The Role of Micro-Mobility in Environmental Monitoring: Reflections and Opportunities on the Use of Pervasive Sensing

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***Abstract*—Micro-mobility vehicles are not just friendly transportation options for the environment but also can aid in protecting it. Currently, obtaining environmental indicators at a city-scale is challenging due to limited spatial and temporal coverage in existing solutions. This paper contributes a sensor-based micro-mobility framework for equipping micro-mobility vehicles with sensors for environmental monitoring. To build this framework, we conduct a literature review on sensor re-purposing for environmental monitoring. With this information, we then describe how our framework can facilitate the analysis of sensors embedded in micro-mobility vehicles. Our framework organizes research challenges based on the range level of the sensors to collect data samples to characterize the surrounding environment, with each level combining multiple modalities, or introducing participatory sensing to improve veracity of the measurements. We then discuss the fundamental issues in data collection that arise at each level and highlight the most feasible applications for environmental monitoring that can be supported by micro-mobility. We conclude with a summary of core research challenges, opportunities, and a discussion on the implications of using these vehicles.**

***Index Terms*—Data collection; Vehicles; Human Mobility**

I. Introduction

Micro-mobility vehicles are emerging as an innovative transportation mode, offering convenient and environmentally friendly options for short-distance travel in urban areas. Apart from aiding users in their movement, micro-mobility vehicles also capture fundamental human mobility patterns and activities within city areas of interest [1]. These inherent characteristics make these vehicles powerful tools for characterizing and monitoring the health of human habitats. As a result, micro-mobility vehicles are not just friendly transportation options for the environment but also can aid in protecting it. Environmental sustainability refers to the practice of protecting natural resources and ecosystems, conserving them for the well-being of current and future inhabitants [2]. Thanks to the emergence of pervasive sensing, monitoring solutions to obtain environmental indicators can be easily designed and developed using low-cost technologies. Environmental indicators are measures that represent what is happening in the environment. Pervasive sensing relies on the use of off-the-shelf and rapid prototyping sensors, and the re-purposing of collected data to derive indicators from a range of specialized applications. For instance, a rapid prototyping spectrometer can analyze different characteristics of water quality to determine whether it is polluted [3], and cameras can characterize different waste in urban areas [4]. A key limitation of these solutions is directly linked to the deployment of the sensor, which provides very sparse spatial and temporal coverage of an area. Equipping micro-mobility vehicles with sensors for environmental monitoring poses a great opportunity to improve the monitoring density of natural ecosystems.

Existing solutions for environmental monitoring rely mostly on specialized, costly and bulky equipment. For instance, massive air quality towers and water stations [5]. Besides requiring fixed deployment and experts to operate them, a key problem with these solutions is its limited coverage [6], making them unsuitable to obtain environmental indicators at city-scale. Other solutions for environmental monitoring rely on the static deployment of IoT devices (blended within 3D printing designs [7]). For instance, weather stations can be easily fabricated and deployed with rapid prototyping IoT devices. The main problem with these solutions is that their sensor estimations are highly inaccurate, requiring frequent re-calibration with reference equipment [8], e.g. nearby towers or retrieval of online information. Another solution is the use of personal and wearable devices. Indeed, sensors in smartphones and wearables are piggybacked from app usage sessions, such that data from the individual's surrounding is collected and environmental indicators can be derived [9]–[11]. New sensors have also been designed, such that those can be easily embedded within user's personal items, e.g., backpack or handbag. Sensor inaccuracies from these solutions are mainly overcome using crowdsensing and crowdsourcing methods [12]–[14]. A key problem with these solutions however is the incentive of individuals for performing such data collection tasks, making the system unsustainable in the long term [15]. At the same time, more advanced and autonomous solutions have proposed the use of autonomous vehicles (UAVs, AUVs, and AGVs) embedded with sensors to monitor environmental ecosystems [16]. Unfortunately, autonomous vehicles have not reached a full autonomy level to perform these tasks yet. While several solutions are available for environmental monitoring, those are not enough by themselves to obtain dense indicators at city-scale, requiring to explore new solutions to augment and complement existing deployments.

