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Passively generated big data for micro-mobility: State-of-the-art and future research directions

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ABSTRACT

The sharp rise in popularity of micro-mobility poses significant challenges in terms of ensuring its safety, addressing its social impacts, mitigating its environmental effects, and designing its systems. Meanwhile, micro-mobility is characterised by its richness in passively generated big data that has considerable potential to address the challenges. Despite an increase in recent literature utilising passively generated micro-mobility data, knowledge and findings are fragmented, limiting the value of the data collected. To fill this gap, this article provides a timely review of how micro-mobility research and practice have exploited passively generated big data and its applications to address major challenges of micro-mobility. Despite its clear advantages in coverage, resolution, and the removal of human errors, passively generated big data needs to be handled with consideration of bias, inaccuracies, and privacy concerns. The paper also highlights areas requiring further research and provides new insights for safe, efficient, sustainable, and equitable micro-mobility.

1. Introduction

Micro-mobility, particularly shared micro-mobility services, has become increasingly popular in the last decade. For example, the number of bike-sharing systems worldwide has grown from ten in the 1990s to almost 2,000 in 2021 (Yu et al. 2021), and the total number of trips by station-based bike-sharing services in the US has increased from less than two million in 2010 to over 35 million in 2018 (NACTO 2019). This growth has been enabled by the development of Information and Communications Technologies (ICT), including mobile networks of high area coverage, speed and capacity, the widespread usage of connected mobile devices such as smartphones, and GPS devices. It is also supported by a reduction of theft and vandalism threats due to the introduction of the smart card or magnetic strip technology, which automates the check-in and check-out process (Shaheen et al. 2010). Furthermore, the advancements in battery technology accelerated the widespread deployment of battery-powered vehicles such as electric kick scooters ("e-scooters") and electric bicycles.

The term "micro-mobility" has been introduced to capture a wide range of vehicles and services. This paper follows the definition of micro-mobility brought forward by the International Transport Forum, referring to the use of vehicles not heavier than 350 kg and with a design speed not higher than 45 km/h which is broad enough to include both human- and electric-powered vehicles, for example, bicycles, e-bikes, skates and kick scooters (ITF 2020). Some other definitions used in the literature limit it to the use of shared vehicles (McKenzie 2020; Zhang and Song 2022), motorised vehicles (Eccarius and Lu 2020; Avetisyan et al. 2022), and trips of short lengths

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and with a first/last mile characteristic (Eccarius and Lu 2020; Tuncer et al. 2020; Abduljabbar et al. 2021; Elhenawy et al. 2021; Zhao et al. 2021).

Micro-mobility, powered by ICT, is characterised by its richness in passively generated big data, i.e. data about people's activities automatically collected as a by-product of another, potentially not transport-related action (Wang and Chen 2018). Typical examples include the usage of a mobile phone, a credit card, or the connection with a wifi network from which information about people's mobility behaviour can be inferred (Xu et al. 2015). A vast amount of passively generated data has already been captured in practice and used in recent research. However, to the authors' best knowledge, no review is yet focused on this important topic. Knowledge and findings are fragmented so far, limiting the value of the data collected. To fill this gap, this article provides the first review of how recent micro-mobility research and practice have exploited different types of passively generated big data, its applications to address major challenges of micro-mobility, as well as its advantages and limitations. Overall, this paper aims to answer the following research questions:

RQ1: How have different types of passively generated big data been used in micro-mobility research?
RQ2: How does passively generated big data help address challenges for micro-mobility?

To answer these research questions, a systematic review of the literature is conducted following Xiao and Watson (2019). Our review is based on a survey of relevant studies and an extensive online search, relying on the Scopus database and Google Scholar, using the keywords "micro-mobility", "micromobility", "e-scooter", "electric scooter", "bicycle", "cycling", "bike". Research papers identified with these keywords were reviewed following the workflow illustrated in Fig. 1 to establish the database. Publications were included in the analysis if they were based on passively generated big data and dealt with micro-mobility (both defined above). In total, 71 publications written in the English language were included in the review which were categorised according to data type, research aims, methods, and results. Micro-mobility-related challenges were identified and categorised under the classifications safety, society, environment, and system design. Research gaps were identified where existing data and analysis methods do not sufficiently address these challenges.

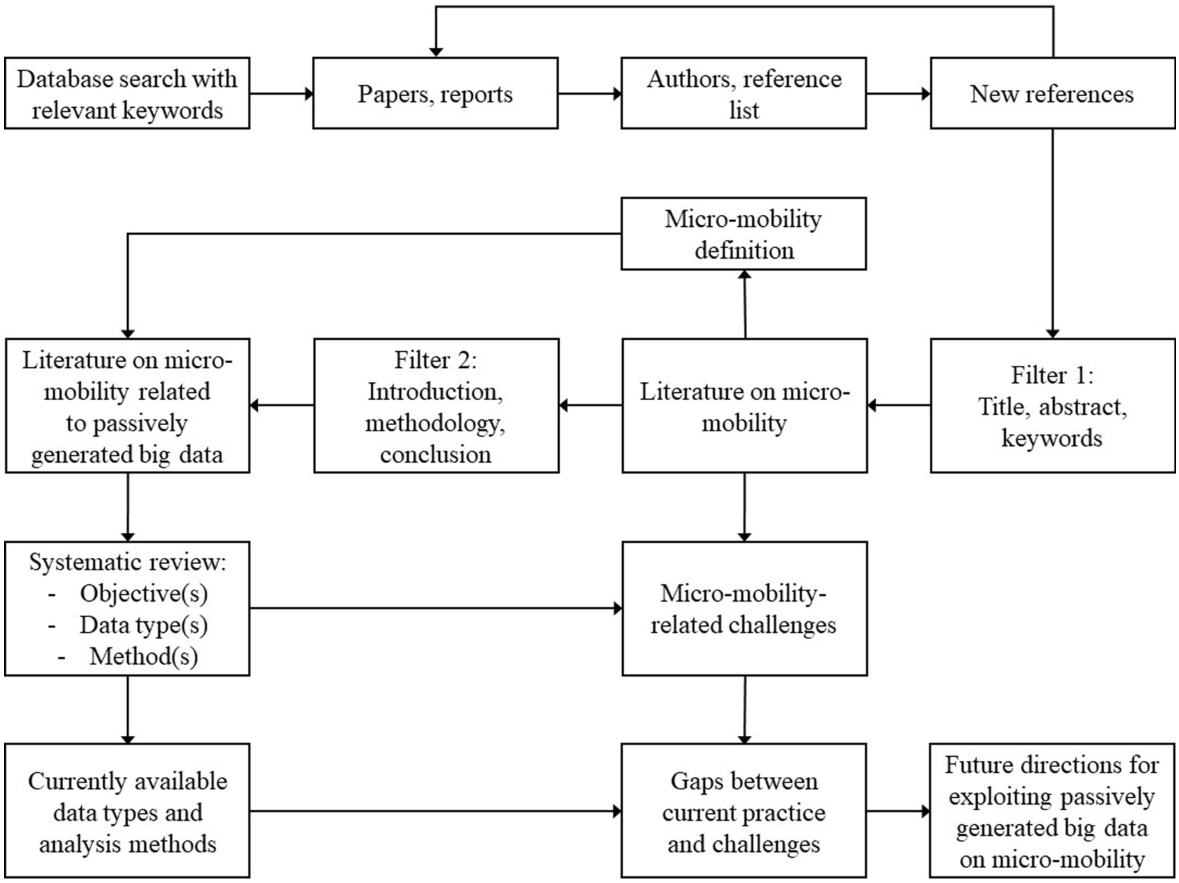

Fig. 1. Workflow of the review process.

