, presents a comprehensive overview of datasets used by articles to address micro-mobility challenges, including information on data availability statements, collection years, system and fleet type, targeted issues, and data analysis country.

Table 3. Used datasets for addressing micro-mobility challenges

Ref	Data type	Statement	Year	Fleet type	Problem	Country
[15]	trip/weather	public	2015-2017	docked bike	imbalance	Korea
[18]	trip	public	2013-2016	docked bike	imbalance	NewYork
[16]	trip/weather	public	2016	docked bike	imbalance	China
[25]	trip	private	2019	dockless scooter	relocation	Canada
[12]	trip/weather	private	2019	dockless scooter	relocation	Korea
[37]	trip	open	2019	dockless bike	maintenance/relocation	NewYork
[41]	trip	open	2017	dockless bike	maintenance/relocation	China
[14]	trip/weather	private	2020	dockless scooter	relocation	Korea
[26]	sensor	open	2020-2021	dockless scooter	infrastructure/safety	Italy
[38]	trip/weather	public	2013-2017	docked pedelec	maintenance cost	NewYork
[7]	trip	open	2018-2019	dockless scooter	infrastructure/safety	Texas
[22]	region/traffic	private	2018	dockless scooter	relocation	Turkey
[2]	sensor/traffic	private	2015	docked bike	station placement	US
[10]	crashes/trips	private	2019-2021	dockless	infrastructure safety	Italy
[27]	trip/weather	private	2020	dockless scooter	relocation	Chicago

The authors in [15, 18], describe a method for solving placement problems in physical dock-based systems by utilizing trip data and advanced deep-learning architectures. The solution relies on predicting user demand and using graph networks to model the connections between stations as nodes and the dependencies between them as edges, with the ultimate goal of balancing the fleet. In [16],

the researchers propose a reinforcement learning ¹ framework based on recorded trips between docked stations. This would help the system find a good balance. The solution consists of loading from a blocked predicted station and unloading at an empty station. In [25, 12], the researchers use real-world trip data, taking into account weather and temporal criteria, to enhance the fleet locations and decrease the research time to find a fleet. They represented the demand using heatmap images as a strategy to identify future frequent areas. They employed machine learning forecasting techniques to predict the demand density at each hour within the operational zone. This strategy can help operators choose the best locations for their fleets and enhance the user experience by analyzing demand density images. To address both maintenance and redistribution challenges, the authors, in [37], propose a reinforcement learning-based multi-agent system that enhances micro-vehicle availability while minimizing the need for relocation and battery replacements. This solution is designed using a trip dataset and is capable of improving operational efficiency. In [41], the researchers prove the effectiveness of initiating users to balance dockless systems and aggregate low-battery fleet together, saving the cost of maintenance. They propose a prediction tool capable of estimating user demand from recorded trips within an area using machine learning. In [14], the authors show that weather data can be used to predict how many users will want to use dockless systems. The solution can increase user satisfaction by minimizing the research time required to find a fleet.

To enhance micro-mobility safety as well as improve infrastructure, authors in [26], propose a safety-based efficiency indicator for urban areas, using a data envelopment analysis. This indicator allows evaluation of the safety efficiency for each studied area according to factors such as road intersections, vehicle speed, and the presence of bicycle lanes. The authors, in [38], focus on the development of an efficient prediction machine learning model that predicts the demand for pedelec use every 48 hours and an optimal route plan for pedelec battery charging using real-world datasets. In [7], a method is presented for estimating street segment-level e-scooter flows using an open-source dataset that includes millions of trip origins and destinations. The authors prove that the proposed model can help cities better support the emerging shared micro-mobility service. Researchers, in [22], suggest a decision support system for e-scooter sharing systems that helps dynamically place e-scooters in urban areas where they are required. The goal of this system is to provide select options by combining real-time social media data with traffic density information and region data given by the multi-criteria analysis made using the Analytical Hierarchy Process (AHP). In [2], a station placement strategy is proposed in order to determine the best locations for 5 new bike-sharing stations in Fargo, North Dakota. The workflow combines a geographic information system (GIS), level of traffic stress (LTS) ratings, and location-allocation optimization models. Authors in [10] highlight

¹ Reinforcement learning is a branch of machine learning that involves the training of artificial agents to interact with their environments and learn the best actions to take using a deep neural network to increase reward and solve the problem.

the inefficiency of ad-hoc planning in developing safe infrastructure for micro-mobility, which is essential for creating climate-friendly, sustainable, and livable cities. They propose an automated network planning process that utilizes data from various empirical sources, including existing infrastructure networks, bicycle crashes, and trip data from Bird company. The modeling framework presented in the study is applied specifically to the city of Turin, Italy, but it can be extended to other cities as long as similar data is available. It is able to create new cycling tracks that prioritize both travel demand and cycling safety and can be integrated into the existing infrastructure. The authors, in [27], focus on redistribution fleet optimization by predicting user demand using a trip dataset. The solution can help operators pick the ideal areas for fleet deployment according to user needs. Additionally, it can be adapted to any redistribution strategy and can be used in various ways like reducing collision risks in areas where the model predicts high demand or optimizing pricing strategies by analyzing the number of future demands.