In this paper, we describe a research vision in which micro-mobility infrastructure deployed in urban areas is exploited for environmental monitoring (as shown in Figure 1). To achieve our vision, we present a framework that aids in equipping and re-purposing sensors in micro-mobility vehicles to perform different types of environmental monitoring. To analyze this, first, we review the type of applications for environmental monitoring that have been developed by re-purposing different sensing technologies. After that, we reflect on how sensors can be embedded in micro-mobility vehicles and the level of coverage that sensors can provide. As single individuals (driver) are operating the vehicles, by using the Edward Hall's proxemics theory [17], we also analyze the level of opportunistic participation (or human-assistance) that individuals can provide to overcome the limitations of sensors, e.g., using experience sampling method [18]. In the light of our analysis, we then provide a detailed discussion about core challenges and opportunities that can be exploited by augmenting micro-mobility vehicles for environmental monitoring.

II. Review on Sensor Re-purposing for Environmental Monitoring

We begin by reviewing current on-going efforts on sensor re-purposing for environmental monitoring. Thus, we describe our literature review process and its output, followed by highlighting how these solutions can benefit from assistance of users.

Environmental indicators: UNECE (United Nations Economic Commission for Europe) has categorized environmental sustainability into four (4) different types of areas, including, air quality, water quality, noise quality and biodiversity. Air quality indicators quantify the amount of pollutants present in the air [19]. Likewise, water quality indicators measure level and concentration of contaminants mixed with water, e.g., chemical and plastic particles [20]. Similarly, indicators of biodiversity changes include the decline or disappearance of animal species and its re-location; or the pollution of soil [21]. Lastly, noise indicators measure not just the presence of noise but also its duration as it can impair our cognitive abilities [22].

Inclusion criteria and scope: The literature review considers work from 2011 to 2021, e.g., (ten-years) and is conducted during 2023. One year gap was kept in between to consider work that has gathered attention and interest from the community. Two primary computer science databases are used, the ACM library and IEEE Xplore. These databases are queried based on a defined constructed criteria consisting in a set of keywords. Environmental sustainability keywords are defined first following standard and common terminology. Thus, first, four categorical keywords are considered, *"air"*, *"water"*, *"biodiversity"* and *"noise"*. These keywords are searched in the title. After this, domain-specific keywords are selected to search for work that relies on sensors and human involvement to perform environmental monitoring. Thus, keywords, *"monitoring"*, *"outdoor"*, *"participatory"*, and *"sensing"* are considered. The monitoring keyword is selected to depict sensor sampling continuously (title search). The outdoor keyword is selected to consider outdoor environments (full text and meta-data search), and the sensing keyword aims to capture analytic methods (pipelines) that re-purpose sensor data to enable environmental applications (full text and meta-data search). The use of the participatory keyword is of particular importance as it depicts human involvement, which makes it feasible for an environmental solution to be mapped to micro-mobility drivers (full text and meta-data search). Moreover, this also allows us to set apart and filter work that just focuses on engineering and technical developments, e.g., improved signal processing or alternative algorithmic design or new sensors. Other keywords such as *"pervasive"* and *"micro mobility"* are not considered as these provide a few or none results. A query then is formed by combining all domain-specific keywords and one categorical keyword at the time. To make our review concise, filters to each query are also applied and these included selecting only full (mature) articles written in English, and excluded demonstration, book chapters, short papers, posters, workshop papers, lectures, keynotes, interviews, opinions, columns and invited papers.

Output: Queries to the ACM library retrieved, 17 papers (Noise), 7 papers (Biodiversity), 2 papers (Water) and 20 papers (Air). Likewise, Queries to IEEE Xplore retrieved, 8 papers (noise), None papers (Biodiversity), 2 papers (Water) and 21 papers (Air). Queries were performed several times to ensure their replication in the defined period. This set of papers was read further to prone down the amount of papers to 30. Our review focuses on off-the-shelf sensors found in smartphones and wearable devices; and rapid IoT prototyping. A key reason is that these sensors can be embedded into the micro-mobility vehicles with ease. Methods that require large deployment of sensors but fall into our criteria are excluded as it is unfeasible to integrate them into a single micro-mobility vehicle, e.g., embedding GPS into litter to track it. When differences between contributions were found to be incremental, year was chosen as an exclusion factor, selecting the most recent year in the review period. When exclusion by year was not possible, citation count was used instead. *Our literature review is thus built based on* 30 *papers.*