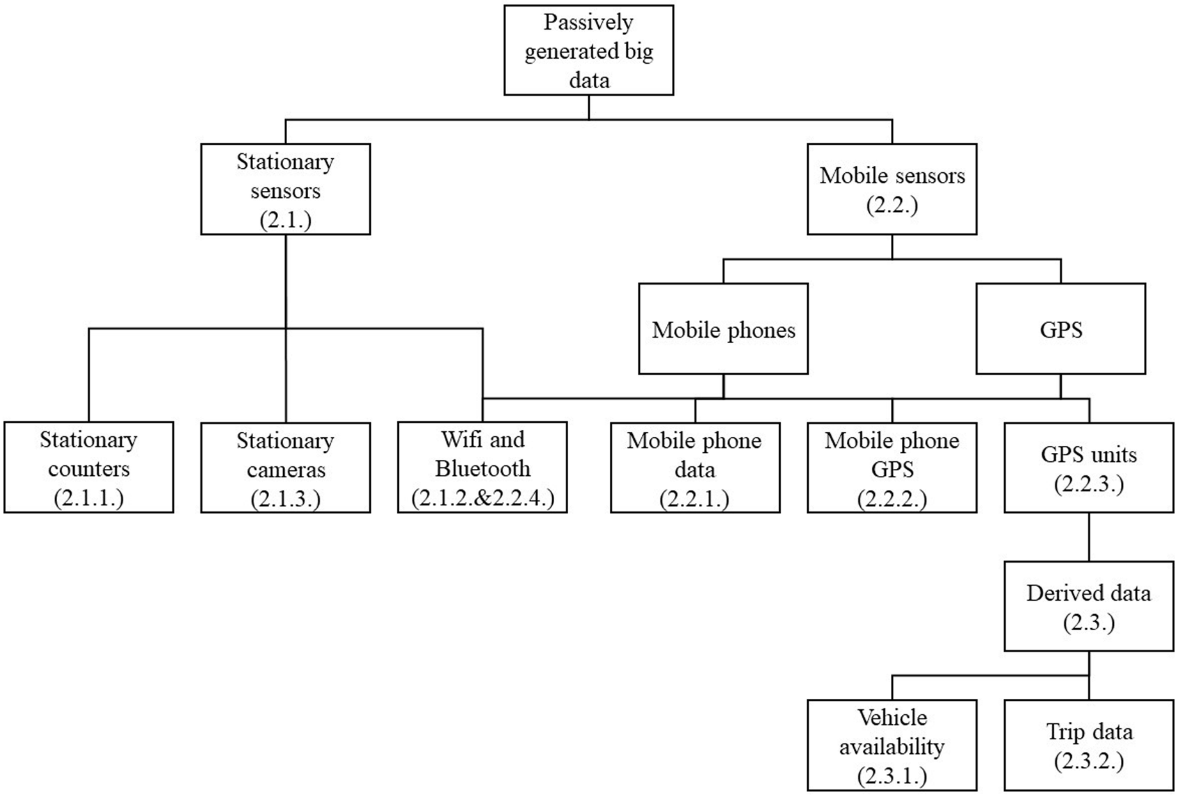

Fig. 2. Reviewed data types (respective sections in brackets).

Elements such as the built environment, including infrastructure (Broach et al. 2012), mode accessibility (Braun et al. 2016; Reck et al. 2022), and land use (Noland et al. 2016), as well as socio-demographic factors (Moudon et al. 2005), have significant influence not only on micro-mobility but on mobility behaviour in general. Therefore, techniques specifically aiming at gathering information about these factors, such as land surveying technologies, and census data gathering methods, can also help micro-mobility analysis. However, following the review process illustrated in Fig. 1, such literature is filtered out if it is not directly dealing with micro-mobility and passively generated big data.

The remainder of this paper is structured as follows: Section 2 analyses how each type of passively generated big data is used for micro-mobility-related research. The structure of Section 2 follows the classification of passively generated big data, as illustrated in Fig. 2. The subsequent Section 3 discusses how passively generated big data has been used to address major challenges regarding safety, society, environment, and system design. Research gaps are identified and future research directions are suggested. Section 4 concludes the paper with a summary.

2. Passively generated big data for micro-mobility analysis

In total, 71 research articles have been included in the review, out of which 56 covered the mode of cycling (both electric and conventional) and 22 e-scooters, comprising both private and shared operation types. Nine articles used data from more than one micro-mobility mode and five included not solely micro-mobility, but also at least one other mode of transport (e.g. walking, public transport, cars).

Each data type used in the literature has been recorded as shown in Fig. 3. Most of the reviewed literature uses trips, vehicle availability, stationary counters, and mobile phone GPS data. Although considerable literature utilised data from stationary cameras, GPS units, wifi and Bluetooth access points, and mobile phone records, only a few of the identified literature had micro-mobility as the primary research subject. Furthermore, the majority of literature focused on the planning of micro-mobility services, whereas the literature on micro-mobility monitoring and operations forms a much smaller portion of the reviewed articles. It is worth noting that, to the best of the authors' knowledge, no research so far investigated real-time interventions such as dynamic traffic control.

As Fig. 4 demonstrates, most of the reviewed literature stems from recent years, a majority from 2021. When comparing the uptake of different data types over the years, the increasing deployment and popularity of shared micro-mobility services are reflected in the rise of published articles using vehicle availability and trip data since 2015, with over ten articles using trip data in 2021 alone. Additionally, the apparent increase in the published research in the domain of passively generated micro-mobility data over the past years is also mostly due to the increasing utilisation of vehicle availability and trip data. This indicates that especially shared micro-

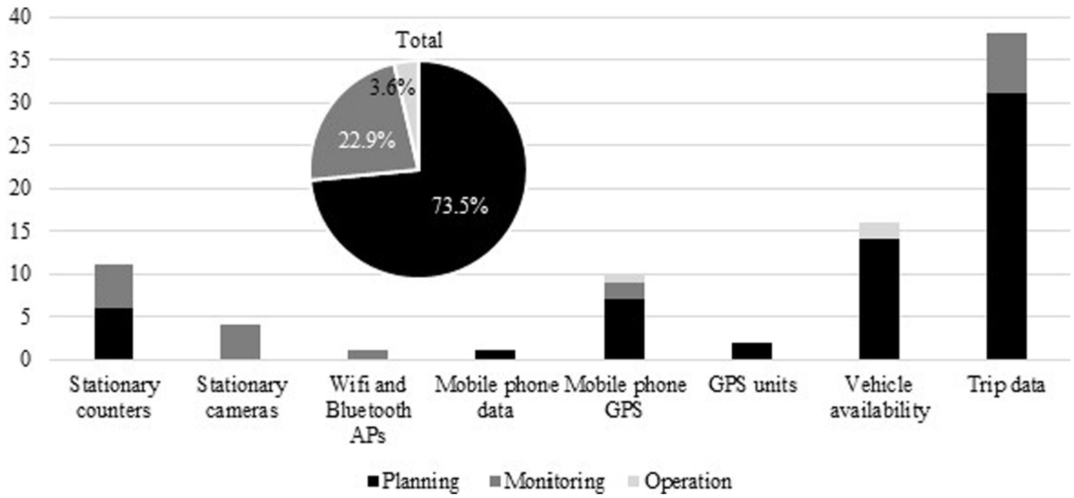

Fig. 3. Number of analysed publications research category and data type.

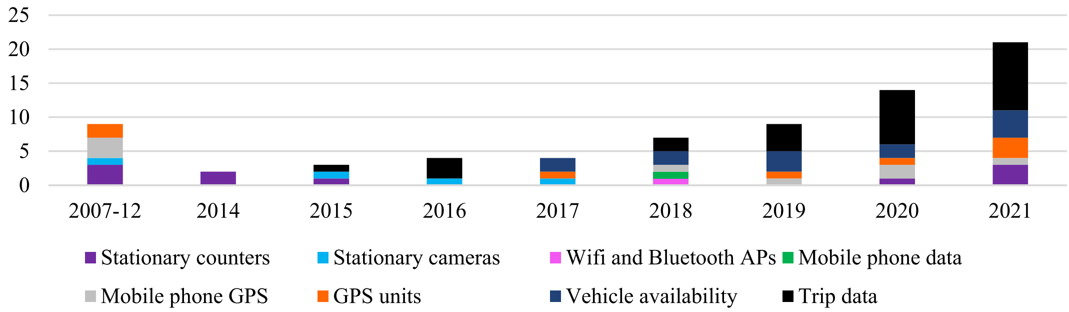

Fig. 4. Number of analysed articles by data type and publication year.

mobility services which – in contrast to private vehicles – produce these data types, have been responsible for increasing interest in this research domain. The rapid increase also demonstrates the timeliness and value of the review.

The remainder of this section first explores how stationary sensors, such as stationary counters, wifi and Bluetooth access points, and stationary cameras, are used in micro-mobility research. Next, we analyse the use of mobile sensors, especially mobile phone data, mobile phone GPS data, and data from GPS devices. Furthermore, we specifically discuss two types of derived data, vehicle availability and trip data, due to their prominence in the literature.

2.1. Stationary sensors

The stationary sensors covered in this section comprise stationary counters, wifi and Bluetooth access points, and cameras.

2.1.1. Stationary counters

Stationary and automated counting technology can replace and complement manual stationary counting. Different technologies can help detect vehicles of different types (Rajbhandari et al. 2003; Ryus et al. 2014), including micro-mobility (Nordback and Janson 2010; Nosal and Miranda-Moreno, 2014). Some relevant technologies include pneumatic tubes, inductive loops, infrared and piezo-electric strips (Ryus et al. 2014). Despite challenges in distinguishing between vehicle types, detecting vehicles travelling close to each other, and detecting vehicles outside the range of the sensor, stationary automated counters provide results of acceptable accuracy if deployed and calibrated correctly (Nordback and Janson 2010; Ryus et al. 2014; Brosnan et al. 2015).