This last solution and the majority of solutions proposed to address micro-mobility issues such as relocation problems, infrastructure safety, or maintenance costs rely on predicting user demand using advanced machine learning techniques. By leveraging this prediction, operators can optimize their services to better align with user needs and improve overall satisfaction. To accomplish this, data collected from shared micro-mobility systems, such as trip data, fleet positions, and infrastructure-related data, is processed using data science, data cleaning, and analysis techniques to prepare it for modeling. In this context, data visualization techniques can also be used to help in identifying other influential factors that should be prioritized in predicting user demand, like weather or traffic data. Through visualization, patterns, and trends within the data can be more easily identified, leading to a better understanding of the complex relationships between different variables.

4.2 A review of a real-world micro-mobility dataset (Bordeaux, 2021/2022)

We are delighted to collaborate with Bird [3], a leading operator in the micro-mobility space, to analyze their recent dataset on self-service fleet usage. This dataset provides a unique opportunity to explore real-world mobility trends in the city of Bordeaux, France, and address micro-mobility challenges, including user satisfaction and fleet availability. However, the dataset is not yet publicly available due to privacy concerns. In this section, we present the features of this dataset as well as strategies for leveraging it to improve service quality and meet user needs. Figure 2 shows the operating zone in Bordeaux, which covers a 36.56 Km² area and includes more than 100 virtual stations for e-bikes and e-scooters.

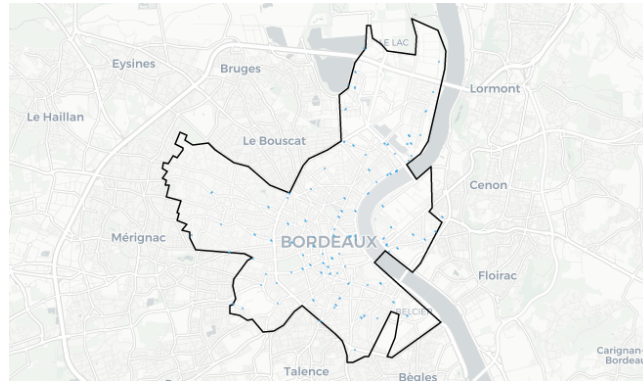


Fig. 2. Bird's operating area in Bordeaux city

Bird is one of the companies that rely on virtual stations to park its fleets in Bordeaux for regulatory reasons, in which users are obligated to park in well-defined georeferenced areas without physical boundaries with a radius of 15 meters [3].

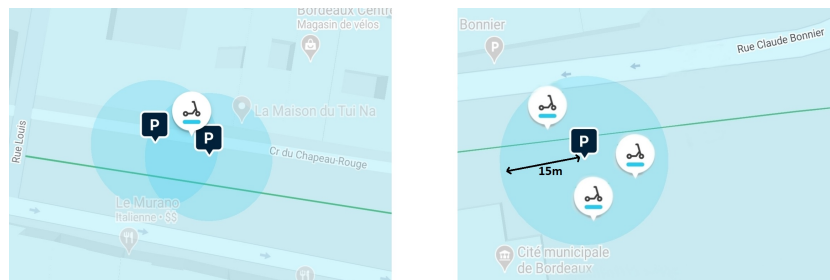


Fig. 3. Example of Bird virtual station

Bird provides us with a trip dataset for electric scooters and bikes that have been recorded, with the beginning and ending GPS positions collected in the city of Bordeaux. It includes over 71 thousand recorded trips between arrival and departure stations over the twelve 2021 months and the three winter months of 2022. Each transaction record includes the following details:

- Trip ID (Object): refers to the trip identifier.
- Vehicle checks out/in time (Object): refers to the date of reservation and the return of the fleet.
- Start and End position latitudes and longitudes (Float64): refers to the precise GPS start and end positions of the trip.

A list of fixed virtual stations is also given because trips are recorded with the exact GPS departure and arrival position rather than the virtual station to which they belong. This list includes the latitudes and longitudes positions and the identifier of the station.

The graphs shown in Figure 4 illustrates the average demand (number of trips) for Bird’s micro-mobility services during different times of the day across different seasons.