Environmental monitoring sensors: Our results from the queries indicate that environmental monitoring applications supported by sensors are mostly investigated for air quality monitoring [5], [8], [16], [23]–[29]. Likewise, noise monitoring has been investigated by relying on micro-phones embedded in personal devices [10], [11], [13], [22], [30]–[33]. While we found relevant work in water and biodiversity monitoring, the amount of work is reduced when compared with air and noise. Biodiversity monitoring is performed through micro-phone and camera measurements [13], [21], [34]. To verify that no other synonyms were used instead, we evaluated changing the *biodiversity* keyword by *species and fauna*, this however did not list more entries nor additional

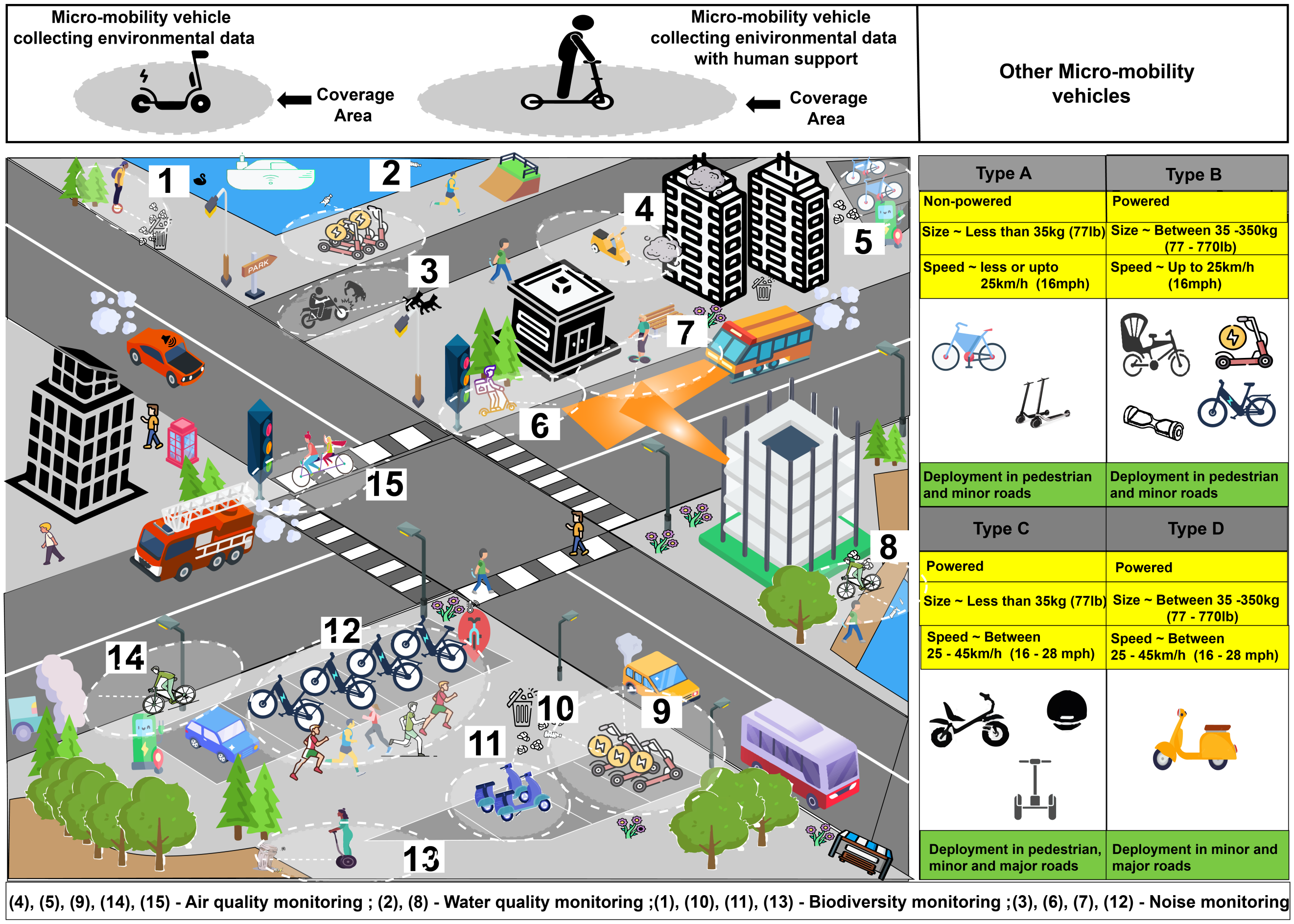


Fig. 1: Environmental monitoring applications supported by micro-mobility.

papers. Water monitoring is also conducted through camera measurements and visual inspection from users [4], [20], [35], [36]. From the reviewed work, it is possible to observe that while human assistance is used to support environmental measurements, the assistance of humans is performed over two general types of sensors. Thus, we characterized these sensors as 1) Non-contact and 2) Contact based sensors. This is important as this also depicts the way in integration of a sensor in the micro-mobility vehicle. Non-contact sensors can obtain measurements from a distance relative to the vehicle, e.g., cameras; whereas contact sensors collect measurements in close proximity and within the vehicle, e.g., motion sensors.