Stationary counters lack the capability to track or re-recognise individual vehicles if no unique identifier can be added from other sources. Different studies, however, use stationary counting data to derive models for accumulated traffic flows based on network configuration (Loder et al. 2019; Gehrke and Reardon 2021). This is used to assess the influence of weather and seasonal changes on bicycle traffic (Tin Tin et al. 2012; Nosal and Miranda-Moreno, 2014), and to understand how the COVID-19 pandemic and related governmental and public reactions influenced traffic (Bian et al. 2021).

When not considering the detection errors, stationary counting data can provide ground truth information for their locations. Therefore, data from stationary counters can be used to assess and calibrate models based on other data sources, such as OD matrices derived from mobile phone data and census information (Portland Bureau of Transportation 2015; Olmos et al. 2020). Similar to deploying people "on the ground", stationary automated counters have the disadvantage of only being able to detect information at one particular point. However, they are not limited by temporal constraints and can be used for many years. This reduces the necessary effort to obtain stationary traffic data and allows long-term studies. Compared to human counters, their shortcomings include the inability to provide contextual information about the detected traffic, and the inability to adjust for external disruptions such as construction works, accidents, or road closures. With the rising popularity of novel micro-mobility modes – namely e-scooters and hoverboards – the technology of stationary counters needs to be adjusted to be able to differentiate between different modes.

2.1.2. Wifi and Bluetooth access points

Wifi and Bluetooth signals provide information about a person's device location at a certain time. Therefore, they are a source of interest for mobility research in general (Sapiezynski et al. 2015; Traunmueller et al. 2018) and also micro-mobility research in particular (Mei et al. 2012; Ryeng et al. 2016). Such data can be collected from mobile devices (i.e. having a list of "visited" wifi access points for each device, covered in section 2.2.4) or from wifi access points (APs) (i.e. creating a list of devices having connected with each AP).

AP data can be obtained by either using existing APs and saving their connection records or deploying additional APs that the researcher controls. In these cases, the locations of the APs are known a priori, and specific analysis areas can be defined. Also, no additional action is needed from the mobile devices' owners. Depending on the area to be monitored and the granularity needed, a smaller or larger number of APs need to be deployed or accessed. For example, APs can be used to analyse visiting patterns at singular points that are of interest to the researcher (Uras et al. 2019) which only requires limited resources. To detect flows between points, but without considering detailed routes (Laharotte et al. 2015; Uras et al. 2019; Behara et al. 2021), APs need to be deployed at different spots and unique mobile device identifiers need to be accessed. The identification of routes taken by individuals (Basalamah 2016; Traunmueller et al. 2018) requires an even higher number of APs.

Wifi and Bluetooth signal data per se are mode independent, but the mode can be inferred based on the context of the data, e.g. if the wifi APs are installed inside a public transport vehicle or a building. This is not the case, however, for example, for outside settings on a major street with multiple modes available. There are various methods to handle this. One method is the cross-validation with third data sources such as stationary, mode-sensible counters, shared micro-mobility hiring data etc. (Reddy et al. 2008; Kalatian and Farooq 2018). Another method is the application of rule-based heuristics taking into account travel speeds and times etc. (Lesani and Miranda-Moreno 2019).

The review identified one study, which by design, only included cyclists in order to compare the capability of Bluetooth and wifi probe data to detect the travel speeds of cyclists (Ryeng et al. 2016). On the other hand, the review identified no article having implemented a mechanism to detect micro-mobility travels from stationary Bluetooth or Wifi signals, indicating the existence of a research gap. As wifi technology is deployed densely in urban environments, it could be a helpful tool to gain insights into micro-mobility usage, independent from shared services and the costly installation of additional counting or tracking technology. Also, triangulation could be used to track small-scale behaviour and thereby inform micro-mobility and pedestrian simulation.

2.1.3. Cameras

Various types of cameras can be used to collect data (Ieromonachou et al. 2006; Namazi et al. 2019), and particularly micro-mobility data (Law et al. 2014; Reinders et al. 2018). CCTV has been deployed in public spaces, in buildings and on public transport to increase the feeling of safety and allow the prosecution of criminal offences. Cameras are integrated with vehicles such as cars to allow for the reconstruction of accidents or to support parking aids. Also, most people carry cameras integrated into their smartphones and other mobile devices. As with other technology-based solutions, the moving pictures derived from both stationary and mobile cameras can be used to carry out ex-post or real-time analysis of traffic and to obtain information about entities considered static such as the built environment or road markings.

Traditional CCTV surveillance enables remote monitoring of events in real-time at different locations and therefore reduces the number of surveillance personnel on the ground. However, humans are still needed to monitor and assess what can be seen in the pictures. If the recording is stored, past events can also be reconstructed by being watched and interpreted by humans. The same principle, of course, can also be applied for transport-related purposes. Cameras can be installed to assert road pricing schemes, for traffic management purposes, to visually monitor traffic on roads or intersections and to apply measures such as flexible speed limit changes to ease conditions (Ieromonachou et al. 2006; Papageorgiou et al. 2007; Namazi et al. 2019).

In addition, remote manual counting can take place. For example, in the context of micro-mobility, the counting of cyclists on a particular road segment can be done remotely. This has the advantage that humans do not have to face unfavourable conditions like weather or difficult accessibility of the counting site when counting. However, contextual information might get lost due to the limited range of the camera, and errors can occur due to bad imagery. Manual remote monitoring for micro-mobility can be applied either as a means on its own (Ward 2006; Law et al. 2014) or to verify observations from other sources such as stationary counters (Rogers and Papanikolopulos 2000; Ryus et al. 2014; Brosnan et al. 2015).

As the manual assessment of camera images is still laborious and error-prone, efforts have been put into applying automated image recognition techniques. These techniques have been applied to detect and analyse micro-mobility. Rogers and Papanikolopulos (2000), for instance, propose to use generic blob analysis to identify objects on images, which are then recognised as bicycles or other objects. Their algorithm still had a comparatively high error rate and was especially prone to misinterpret objects distantly related to bicycles (e.g. wheelchairs). This problem is also reported in other works (Lin and Young 2017). Further research has been carried out to distinguish bicycles from other related objects such as motorbikes (Messelodi et al. 2007), or pedestrians and people pushing a bicycle (Ishii et al. 2020). Specifically used for counting purposes is the convolution neural network-based algorithm developed by Ding et al.

(2019). Although applied in an underground station to detect passengers, they provide important insights into linking image recognition data with wifi signalling data. This approach can also be used in the context of micro-mobility, especially when considering that shared vehicles are in most cases used by people carrying their wifi-enabled mobile devices.

Apart from identifying travellers, image recognition is also applied to extract information about infrastructure and characteristics of the environment potentially influencing mobility behaviour. In this case, mobile cameras can be used to gather information about the network. This can be done by purposefully deploying mobile cameras to extract information e.g. about the position of bicycle-relevant traffic signs (Reinders et al. 2018) or by using already available data. Google Street View, for instance, is an increasingly popular data source used in research to derive infrastructure-related indices that can be used to evaluate people's route choices (Li et al. 2018; Ito and Biljecki 2021; Sevtsuk et al. 2021).

2.2. Mobile sensors

Data from mobile sensors covered in this review include mobile phone data, GPS data from mobile phones, data from GPS units as well as wifi and Bluetooth-enabled devices.

2.2.1. Mobile phone data

Mobile phone records are increasingly popular in transportation research in general (Bachir et al. 2019; Huang et al. 2019) and micro-mobility in particular (Zhou et al. 2018b). The fact that most of the population owns a mobile phone (ICT 2013; Trucano 2014) makes mobile phone data a valuable data source. Mobile phone data can be divided into two categories: actively generated data and passively generated data. Actively generated data are generated by actions of the mobile phone user, such as beginning or ending a call, sending or receiving a text message, or accessing the internet. Each of these actions generates a set of data comprising time and localisation of the mobile phone. Passively generated data, in contrast, do not need action by the user. Generally, they are generated whenever a position update is taking place. This is the case when a mobile phone is switched on and connecting to the mobile network; when the mobile phone location area changes; or in a regular time interval (Anda et al. 2017).

Mode detection from mobile phone data is an area of significant research interest. Huang et al. (2019) provide an overview of transport mode detection methods. They find that most of the reviewed articles use a rule-based heuristic, whereas only a few use a clustering algorithm or supervised machine learning. A shortcoming of existing mode detection methods is the limited number of modes detected and their missing validation through ground truth data. A binary set of modes is common in mode detection research (Phithakkitnukoon et al. 2017; Bachir et al. 2019). Zhou et al. (2018b), in contrast, present a framework to distinguish between four different modes (walking, bicycle, car, subway), taking into account acceleration and velocity characteristics. Unfortunately, their framework is tested for a small sample size of 200 users and uses GPS tracking data in addition to mobile phone data.

Extending mode detection methods to micro-mobility is foremost necessary to gain further insights into its usage using mobile phone data. For example, spatio-temporal patterns of micro-mobility can be analysed similarly to how Zhong et al. (2017) analysed travel patterns within a mobility hub in Shanghai, China, if micro-mobility modes can be identified.