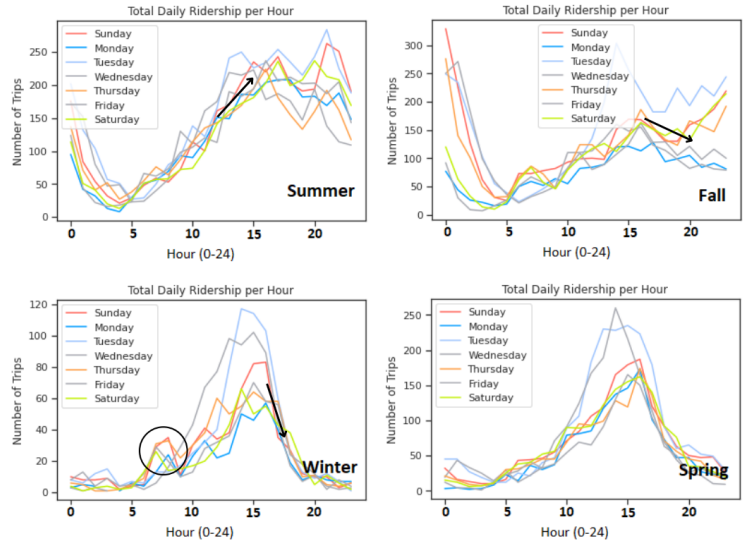


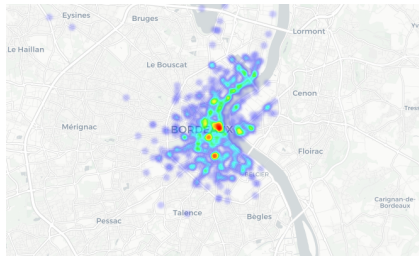
Fig. 4. Average demand for each season by hour and day (from Bird’s data)

Table 4 represents the average number of demands made up to the maximum during each time period, categorized by day type (weekday vs. weekend) and season. This data is derived from Graph 4, which provides a visual representation of the same information.

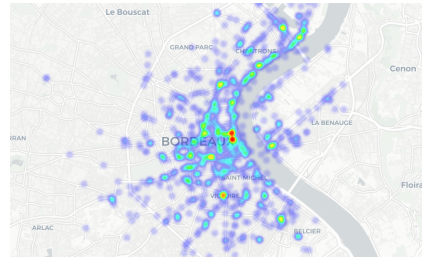
Table 4. Average number of trips by the time of day, day type, and season

Season	Day	Morning(5am - 12pm)	Afternoon(12pm - 6pm)	Evening(6pm - 12am)
Summer	Weekday	132-180	215-230	200-300
	Weekend	90-175	187-240	225-300
Fall	Weekday	70-150	120-150	100-300
	Weekend	60-100	140-150	120-160
Winter	Weekday	45-80	85-120	40-50
	Weekend	35-40	60-80	35-40
Spring	Weekday	100-175	137-250	75-100
	Weekend	60-100	100-180	75-100

As expected, the demand for trips during the summer increases significantly in the afternoon and evening hours, especially on weekends, with a peak demands of up to 300. In contrast, there is relatively low demand during the morning rush hour. During spring and winter, however, the demand is lower during the evening rush hours and higher in the morning or afternoon, particularly on weekdays, with demand reaching up to 250. The data demonstrate that Bird’s customers use the services primarily for leisure purposes, as demand consistently peaks during the evening rush hour or evening hours, in each season. Figure 5 shows a heatmap visualization for user demand. We can easily notice from the maps that the majority of the frequented areas are touristic or commercial.



(a) Heatmap visualization for starting Bird positions



(b) Heatmap visualization for starting Bird positions zoomed

Fig. 5. Heatmap visualization for Bird demand density

We can notice, from figures 3 and 5, that the area’s type and period have a great impact on user demand. However, regarding the imbalance problem, it is not sufficient to determine the exact ideal locations to place the fleets dynamically according to the user’s needs and enhance user satisfaction and service. Recent studies have demonstrated that using advanced prediction techniques, such as machine learning, can help predict the user demand for an area or a station. These predictions can be based on temporal criteria, such as specific days or time periods of the week [41, 18, 12]. Given also that weather variables have a significant impact on the use of micro-mobility modes [38, 21]; it enables more accuracy in the prediction of user demand by taking into consideration a variety of variable factors like temperature, humidity level or wind speed.

In consequence, we can say that the use of real trips, that have been recorded over time, can effectively help increase the availability of fleets in areas where high future demand is predicted; this helps to reduce the amount of time that users must spend searching for a fleet. This forecast enables operators to properly assess their demand and can provide additional virtual stations in popular regions during specific times, like the summertime, close to tourist areas. By enhancing the user experience, these techniques help operators boost their revenue and improve their services.

Additionally, the user demand prediction tool can improve various aspects, such as pricing strategies and offers, during peak demand periods. It can also improve safety and reduce collisions in areas predicted to be in high demand, or decrease the cost of maintaining devices and replacing batteries. This can be achieved by planning collection operations during times when there is little demand.

5 Conclusion

Shared micro-mobility services face numerous challenges that can negatively impact user satisfaction and company revenue. These challenges include system imbalance, high maintenance costs, infrastructure problems, and safety concerns. To overcome these challenges, machine learning techniques, analytical systems, and decision support systems have been proposed as solutions. These approaches rely on the collected data from shared micro-mobility services, and it has been demonstrated their significance as a crucial element in enhancing service usage. In this study, we analyzed a real-world dataset of recorded trips in Bordeaux, France. The goal was to explore how to leverage this data to improve fleet availability and service quality. By identifying patterns and insights within this data, we can make informed decisions and implement targeted strategies to create a better experience for users and drive greater revenue for companies [27].

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