Figure 2 shows the two categories of sensors that can be used for environmental monitoring, accompanied by examples. Two critical issues are observed to be recurring problems for all environmental monitoring solutions, energy consumption and sensor coverage. Energy footprint is key for collecting samples continuously, whereas sensor coverage defines the surrounding area that can be characterized by the sensor. The figure also illustrates four quadrants representing trade-offs between energy and sensor coverage. The first quadrant (I) comprises sensors that have high energy footprint while enabling high coverage from a distance, e.g., cameras, thermal cameras and microphones. The second quadrant (II) consists of sensors that also provide significant coverage from a distance, but their energy footprint is lower, e.g., Bluetooth and WiFi. Likewise, the third quadrant (III) depicts sensors that have low energy footprint, but their coverage is linked to the object in which they are embedded. Similarly, the fourth (IV) quadrant consists of sensors that have a high energy footprint and their coverage from a distance is tied to the surrounding (meters or centimeters) of the object in which they are embedded.

III. Micro-mobility for Environmental Monitoring

We next analyze how existing sensing solutions can be integrated into micro-mobility vehicles. As human assistance from drivers may be required when collecting data, we then apply the Edward Hall's discrete proxemic zone theory on the drivers. With this information, we present a micro-mobility framework that highlights possible applications that can be supported when equipping micro-mobility vehicles with sensors for environmental monitoring.

A. In-built sensors in micro-mobility vehicles

As shown in Figure 2, several sensors are available for environmental monitoring and these can be embedded in micro-mobility vehicles. Micro-mobility refers to a diversity of small, lightweight, and powered/non-powered vehicles that operate

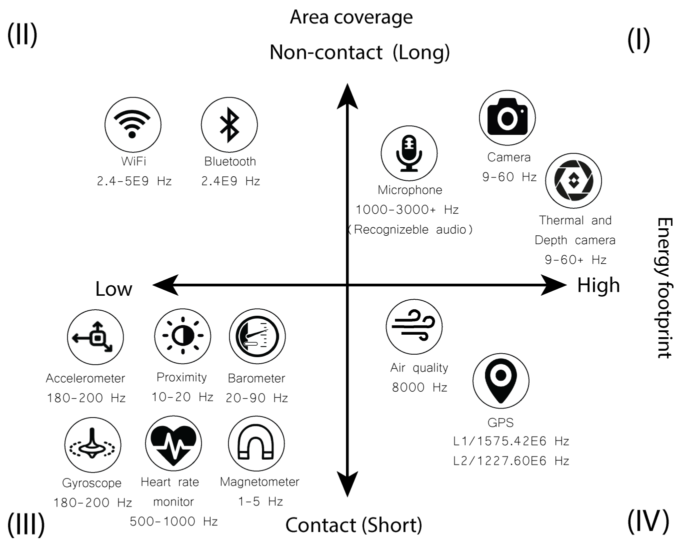


Fig. 2: Sensor classification depicting the trade-off between coverage and energy footprint.