2.2.2. Mobile phone GPS

Drawing from similar advantages as mobile phone data (i.e. almost constant companion of individuals, regular location updates), the GPS antenna installed in mobile phones can also be used for transport analysis in general (Zhou et al. 2018b; Reck et al. 2022) and micro-mobility analysis in particular (Charlton et al. 2011; Guidon et al. 2020). In contrast to mobile phone data, records of GPS locations are not usually stored by mobile phone providers, and the data have to be obtained directly from the phone. This happens regularly through applications installed on the mobile device. They can either be installed to serve specific research purposes (i.e. participants have to be actively recruited) (Olmos et al. 2020; Reck et al. 2022) or have a primary purpose different from the research (e.g. fitness tracking) and produce useful data for research as a side effect (Heesch and Langdon 2016; Sadeghvaziri et al. 2016; Pritchard 2018; Munira and Sener 2020).

Mobile phone GPS data have the advantage of being independent of mobile phone providers – in contrast to mobile phone data. Also, if the data is collected through applications installed for specific research purposes, consent for data gathering is already given. In contrast to mobile phone data, the speed and direction of the individual can be obtained from GPS data (Wang et al. 2010).

Origin and destination, and thereby trip detection, is the basis of transport analysis and planning. As for mobile phone data, most research is based on a distinction between non-movement and movement, with trips being the legs between two phases of non-movement. Mode detection methods can be based on realised speeds or spatial closeness to possible routes of differing modes. As with other data types, verification of the proposed models remains a problem. This can be addressed by crossing GPS data with data from other sources, for example, by intentionally recording GPS trips for which the mode is known (Gonzalez et al. 2010; Hood et al. 2011; Munira and Sener 2020), by using mobile phone or other digital data-derived information as a point of reference (Zhou et al. 2018b; Olmos et al. 2020; Marakkalage et al. 2021), or by using census and survey-based data sources (Olmos et al. 2020). If no true validation information is available, the number of detected modes tends to be limited.

Since mobile phones can combine sensors of various sorts and interaction with the user is possible, they are a promising option to gain insights into transport behaviour and to obtain useable labels for machine learning techniques. Reck et al. (2022) used this method by using a mobile phone application that allows participants to edit the micro-mobility trips detected and identified through smartphone sensors. Based on this, they developed a mode choice model that can include a comprehensive set of choices. Using smartphone applications as a data source – especially when specifically designed for research purposes – has the advantage that the user can serve as a controlling entity which can double-check the already executed map-matching and provide additional information

(Charlton et al. 2011; Hood et al. 2011; Reck et al. 2022).

Given that the trip mode is known, for example through information provided through an additional smartphone application or survey, GPS traces are used to analyse routing decisions. Particular attention can be paid to how factors like the built environment, scenery, or weather conditions affect routing for micro-mobility (Charlton et al. 2011; Hood et al. 2011), but also for other modes such as pedestrians (Vanky et al. 2017; Li et al. 2018; Sevtsuk et al. 2021). Based on these analyses, recommendations can be derived for infrastructure planning, be it linear bicycle infrastructure or shared micro-mobility docking station positioning (Zhang et al. 2019a; Olmos et al. 2020). Also, operational strategies such as rebalancing can be optimised and environmental impacts estimated (Zhang et al. 2019a). Future research should develop mode detection algorithms based on GPS data, taking advantage of the fact that ground truth information can be collected through a relatively small number of smartphone users by presenting them with a question.

2.2.3. GPS units

Other than being installed on smartphones, GPS units can also be carried with or fixed at a vehicle to track its position at a pre-defined rate and precision. Such GPS units were a less laborious and more precise method to gain information about individuals' behaviour compared to traditional methods such as ex-post surveys or snail trailing. It has been found – with the limitations brought by testing devices available at a certain point in time – that mobile GPS units outperform smartphone GPS in terms of precision (Lindsey et al. 2013). This makes them an attractive data-gathering tool for micro-mobility research (Menghini et al. 2010; Bao et al. 2017; Li et al. 2020b), even in an era of widespread smartphone usage.

GPS tracking data is particularly useful for investigating routing decisions and analysing traffic volumes. Traditionally, route choice models for micro-mobility based on non-smartphone GPS tracking are mainly for the mode of cycling. They help to understand which infrastructure characteristics (e.g. gradient, number of turns, traffic parameters, separation from other modes) are preferred by micro-mobility users. Discrete route choice models have been developed for different case study areas (Broach et al. 2010; Menghini et al. 2010).

The spread of shared micro-mobility services of vehicles with built-in GPS sensors opened the door for less laborious and more comprehensive data collection of micro-mobility users' routes. One significant advantage is that the tracking data collection does not require any additional action from the users. Meanwhile, it allows for collecting additional information like demographic or subscription type. However, it always needs to be considered that people using micro-mobility are not representative of the whole population, that deployment areas of micro-mobility services, their terms of use, the portion of the population having access and using them might be more favourable towards certain parts of the population than others.

Shared micro-mobility tracking data has been exploited to report hotspots in terms of both areas of origins and destination, and routes (Li et al. 2020b), to derive trip purposes by using the tracking data in combination with land use and points of interest data (Shah et al. 2021), to analyse how trip characteristics of regular users are different from irregular users (e.g. He et al. 2019), to find out how far micro-mobility users deviate from shortest paths (Li et al. 2020b; Shah et al. 2021), how to optimise bicycle network extension planning (Bao et al. 2017), to identify changes in micro-mobility usage due to the measures taken in response to the COVID-19 spread (Dean and Zuniga-Garcia 2022), and to identify infrastructure and user characteristics that influence route choice (Zhang et al. 2021; Zuniga-Garcia et al. 2021).

2.2.4. Wifi and Bluetooth devices

Apart from using the records of wifi or Bluetooth APs, wifi and/or Bluethooth-enabled devices themselves can be a valuable source of mobility-related data as they can provide a list of "visited" APs. Data from wifi and Bluetooth devices has the advantage of allowing researchers to comprehend individual traces without having to identify recurring individual devices from the AP records. On the other hand, however, individuals have to be recruited to participate in a study and potentially allow an additional application to be installed on their devices to store and forward connected data from their devices. In addition, complimentary data (such as GPS) have to be collected to identify the location of the APs in question since they are not known *a priori*, and the analysis results depend on the density of deployed APs (Sapiezynski et al. 2015).

Research has also looked into the combination of wifi and Bluetooth data with other data sources, such as GPS and mobile phone data, either to overcome limitations regarding indoor localisation (Marakkalage et al. 2021) or to understand region-wide mobility patterns (Wang et al. 2019). In some cases, for example mobile App-based locations, data are automatically generated from multiple sensors. However, to the best of the authors' knowledge, such multi-sourced data is not yet used to specifically study micro-mobility. Also, as with other mobile sensor data, data obtained from wifi and Bluetooth-enabled mobile devices is mode-independent. Travel mode can be inferred if the position of the APs is known as being at a location accessible by one mode exclusively. Alternatively, mode-detection algorithms taking into account travel speeds, travel directions, and the relative position of users to APs could be developed using heuristic methods or machine learning techniques.

2.3. Derived data

Derived data types, namely vehicle availability and trip data, are discussed in this section.

2.3.1. Vehicle availability data

The emergence of shared micro-mobility brought with it a new type of vehicle data which has only been known for taxis before: vehicle availability data. This refers to the position of all unoccupied, and therefore available for hire, shared vehicles in a shared micro-mobility system. The data typically contains a unique vehicle identifier, a timestamp, and the position of the vehicle at a given time. The vehicle's position can be described either by geographic coordinates (obtained e.g. through a built-in GPS sensor) or, in the case of station-based systems, a unique station identifier. Positioning errors need to be taken into account for the former case.

In contrast to other vehicle-based data, vehicle availability data is comparatively easy to obtain for researchers. This is because it is vital for the service providers' efficient operation to recognise unoccupied and free-to-hire vehicles. They often make this information public (e.g. through a smartphone application) to allow potential users to find available vehicles in their search area. Many micro-mobility services provide APIs through which a dataset of all available vehicles can be requested. This can be queried through the General Bikeshare Feed Specification (GBFS), which can be used for all kinds of micro-mobility services (NABSA 2021a; NABSA 2021b). A dataset comprising all available vehicles and their positions over a certain period of time can be generated through a series of queries.

Occupied and non-available vehicles usually are not reported in such datasets. Hence, when repeated API requests are carried out, vehicles will disappear and reappear in the datasets. If not the availability of vehicles in an area or at a station respectively is of interest (Ashqar et al. 2017), an algorithm is necessary to identify trips with their respective origins and destinations. Since some companies regularly change the released vehicle identifiers (Merlin et al. 2021), this is not necessarily trivial. However, if unique vehicle identifiers are available, this usually happens through a rule-based approach which, in short, distinguishes between times of non-movement (for which data is available) and movement (for which no data is available). A trip is considered to have happened from the last timestamp before disappearing from the dataset until reappearing (Younes et al. 2020; Reck et al. 2021; Zhao et al. 2021; Mangold et al. 2022). Trips can also happen between two data snapshots and can be identified if the distance between two snapshots of a vehicle is within a reasonable distance (McKenzie 2020). Apart from trip identification, pre-processing is necessary to detect and handle errors in the dataset and exclude trips for operational purposes made by staff (Xu et al. 2019; Younes et al. 2020; Zhao et al. 2021).

Vehicle availability data is mainly used to analyse origin–destination pairs. Three categories of analysis are frequently used: the analysis of one micro-mobility system and its influencing factors; comparing micro-mobility systems in different settings (e.g. cities); comparing different micro-mobility systems in the same setting (e.g. city). Factors found to influence micro-mobility usage include natural events such as weather (Ruffieux et al. 2018), trip distance and time of day (Reck et al. 2021), socio-economic factors (Faghih-Imani et al. 2017), the built environment (Faghih-Imani et al. 2017; Xu et al. 2019), and COVID-19 pandemic (Li et al. 2021). Vehicle availability data from shared bicycle services in two Spanish cities have been used by Faghih-Imani et al. (2017) to model departure and arrival rates, depending on bicycle infrastructure, land use, points of interest (POIs), and socio-economic factors. In addition, they also model rebalancing operations observed in the data with a binary choice model. They, however, neither propose a better rebalancing strategy than the one observed, nor a framework to derive one. The work by Ruffieux et al. (2018), in contrast, uses their demand forecast model to propose a rebalancing strategy that keeps the station-based system in balance.

Differences between dockless and station-based systems have been extensively studied, as this decision can have a significant influence on the scheme's success. Results from McKenzie (2019) indicate that e-scooters, in contrast to shared bicycles, are not widely used for commuting but for leisure trips. This finding is broadened by Younes et al. (2020) with their discovery that e-scooter users in their spatio-temporal patterns are more similar to casual station-based bicycle sharing systems than to subscription users. Furthermore, Reck et al. (2021) find that docked modes are preferred for commuting. Hence, docking infrastructure for currently dockless modes could be vital for bolstering micro-mobility as an attractive alternative to private cars to tackle urban congestion during rush hours. Evaluating different micro-mobility modes and their relationship to other modes is of importance for research and practice. The relationship between micro-mobility and public transport has been examined (Yang et al. 2019) as well as how ride-hailing services relate to micro-mobility usage patterns (McKenzie 2020).

2.3.2. Trip data

Trip data at minimum contains information about trips' start and end locations and times. Optionally, trip data can also contain information about the rider, a vehicle identifier, and further trip-related information such as the price. By nature, trip data is constructed by processing information from sensors (mostly GPS units) incorporated in vehicles. Trip data can be made directly available by operators or authorities through their websites and APIs.

Trip data reduces the processing burden for researchers but also decreases the control of the researchers on the process. For example, the rules applied to data cleaning (e.g. to exclude unreasonable trips or location changes carried out by non-users) are not necessarily made transparent. To address privacy concerns, trip data might be fuzzed to make user tracking impossible (Ciociola et al. 2020) and provided on a spatially aggregated instead of an individual level. For this purpose, sectors already used in other contexts such as Transport Analysis Zones or census tracts (Bai and Jiao 2021; Lee et al. 2021b), artificial regular constructs such as nets of regular spatial patterns, or network-derived features such as street segments (Bai and Jiao 2020) can be applied. Trip start and end locations for docked systems can also be provided in the form of a station identifier which needs to be mapped by the researcher (He et al. 2019). When comparing data provided by different entities applying varying privacy policies, measures have to be taken to ensure comparability.

Trip data is frequently used in the literature to derive data-driven demand models (Zhou et al. 2018a; Li et al. 2019b; Boufidis et al. 2020; Ciociola et al. 2020; Xu et al. 2020), to examine how socio-economic and built environment factors (He et al. 2019; Bai and Jiao 2020; Guidon et al. 2020; Li et al. 2020a) or weather (Li et al. 2015; Liu et al. 2016a; Hulot et al. 2018; Zhou et al. 2019; Noland, 2021) influence micro-mobility usage. Also, attention has been paid to the implications of system design changes (e.g. charging strategies, fleet sizes, rebalancing strategies, station distribution, prices) on system performances (Li et al., 2019a; Ciociola et al. 2020; Lee et al. 2021b; Mclean et al. 2021). Equity considerations have been addressed by analysing destination choices of bike sharing users from disadvantaged areas (Qian and Jaller 2021). Demand estimation for new deployment scenarios attracts significant research interest

(Guidon et al. 2020; Lee et al. 2021b), as it helps to justify and estimate business cases for stakeholders.

A shortcoming of trip data is that they only contain information about trips that have been carried out and therefore do not allow to derive conclusions about unmet (i.e. a person wants to use shared micro-mobility, but no vehicle is available) or potential demand (i.e. a person could use shared micro-mobility, but does not do it). The authors propose that unmet demand could be identified by exploiting records of people opening mobile phone applications without eventually renting a vehicle. Potential demand for micro-mobility could be derived from analysing trips that have happened and identifying alternatives under the use of micro-mobility. The former is, however, under the control of micro-mobility companies and not easily obtainable. The same applies to tracking data which could help to enrich the often freely available trip origin and destination data for applications such as route choice modelling.

2.4. Advantages and limitations

To summarise, passively generated big data has significant advantages over traditional transport data obtained through questionnaire surveys, focus groups, manual observations etc. Firstly, passively generated big data increases data sampling rates, resulting in significantly higher temporal and spatial coverage and resolution. For instance, 96 % of the world's population owns a mobile phone (ICT 2013), whereby a typical response rate of surveys is 1 % of households (Stopher and Greaves 2007). Also, survey response rates of the UK National evaluation of e-scooter trials range between 13 and 14 % through operators and 5–6 % through online survey channels, while close to all 14.5 million e-scooter trips were recorded (Department for Transport 2022). With a larger sample, analysis of micro-mobility will be more accurate, and variations will be more easily identified, especially if individuals can be re-identified in the big data sets. Secondly, passively generated big data reduces errors from human factors of both surveyors and respondents. On the one hand, passively generated big data does not suffer from measurement errors, where different observers can interpret their tasks differently or do not fulfil their tasks accurately, for example, because they are distracted (Gillen et al. 2019). On the other hand, passively generated big data does not rely on any participant to provide correct information and is therefore not influenced by response bias. For example, the survey respondent may not recall the correct answer or deliberately give a response that is considered socially acceptable (Bergen and Labonté 2020). Therefore, passively generated data can also be used for the counterfactual analysis of survey results (Department for Transport 2022).

However, passively generated big data also has some limitations. Firstly, data coverage of time, space, and population varies, which can introduce bias. For example, high spatial coverage requires a large number of stationary sensors to be deployed to fully cover the area of interest. For population coverage, although stationary sensors can detect the entire population within the range of the sensors, the corresponding trip chains can only be derived if people or their devices can be recognised, for example, with the help of unique device identifiers or face recognition techniques. Mobile sensors, in contrast, can capture the entirety of people's movements, but there can be a sample bias in the population covered, for example, when the researcher has a mobile phone dataset from only one mobile phone company, or vehicle availability data from just one micro-mobility provider. In addition, self-selection bias occurs as ownership of mobile phones differs between population groups (ICT 2013) and when GPS data from mobile phones is gathered through applications used by only a proportion of all mobile phone users.

Secondly, privacy concerns need to be addressed as passively generated data can directly contain or be used to infer personal information, such as people's habits, personalities, and contexts (Harari 2020). This is particularly important as data can finds its way into the public through dubious channels (Sullivan 2006).

Measures to enhance and protect people's privacy usually result in reduced precision. For example, micro-mobility trip data can be aggregated (Bai and Jiao 2020; Bai et al. 2021), and vehicle availability data can be designed not to capture individuals during their travels (Merlin et al. 2021). In the case of mobile phone data, the device's location can be derived precisely, as the distances of the device to minimally three base stations are sufficient to calculate its position. However, due to privacy concerns, this triangulation is not allowed under various legal regimes, hence alternatives to triangulation can use mobile phone data with reduced precision (Bachir et al. 2019).

Thirdly, errors and noise in the data, which arise either purposefully (e.g. to protect privacy) or due to technical reasons, need to be considered. GPS data, for example, is affected by systematic errors and random noise, which result in missing data points (Quddus et al. 2006) or positioning errors depending on the heights of nearby buildings and the number of available satellites (Williams and Morgan 2009). As micro-mobility is popular in dense high-rise environments, GPS accuracy needs to be considered when derived data, such as vehicle availability and trip data, is analysed. In the case of mobile phone data, the temporal and spatial density of users' recorded activities depend on the usage type and the network design. More records are created, for instance, if a user makes more frequent phone calls or regularly travels longer distances (Huang et al. 2019). This increases the information density and location estimation accuracy for more active mobile phone users.