in a moderate speed (below 25 km/h) and are commonly driven by a single user at the time. Micro-mobility vehicles may include, bicycles, e-bikes, e-scooters, e-skateboards, and pedelecs (pedal assisted bicycles) among the most commons. Micro-mobility vehicles are typically embedded with common (motion) sensors to detect navigation and prevent unexpected user's movements that can lead to accidents [1]. Other sensors embedded in micro-mobility vehicles also include GPS for route planning and localization; and integrated cameras that allow remote operators to get a glimpse of the surrounding of the vehicle. Several in-built sensors can be re-purposed, whereas others can be easily embedded, but this requires to consider several critical aspects affecting the performance of vehicles.

B. Sensor-based micro-mobility framework and proxemic analysis

Integrating sensors for environmental monitoring in micro-mobility vehicles requires to assess the level of data quality from the samples that are obtained from the vehicle while operating. By default, data measurements collected from these low-cost sensors are prone to inaccuracies and high variance. Thus, improving the veracity of the data is the first step to adopt a sensor. A plausible solution is to send the collected data from the vehicles to remote or edge servers, which can contain data aggregation, fusion and processing pipelines to extract the environmental indicators - or even to build machine learning models from the data [37]. However, this solution imposes heavy load in the underlying backbone infrastructure (network and servers), increasing the carbon emission problem of data centres. Thus, more sustainable methods for the environment have to be explored and adopted.

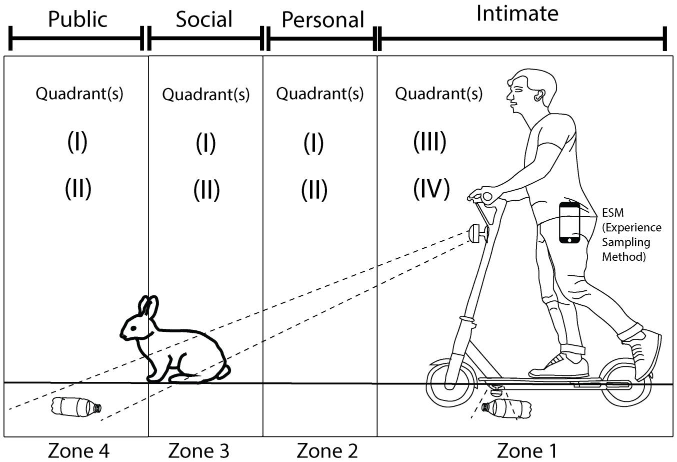
As shown in Figure 3, micro-mobility vehicles are operated by individuals. Thus, it is possible to opportunistically exploit human-assistance to improve further the collected data before processing it. Collected measurements can then be corrected and further validated through human support, requiring less manipulation to extract indicators. An example of this method is the use of human-assisted labelling for images, ESM (Experience-Sampling-Method) and participatory sensing methods [18]. Introducing human-assistance for sensor data collection on micro-mobility vehicles requires analyzing the perception of individuals (drivers) towards the embedded sensors. To enable human-assistance, sensors on the vehicles need connectivity to personal devices of individuals, augmenting their overall range with multi-device sensing capabilities.

To analyze the potential of human assistance (drivers), we apply the Edward Hall's discrete proxemic theory [17] on individuals operating micro-mobility vehicles. These proxemic zones refer to the personal space individuals maintain around themselves in social interactions. Marquardt builds on this idea in [17], proposing proxemic interaction zones that devices can exploit to obtain nearby knowledge of people and other devices. Proxemic zones characterize the interpersonal relation that devices can have to individuals as follows: Zone 1 (intimate) considers $0 - 0.5$ m, Zone 2 (personal) considers $0.5 - 1$ m, Zone 3 (Social) considers $1 - 4$ m, and Zone 4 (public) considers 4 m and beyond. Since micro-mobility vehicles become another device tool for users, which is also in motion traversing different social spaces, we build on these proxemic zones to analyze the perception of users towards contributing with the collection of environmental data from the vehicles. Figure 3 shows the augmented framework, which includes further sensor classification quadrants to depict the relative coverage of a sensor once embedded in the vehicle. We proceed to analyze each Zone of the framework in detail.