Given these limitations of passively generated data, data from traditional sources still has an indispensable role in micro-mobility research and practice. Stated preference surveys, for instance, can provide valuable insights into the willingness to adapt new modes such as micro-mobility (Eccarius and Lu 2018; Peters and MacKenzie 2019; Sanders et al., 2020; Sorkou et al. 2022; Torabi et al., 2022). In the case of British e-scooter trials, for instance, user surveys provided important insights into mode shift and mode choice motivations which could not have been obtained from the available passively generated big data (Department for Transport 2022). Manual observations "on the ground" through "gate counts" (i.e. counting at specific locations), "snail trailing" (i.e. following individuals), and "static snapshots" (i.e. registering behaviour in a public space over a short period) (Yamu et al. 2021), can provide contextual information not available through automated methods and – as well as census data – serve as ground truth for the calibration of models based on passively generated big data and as additional data sources in places where automated methods are not available (Gehrke and Reardon 2021).

3. Applications to address challenges of micro-mobility: state-of-the-art and future research directions

Despite city administrations' promoting shared micro-mobility to reduce the number of trips made by car (Gebhardt et al. 2022), to solve the "last-mile problem" of public transport (Hosseinzadeh et al. 2021), to minimise air pollution and greenhouse gas emissions (Glenn et al. 2020), and to use space and energy more efficiently (Gössling, 2020), the emergence and growth of micro-mobility services bring significant challenges for a wide range of stakeholders: micro-mobility users, users of other transport modes, planners, authorities, as well as companies offering both micro-mobility and other transport services. These challenges can be broadly divided into four categories: safety, societal impact, environmental effects, and system design. Passively generated big data has considerable potential to address these challenges related to micro-mobility research and practice. This section highlights areas that require further research and provide new insights for the development of safe, efficient, sustainable, and equitable micro-mobility services.

3.1. Safety

In transport studies, safety is mainly interpreted as the (relative) absence of accidents and resulting injuries or casualties and property damages (Stoop and Thissen, 1997; Jones-Lee, 1990; Vanparijs, 2015). With regard to micro-mobility, safety is essential to protect people from being injured, to reduce resulting healthcare costs (Sikka et al. 2019) and is an important factor in people's decision to use micro-mobility (Sanders et al., 2020).

The widespread introduction of e-scooters has raised concerns about the safety of e-scooter drivers themselves, as well as pedestrians and other traffic participants. This is especially problematic as the "status of e-scooters within existing traffic rules is unclear when they are first introduced" (Tuncer et al. 2020). Even though administrations worldwide have started to incorporate novel micro-mobility solutions into their traffic regulations (Tuncer and Brown 2020), safety concerns are still present in the public debate and regularly mentioned by potential e-scooter riders as an obstacle (Department for Transport 2021). E-scooter-related risks include collisions of traffic participants, as well as maltreatment and malfunctions of the vehicles. The latter cannot only cause severe damage and injuries but also disrupt other mobility services, for example, when an e-scooter catches fire on public transport (BBC, 2021a). Passively generated data can help to overcome these safety-related issues of micro-mobility on different levels.

Firstly, it can provide a wider database of accidents involving micro-mobility. This is necessary, as in contrast to accidents involving motorised vehicles, a lack of systematic and standardised accident data collection for bicycles and other micro-mobility solutions is evident (ITF 2020; Yang et al. 2020; DfT 2021). Efforts have been undertaken to gather accident data for the novel mode of e-scooters by using hospital records (Mayhew and Bergin 2019; Farley et al. 2020; Bodansky et al. 2022) or by gathering and analysing media reports on traffic crashes that involve e-scooters (Yang et al. 2020). However, these analyses only include accidents with outcomes so severe that people are admitted to hospitals or included in media reports, missing all incidents below these thresholds.

To gather more accident data of higher quality, a traditional approach is to delegate detailed accident information capturing to the police forces. This, however, would still miss out on accidents below a certain level of severity and those involving people who do not want to have contact with the police. Alternative approaches can take advantage of the passively generated data and novel technologies used for micro-mobility services. For example, users could be encouraged to report accidents by themselves through a mobile phone application (ITF 2020). The authors believe that sensors in vehicles can help to detect abnormalities in rides, such as abrupt standstills (detectable through GPS sensors) or changes in vehicle orientation (i.e. lying instead of standing up). Also, images from traffic surveillance cameras in combination with image recognition techniques could be used to detect micro-mobility accidents automatically. Furthermore, sensors included in shared micro-mobility services' users' mobile phones can potentially help gain insights into accidents, e.g. through GPS sensors, or gyroscopes to detect riders falling. Improved data on micro-mobility accidents could help identify risk factors in driving behaviour, infrastructure design, traffic conditions etc. of different modes. For this, it is also useful to connect traffic with infrastructure and accident data to discover patterns that can help to design and plan safe micro-mobility.

Secondly, already gathered data needs to be analysed and processed more systematically to gain a better understanding of the state of traffic and infrastructure. For example, research has shown that data from sensors in shared micro-mobility vehicles and their users' smartphones can help to monitor infrastructure conditions (Ma et al., 2021a,b; Cafiso et al. 2022). Widespread and systematic usage of this sensor data could help to detect and eliminate infrastructure-related safety threats (e.g. potholes) early on.

Furthermore, passively generated data, for example from stationary cameras, could support automated intersection control to avoid conflicts and accidents between different modes. This is relevant also to micro-mobility as places with a high share of bicycle traffic already face capacity problems on their infrastructure (Hoogendoorn and Daamen 2016). Image recognition and processing is one possible method which is already widely used for motorised vehicles (Wang et al. 2021), but without any application for micro-mobility so far to the best of the authors' knowledge.

Thirdly, passively generated data can support automated safety features of vehicles, for example by detecting potential safety hazards from moving (micro-mobility) vehicles. This will become increasingly important with the growing deployment of autonomous cars but can also create benefits for human drivers as micro-mobility users tend to follow non-linear patterns and make unexpected movements. Apart from the development of microscopic movement models for micro-mobility users with input from, for example, car cameras (Jung et al. 2012), also the development of communication protocols between connected vehicles and micro-mobility users (e.g. via their smartphones) can help overcome this problem and increase trust in micro-mobility.

3.2. Society

It is crucial to understand how transport shapes society and vice versa. As for mobility in general, micro-mobility has the potential to increase social justice by increasing access to "life-enriching opportunities" such as employment, education, and leisure activities (Martens et al., 2019). Research has been identified that asses how micro-mobility services can create mobility opportunities for groups with reduced access to other transport modes (Eccarius and Lu 2020; Sanders et al., 2020; Zuo et al. 2020), indicating that factors such as public transport network configuration, job concentration, and the distribution of socio-economic variables among the population contribute to the distribution of mobility opportunities (Pritchard et al. 2019; Zuo et al. 2020). Empirical research is still falling short of assessing how these opportunities are actually used and which factors create barriers for disadvantaged groups. For this, it is crucial to develop accurate mode detection algorithms that include micro-mobility modes and do not only focus on "classic" motorised mobility. Longitudinal studies based on passively generated, mode-independent data such as mobile phone or stationary sensor data can be carried out to identify changes in mobility patterns and realised access to employment, education and leisure activities after the introduction of micro-mobility services.

Micro-mobility-related effects on public health have multiple dimensions (Pucher et al. 2010; Khreis et al. 2017; Glenn et al. 2020): traffic-related injuries need to be reduced, air pollution and noise exposure lowered, social exclusion and community severance decreased, and physical activity supported. These goals and their interdependencies among themselves as well as with the built environment, traffic management, user behaviour, vehicle design etc. need to be addressed in order to provide successful transport systems.

The heterogeneity of the micro-mobility field needs to be considered. For example, research suggests that active travel, such as cycling, reduces obesity rates, increases cardiovascular health and lowers morbidity (Pucher et al. 2010). E-scooters on the one hand, however, might replace more active forms of transport such as walking and cycling, suggesting that their use might have a negative effect on public health (Neven et al. 2020). On the other hand, replacing car trips with e-scooters has the potential to reduce local emissions, and the reduction of street space allocated to cars can incentivise social interactions with a positive effect on people's mental health levels (Izenberg and Fullilove 2016) and e-scooters might promote infrastructural changes and, thus, create an environment and culture facilitating cycling and walking (Glenn et al. 2020). Cross-examination of different types of data, such as shared micro-mobility and health application data, could help to understand this area of tension.