Zone 1: Sensors collecting environmental measurements benefit the most from human-assistance in this area. Human senses, such as sight, sound, and smell, can provide valuable validation for sensor measurements. For instance, micro-vehicles experiencing high levels of light and noise can request further details about the possible causes, e.g., traffic jam or accidents. Labelling of sensor measurements is also simpler in this area as user contributions are just linked to personal data privacy considerations, requiring proper persuasive and incentive mechanisms to engage the users. This area is exploited the most when the micro-vehicle is in parking position.

Zone 2: The area coverage of sensors for environmental monitoring is constrained in this area range. Environmental measurements can change drastically between a few meter distances. For instance, air quality measurements can be completely different after one meter [5], [8]. Similarly, light pollution measurements can change spontaneously as light gets obstructed by urban infrastructure. This area also depicts the upper bound limit for individuals to label environmental monitoring measurements with high confidence. After this, opportunistic human participation requires extra validation of multiple individuals, e.g., using crowdsensing; or from other IoT devices located in range of the vehicles. User participation remains simpler in this area. This area is also exploited the most when the micro-vehicle is in parking position.

Zone 3 - 4: Collecting data for environmental monitoring becomes challenging in this area. The effectiveness of human-



Environmental application	Human partipatory assistance	Parking state	Moving state	Zone 1	Zone 2	Zone 3	Zone 4
Water quality monitoring	X	X		X	X		
Air quality monitoring	X	X		X	X		
Noise monitoring	X		X	X	X		
Biodiversity monitoring	X		X			X	X

Fig. 3: Environmental monitoring applications supported by micro-mobility vehicles and pervasive sensing.

assistance starts decreasing rapidly as personal concerns for data collection change from an individual to a collective one. Privacy implications are more sensitive here as surrounding individuals may create conflicts or raise concerns to the micro-vehicle drivers. This suggests that drivers may be less willing to aid any sensing modality. This area could potentially exploit human memory of individuals to label environmental events in segments within locations, e.g., biodiversity monitoring. This suggest that this area can be exploited when the micro-mobility vehicle is in motion from point A (source) to point B (destination). This however requires to analyze the performance of human memory to retain events over a distance at different speeds. Typically, human (short) memory is constrained to retain up to 7 items at the time [38].

IV. Core challenges and Opportunities

In the light of our analysis, we next describe key challenges and opportunities to perform environmental monitoring with micro-mobility vehicles using sensors. Notice that some challenges are recurring even between different state-of-the-art solutions, supporting further that multiple complementary solutions should be adopted.

Probing times and incentives: Parking times are the most likely to be exploited for requesting human-assistance. Indeed, human-assistance is not to be triggered when the vehicle is operating as it can cause distraction to the drivers, which can lead to unexpected crashes and accidents with surrounding urban infrastructure. Thus, a key challenge is to determine when to request human-assistance. Since micro-mobility vehicles are used by individuals to move between shorter distances, a way to overcome this is to rely on human memory [38]. It is also possible for the vehicle to create a tentative list of sensed events observed while traversing a distance. This list can then be verified by the individuals once the ride is terminated. Alternatively, micro-mobility vehicles could also request to be left in specific locations, such that environmental data is collected before the next passenger uses the vehicle. Incentives to persuade the users on performing these actions are key to make the solution sustainable.

Re-designing of urban spaces: While some micro-mobility vehicles have been introduced considering the urban design of cities [1], other vehicles have been introduced without proper planning nor fixed support infrastructure. Fixed parking, e.g., bicycle racks, foster less dense coverage when compared with random parking. However, the latter is more invasive in urban areas, causing discomfort to individuals. Random parking is preferable for environmental monitoring, but it requires to deal with a key challenge related to develop solutions that can exploit urban spaces without disrupting perception of individuals, or causing obstruction to other urban infrastructure.

Energy consumption: There is large variety of powered and non-powered micro-mobility vehicles. Non-powered micro-mobility vehicles are preferable for environmental monitoring as the energy to power the sensors could be piggybacked directly from the vehicle itself as the user drives it, e.g., using a bike energy-generator. In parallel to this, batteries of powered vehicles can easily support additional sensors in these vehicles, however, this may be counterproductive for their user experience as vehicles are required to be charged more frequently. In addition, extra overhead in energy may require to deploy more charging stations. Overcoming the overhead introduced by sensors requires to rely on additional energy sources - sustainable ones [39]. For instance, solar panels embedded in the vehicle or wireless changing alternatives. A key challenge is to deploy a robust energy support infrastructure that can support the micro-mobility vehicles at city-scale.

Adaptive sampling: Data quality is a recurring key challenge for off-the-shelf sensors and rapid prototyping devices [37]. Micro-mobility vehicles are expected to collect samples during parking times but also during times traversing a distance. To improve spatial and temporal coverage of the collected data, this requires vehicles to adjust their sampling frequency based on their detected state (parked or moving). Duty cycling methods can be applied to overcome this problem. However, since vehicles can move at different speeds (regulated by the user), it is also necessary to take into consideration the speed of the vehicle to calibrate the sampling rate. Moreover, as different sensors are collecting data, sensor data fusion methods are required to obtain descriptive information that can be used to model robustly environmental monitoring events. A way to achieve this is to mimic the current multi-sensor approaches used in self-driving cars, but optimizing data collection, such that it is possible to reduce the collecting and processing cost of data, otherwise, analysis over the data becomes a bottleneck for the constrained micro-mobility vehicle.

Data privacy and security: Human-assistance can become a security breach for personal devices of individuals. As users connect their devices with micro-mobility vehicles, e.g., using QR code, these codes can easily be hampered by attackers to take control on the personal devices of individuals. A key challenge to overcome is to re-enforce security through new authentication methods and make micro-mobility vehicles trustworthy [38]. This can also be overcome by introducing new interfaces in the micro-mobility vehicles, such that personal devices are not required to be connected with the vehicle. At the same time, micro-mobility vehicles are required to implement anonymization and obfuscation methods when collecting data from their surroundings, such that sensitive data from individuals is not collected by third parties, e.g., facial patterns, car plates and other bio-metrical body signatures.

V. Discussion

Micro-mobility has been proposed as a means to support environmental sustainability, with the potential for embedding sensors in vehicles for environmental monitoring. In this context, we conducted a literature review on sensor re-purposing for environmental monitoring and identified technologies to bridge existing gaps [1], [2], [9], [15], [17], [18], [37]–[40]. The integration of micro-mobility vehicles seeks to augment existing environmental monitoring solutions, enhancing both spatial and temporal coverage. However, certain micro-mobility vehicles, like one-wheel models, may have size limitations for sensor embedding. In addition, some vehicles feature specialized infrastructure in urban settings, such as e-bicycles with built-in racks, which can also be leveraged for environmental monitoring purposes.

In terms of micro-mobility operations, adverse weather conditions such as snow or rain can hinder vehicle performance, preventing drivers from effectively validating measurements. Moreover, distracting factors can also make humans ineffective for aiding in environmental monitoring, e.g., listening podcast. Companion vehicles (other drivers) can also reduce the attention of individuals as the drivers are more focus on the social interaction rather to their surroundings.

Furthermore, micro-mobility drivers contributions can open up new opportunities for citizen science and wisdom of the crowd solutions [15]. New applications can empower non-experts to collect data and foster learning in a community while traversing short distances. A key limitation however is that current citizen science methods may not directly apply to micro-mobility vehicles, e.g., probing times via ESM differ when considering smartphones and wearables [18]. Thus, the use of micro-mobility requires a re-evaluation and adjustment of existing methods for efficient implementation. For instance, incentivizing users with free rides when contributing to data collection or placement of the micro-mobility vehicle in a requested location.

VI. Summary and Conclusions

In this paper, we conducted an extensive literature review on sensor re-purposing for environmental monitoring. We then presented a sensor-based micro-mobility framework, the main objective of which is to improve the spatial and temporal collection of environmental data. Additionally, our framework highlights state-of-the-art solutions, emerging challenges, and opportunities for using micro-mobility vehicles in environmental monitoring. We concluded with a discussion about the implications of our vision to society, citizens and urban infrastructure.

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