Furthermore, the effects of micro-mobility on society are diverse and dependent on the specific field of examination and the societal context. Novel data sources can be used, for instance, to examine the role of micro-mobility in major societal challenges, for example, in the context of the COVID-19 crisis (Li et al. 2021; Bian et al. 2021; Dean and Zuniga-Garcia 2022). In addition to already existing examples of social media analysis to find out about the population's opinions and sentiments concerning mobility policies and potential interventions (Rahim Taleqani et al. 2019; Avetisyan et al. 2022), infrastructure and usage data can be analysed together with picture- and video-based social media material to understand and promote socially acceptable micro-mobility behaviour.

To assess how well potential demand for shared micro-mobility is met across societal groups, not only data revealing information about trips that have happened should be collected and analysed but also other information such as searches for available vehicles, the distribution of downloaded and used mobile phone applications across population groups etc. This data in comparison to objectively measurable accessibility information and in combination with qualitative data can help to identify hurdles to the uptake of shared micro-mobility services.

3.3. Environment

With the growing demand for environmentally-friendly transport solutions, one of the main arguments made by micro-mobility companies (especially shared electric vehicles) is that they support the shift toward environmentally-friendly travel. Most of these arguments are related to the reduction of car usage, including lower greenhouse gas emissions (Eccarius and Lu 2020; Zhu et al. 2020), less noise (Gössling, 2020; Zhu et al. 2020), less air pollution (Gössling, 2020; ITF 2020), and less occupied road space in cities (Eccarius and Lu 2020; Zhu et al. 2020).

Micro-mobility has the potential to replace other means of transport, enable environmentally-friendly trip chaining, and reduce traffic. However, based on life cycle assessments (Severengiz et al. 2020), two major micro-mobility modes, bicycles and e-scooters, can have opposite environmental effects on CO2 emissions. Whereas bicycles have the lowest emission per kilometre travelled, e-scooters, even in the best case, are not better than travelling by tramway, bicycle or electric bicycle. Under certain conditions, e-scooter trips do not even account for lower CO2 emissions than electric cars (Gebhardt et al. 2022). This means that e-scooter trips can only be considered environmentally beneficial if they replace (conventional) car trips either by themselves or in conjunction with other modes, particularly public transport.

However, the effects of shared electric micro-mobility on car usage are not yet clear. Research indicates that many of the potential e-scooter users had been public transport users before (Eccarius and Lu 2020; Sanders et al., 2020). Despite the claim that it does not lead to a reduction of CO2 emissions, passengers switching from public transport to e-scooters could still have indirect positive effects on the environment. For example, a less crowded public transport system could potentially attract more car users, creating a positive effect in terms of CO2 emissions. Also, due to less space needed for classic motorised transport, street spaces could be redesigned to allow for more vegetation and reduced separation effects.

Overall, various perspectives need to be integrated for a comprehensive picture. Due to the production process and the electricity needed for recharging, the battery and its life span have a significant impact on the level of environmental friendliness of electric micro-mobility (Severengiz et al. 2020). Therefore, understanding whether a mode shift towards electric micro-mobility happens from environmentally friendlier modes (e.g. walking or cycling) or unfriendlier modes (e.g. car) or whether trips would not have taken place without the supply of electric micro-mobility (“induced demand”) is crucial for assessing its impact on the environment. Developing methods to detect modes from mode-independent data, for example in a network of wifi or Bluetooth network access points can help quantify modal shifts due to micro-mobility.

Although data about battery levels are regularly collected by providers of shared micro-mobility, little analysis of that data has been carried out so far (Reck et al. 2021). It is necessary to identify which user and driving behaviour has a positive impact on the life span and energy consumption. For this, it would be necessary to link micro-mobility tracking data with the respective battery charge levels. For example, it could be beneficial to encourage users not to speed due to the squared relationship between the energy needed for movement and speed. Also – depending on the battery used – discharging a battery below a certain level might have negative impacts on its lifespan, implying that the user should be animated to stop their trip before reaching that threshold. In practice, policies (e.g. monetary benefits, technical boundaries) to encourage micro-mobility users to drive in an environmentally friendly manner can be tested and implemented. One possible approach is to offer monetary incentives for not fully discharging the vehicle’s battery or for avoiding excessive speeds.

Furthermore, all shared micro-mobility services regularly rely on the collection and redistribution of vehicles (rebalancing) to match the fleet supply with the demand. These operations regularly rely on the use of road vehicles which have an environmental impact by themselves that can be reduced by optimising the rebalancing process. This has been examined using historic data for station-based bicycle-sharing services (Zhang et al. 2019a). Further research is needed to understand the environmental impact of rebalancing in dockless systems, particularly e-scooter systems, where charging is another critical operational consideration when rebalancing.

3.4. System design

Micro-mobility companies need to attract users and maximise profits, while city authorities need to optimise mobility for citizens and promote sustainable modes of transport. Therefore, a major challenge for both of them is designing shared micro-mobility services in terms of providing the necessary infrastructure, vehicle design and deployment, and defining usage conditions. At the same time, the micro-mobility system design has a significant impact on the challenges discussed in the previous sections (ITF 2020; Mahfouz et al. 2021; Reck et al. 2022).

Many factors influence the usage patterns and attractiveness of shared micro-mobility services. The most important ones include whether a station-based or a dockless system is implemented. The former gives more control over vehicle flows to the provider and is particularly favoured in areas of concentrated demand, whereas the latter is preferable in areas of lower demand densities (Cheng et al. 2020; Ji et al. 2020; Younes et al. 2020). Whether electric or human-powered vehicles are used is crucial for the uptake in hilly areas (Reck et al. 2021), and the number of vehicles deployed in the system is decisive to reach the intended level of service, to optimise rebalancing operations, and to be profitable, whereby each of these requirements can have different optima regarding fleet sizes (Ataç et al. 2021). Further critical factors include the pricing policy (Zhang et al. 2019b; Reck et al. 2021) which needs to attract users and build a financially sustainable source of income for the provider. The micro-mobility system’s integration with existing public transport, spatially but also fee-wise, is vital to attract users for first and last-mile trips (Lee et al. 2021a). Requirements to wear protective gear can have a positive impact on (perceived) safety but also deter people from using micro-mobility due to a feeling of discomfort wearing them (Busby et al. 2020) which makes finding the right level of enforceable protective clothing requirements necessary. Finally, the decision on which road spaces micro-mobility users are allowed to use at which speed also has a significant impact on the safety of riders, but also on conflicts with other vehicles (ITF 2020).

Micro-mobility systems can be planned and managed with the help of novel data sources and analysis techniques. In terms of planning, passively generated big data can help develop models that allow investigating the appropriateness of specific designs for new micro-mobility services to avoid trial-and-error approaches. Artificial intelligence has been applied to analyse this data and understand the optimal number, distribution, and size of bike-sharing stations (Liu et al. 2016b; Zhang et al. 2019a), the planning of bicycle networks (Bao et al. 2017), and short-term demand prediction (Ham et al. 2021). Future research can examine the integration of micro-mobility with other modes, especially public transport, to find better solutions for the first/last mile problem. To this aim, public transport ridership data should be analysed in conjunction with usage data from shared micro-mobility services, for example with the help of machine learning techniques as they have already been applied to mono-modal demand prediction problems (Ruffieux et al. 2018; Cheng et al. 2020; Abdellaoui Alaoui and Koumetio Tekouabou 2021; Ma et al. 2021b). Furthermore, research should be able to analyse search data in mobile phone applications in order to identify potential demand, or demand that is not met, for a micro-mobility service. This could help not only to optimise a micro-mobility system’s efficiency but also to make it more attractive and reliable, potentially making it a first choice – in combination with public transport – over other alternatives.

Future applications of advanced data analysis techniques in the area of micro-mobility in conjunction with using both static data like built environment factors and dynamic data such as short-term weather forecasts could be used to allow providers of shared micro-mobility to predict short-term demand. Data-driven interventions can be developed such as short-term adjustments of prices to incentivise drop-offs at expected underserved areas and optimising rebalancing operations. Also, artificial intelligence based on both stationary and mobile data could support traffic management and control for micro-mobility – for example short-term green phase adaptions at intersections, as well as the flexible allocation of road space to micro-mobility as it already exists for other modes (He et al. 2016; Haitao et al. 2018). These strategies are increasingly important as cities worldwide aim to prioritise green transport modes within limited urban space.

4. Conclusion and future directions

This paper provided the first review of how passively generated big data has been used in the context of micro-mobility research. The analysis of the reviewed literature showed that the exploitation of micro-mobility-related passively generated big data has increased dramatically with the deployment of shared micro-mobility services in the last few years, demonstrating the timeliness and

		Advantages	Disadvantages	Research questions
Stationary sensors	Stationary counters	- higher temporal coverage than human counters	- limited information about context - accuracy problems - distinguishing vehicle types - detecting correct number of vehicles - re-recognition of vehicles/individuals requires additional technology - lack of contextual information - inability to adjust for disruptions	- models for accumulated vehicle flows - ground truth data for counts based on other sources
Stationary sensors	Wifi and Bluetooth APs	- re-recognition of devices possible - can build on existing, not transport-related equipment - mode-independent	- access to APs for research/deployment of additional APs might pose a challenge - advanced techniques necessary for mode detection - potential privacy concerns	- visiting patterns - routing
Stationary sensors	Stationary cameras	- re-recognition of individuals possible - can build on existing, not transport-related equipment - mode-independent - analysis by both humans and image recognition techniques possible - contextual information can be gathered	- automatic distinction between modes needs to be trained - potential privacy concerns - access to cameras for research/deployment of additional cameras might pose a challenge	- routing - state of infrastructure
Mobile sensors	Mobile phone data	- high coverage of population - mode-independent - cross-validation with data from other sensors from the same device possible	- data access - density of measurements depends on usage behaviour and deployment of towers - mode detection challenging - depending on mobile phone carrier	- large scale mobility patterns
Mobile sensors	Mobile phone GPS	- mode-independent - mobile phone carrier-independent - cross-validation with data from other sensors from the same device possible	- data access/ participant recruitment - sample size and bias - measurement errors	- routing
Mobile sensors	GPS units	- mode known (usually) - higher precision than mobile phone GPS	- data access//participant recruitment - measurement errors	- routing - traffic volumes
Mobile sensors	Mobile wifi and Bluetooth	- mode-independent - individual traces can be followed - cross-validation with data from other sensors from the same device possible	- data access/ participant recruitment - density of measurements depends on usage behaviour and deployment of APs - APs' positions need to be determined using other data sources (e.g. GPS)	- indoor localisation - large scale mobility patterns
Derived data	Vehicle availability	- comparatively easy data access	- only shared vehicles - derivation of trips laborious - routes unknown - individuals not traceable	- demand models
Derived data	Trip	- comparatively easy data access (mostly only OD pairs) - reduced data processing burden	- only shared vehicles - data potentially fuzzed	- demand models - potentially routing

Fig. 5. Advantages, disadvantages, and research questions of the discussed data types.

value of the review. It is found that passively generated big data has significant advantages over traditional transport data, with increased data sampling rates, resulting in significantly higher temporal and spatial coverage and resolution, and reduced human errors from both surveyors and respondents. However, passively generated big data needs to be handled with careful consideration of potential bias, inaccuracies, and privacy concerns, and often needs to be analysed together with data from traditional sources in micro-mobility research and practice. Different types of passively generated big data were comprehensively reviewed, including data collected from both stationary sensors, such as stationary counters, wifi and Bluetooth access points, and stationary cameras, and data collected from mobile sensors, such as mobile phone data, mobile phone GPS data, and data from GPS devices. Two types of derived data, vehicle availability and trip data, and their wide applications in transport research and practice, were discussed in detail. Fig. 5 summarises the advantages, disadvantages and common research questions of the discussed data types.

The literature identified for and used in this paper shows clear patterns between research data types, methodologies, and questions. Micro-mobility route choice models, for instance, have been developed using almost exclusively data from either mobile phone GPS or specific GPS devices. Therefore, traces can be biased toward willing participants or modes for which the data can be automatically collected. Mode-independent data sources with a potentially broader population coverage (e.g. from public wifi or Bluetooth APs) may provide more general insights into routing patterns. For this purpose, more powerful mode detection algorithms are necessary to exploit these mode-independent data sources, as mode detection algorithms identified in this paper do not cover micro-mobility modes other than cycling. Similarly, the literature presented using stationary counter and camera data solely covers cycling. Therefore, further research should explore how other popular micro-modes, such as e-scooters and e-bikes, can be detected from mode-independent datasets and stationary counters. Moreover, it is worth considering to which extent widely deployed sensors such as wifi, Bluetooth, and cameras could help to assess micro-mobility users' behaviours concerning speed, overtaking behaviour, and the use of dedicated infrastructure etc. This can also help cover private micro-mobility vehicles, as only one paper was identified covering the mode of e-scooters and not relying on the data from a shared micro-mobility service. A summary of the suggestions for specific research questions brought forward in this study are presented in Fig. 6.

In addition to the specific future research questions discussed in this review, the authors believe the following three major directions are crucial for future research. First, passively generated big data needs to be used for real-time micro-mobility traffic monitoring and dynamic traffic control. This is especially important with rising micro-mobility traffic volumes which result in both increased levels of modal conflicts in mixed traffic streams. Potential interventions, such as speed restrictions, lane allocation, and traffic light control, can be developed and implemented based on data from wifi and Bluetooth technology, camera footage analysed with image recognition techniques, and stationary counters. These interventions are already common practice in the realm of car

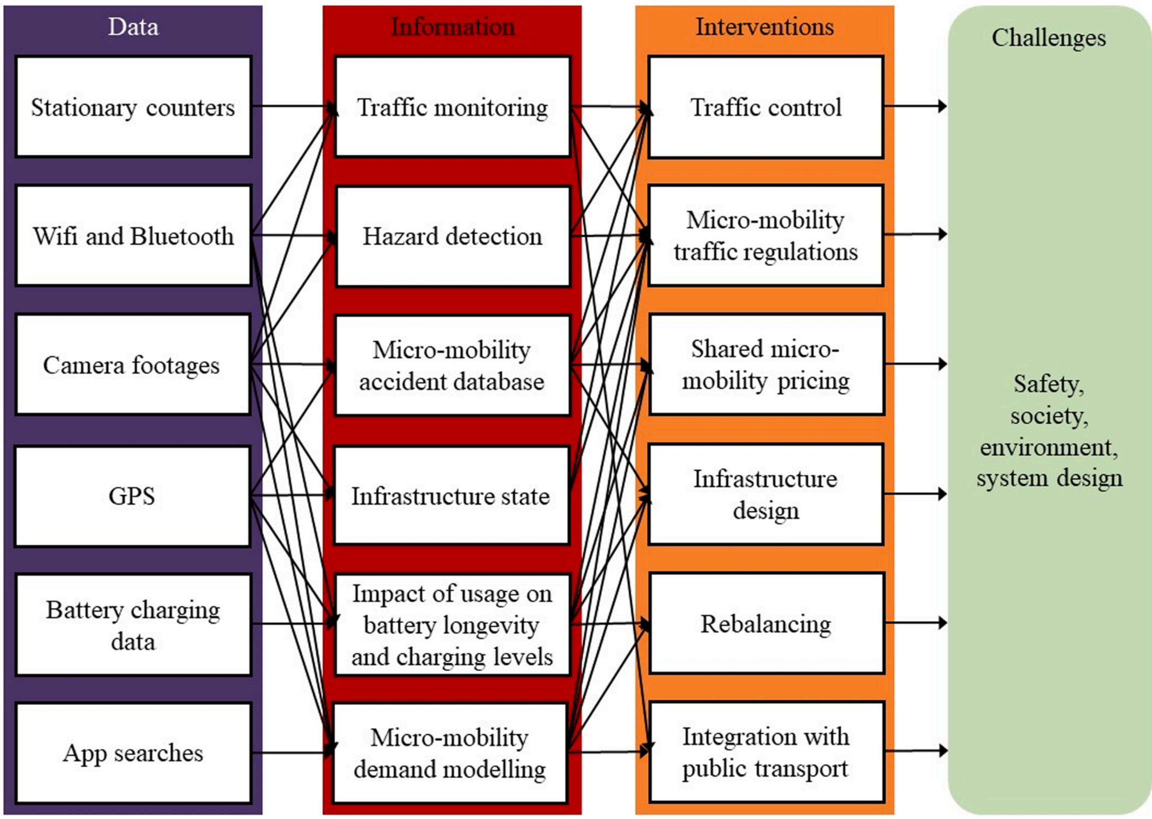

Fig. 6. Summary of suggestions for future research.

traffic but largely missing for micro-mobility. Second, more research is needed to integrate micro-mobility with existing public transport and to strengthen this integrated mode option as an environmentally-friendly and equitable alternative to private motorised transport. Possible interventions include the development of joint booking and tariff systems for this integrated system in the direction of Mobility-as-a-Service, as well as the enhancement services based on the real-time analysis of passively generated big data. For example, this could help to ensure adequate shared micro-mobility vehicles available at public transport stops and to adjust the capacity and departure times of demand-responsive public transport. Third, further data fusion and processing techniques should be developed to effectively combine data from different sources and different modes. This is instrumental for better understanding people's mobility patterns beyond the boundaries of modes, the precision and characteristics of each sensor type, and indoor and outdoor environments, and generating multi-sourced data less skewed by the distribution and usage of devices with specific sensors across the population. Overall, our research demonstrates the power of passively generated big data from micro-mobility, and identifies further potential in the capturing of additional data, the integration of data from different sources, and the development of advanced analytics to support planning, monitoring, operation, and control for safe, equitable, environmentally-friendly, and efficient micro-mobility.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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