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Data Evaluation for Continuous Monitoring of Urban Travel

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Abstract

Key Performance Indicators (KPIs), such as modal split or vehicle kilometres travelled (VKT), are essential for assessing mobility trends and informing policy decisions. Traditionally, such indicators rely on travel survey data, which, while comprehensive, are costly and time-consuming to collect. In recent years, alternative data sources, such as mobile phone data, floating car data, and sensor-based measurements, have become increasingly available, offering new opportunities for more frequent and spatially detailed mobility analyses.
This paper examines various data sources that can be used for KPI calculation, highlighting their strengths and weaknesses. We review existing studies that have successfully combined two or more of these data sources to gain a more comprehensive understanding of travel behavior. The key focus is on methodological challenges of data fusion, including spatial and temporal resolution issues, representativeness, and consistency between datasets.
Furthermore, we discuss the role of travel surveys in supporting data integration. While surveys alone cannot provide continuous travel monitoring, they offer valuable microdata on travel behavior, which can help validate and calibrate other data sources. Finally, we outline best practices for combining different mobility data sources to enhance the accuracy and reliability of transport indicators.

Keywords: Data Fusion; Travel Surveys; Transport Data; Travel Behavior

1. Introduction

Up-to-date indicators to describe mobility and its development over time (e.g. modal split, vehicle kilometres travelled, emissions) are indispensable for policy and planning at all administrative levels. These indicators are crucial for transport planning and climate accounting, for example, to monitor and demonstrate progress in sustainable urban travel. To date, such indicators have primarily relied on travel behavior surveys. However, these surveys are time-

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consuming and expensive, preventing continuous and comprehensive monitoring. Furthermore, such data is therefore unsuitable for continuous and timely monitoring. We therefore need to develop models that can calculate these KPIs by merging various data sources. To the authors' knowledge, there is still no consistent and continuously updated method to calculate these KPIs for all modes. At the same time, new data sources, such as floating phone data, offer promising opportunities to close spatial and temporal gaps in travel demand statistics. Combining these sources through travel demand models appears to be a promising methodological approach. Such models, already established in real-time traffic management for fusing measurement data into consistent traffic situations, provide a framework for integrating diverse data types based on a conceptual understanding of mobility.
A critical aspect when combining data sources is the spatial granularity of the observed travel. This distinction is essential for accurately interpreting the results, particularly in urban travel monitoring. The differentiation between the *polluter pays principle* and the *territorial principle* plays a central role. The *polluter pays principle* refers to traffic caused by the resident population of a study area, regardless of where it occurs. It includes external trips if they originate from the population under consideration, but excludes traffic generated by non-residents within the area. In contrast, the *territorial principle* captures all traffic within a study area, including trips by external parties, but excludes movements outside the area caused by the resident population.
Given these challenges and new opportunities through alternative data sources, this paper aims to address the following research questions:

- Which continuously available data sources are suitable for calculating KPIs?
- What are the strengths (e.g., temporal, spatial coverage) and weaknesses (e.g., selectivity) of the data sources?

The paper is structured as follows: first, we provide an overview of the various data types available in Germany and their respective applications in research; then, we compare these data types, evaluating their strengths and weaknesses. Finally, we will discuss the role of travel surveys in creating data fusion models.

2. Overview of Transport Data

The database and methods used to collect travel data vary by city, yet similar data exists in many cities. This chapter aims to explain the most common data sources that allow for continuous the description of everyday travel in German cities. As the research question focuses on German cities, the discussion excludes public transport (PT)-chipcard data, despite their international prevalence (Radovan et al., 2024). A significant proportion of this data is collected for other purposes, often without explicit transport modeling intentions, and is therefore typically less costly than dedicated collection methods such as surveys. The subsequent sections provide comprehensive explanations of the individual data sources. In addition, the paper presents case studies that utilize this data for the calculation of specific KPIs.

2.1. Car

Permanent Counting Stations
Permanent counting stations (PCS) on roads have been an integral part of traffic surveying for a considerable period. For instance, the German Federal Highway Research Institute (BASt) has been conducting continuous traffic counts on motorways and federal highways using PCS since 1975. These stations are equipped to distinguish nine vehicle types. The results of these counts, which provide an hourly breakdown of the various vehicle types passing a specific cross-section, are published monthly and made available online at no cost (BASt, 2025). The most conventional method employed is the use of induction loops, where magnetic loops are embedded within the road. When a vehicle passes over these loops, the magnetic field experiences a change, which is then detected by a counter. This method also facilitates the differentiation of vehicle types. Other standard counting methods include radar devices and optical image recognition (Leduc, 2008).
The data is permanently available; however, spatial availability is limited, as traffic can only be continuously recorded at road cross-sections where a permanent counting station is installed. Although there is a dense network of PCS on the main roads in Germany, in urban areas, traffic is only continuously recorded at selected locations. In these instances, traffic is typically measured for a limited time frame, often eight hours on two days, and then extrapolated to cover the entire year (FGSV, 2012). Consequently, continuous data is sparsely available within urban areas, thereby diminishing its informative value. All vehicles passing through a given cross-section are recorded, ensuring a complete sample. At counting stations, it is not possible to distinguish between commercial vehicles and private passenger

vehicles. While most counting stations can differentiate between different truck classes and passenger cars, distinguishing between parcel deliveries in small delivery vans is not possible. This must be considered when creating travel demand models (FGSV, 2012).

Floating Car Data

Floating Car Data (FCD) describes the trajectories of cars moving on the road network. It contains the GPS position of the vehicle with a time stamp, which is then used to generate trajectories with a time stamp and speed. The data is usually sent either by the car itself or by smartphones used for navigation. Navigation devices or app providers can record this data. It is then anonymized and made available for sale (Eisinga and Lorkowski, 2025).

The data is available for an unlimited period of time. There are also a few geographical restrictions and several companies collect such data. Eisinga and Lorkowski calculated that about 20-25% of the traffic in the Netherlands is provided by cars that transmit their data to TomTom (Eisinga and Lorkowski, 2025). They did so by calculating the penetration rate of FCD at PCS on various types of roads. They find that FCD is suitable for determining traffic load on the roads using FCD. The more FCD and counting stations available, the more accurate the result. However, only a few counting stations are needed to calibrate the model.

There are currently no studies on sociodemographic representativeness of FCD in Germany or Europe. Given that the majority of new vehicles are equipped with FCD devices, it is reasonable to conclude that there is less data available on individuals with low economic status. However, there are currently no studies that can confirm or refute this theory.

2.2. Micromobility and Active Modes

Strava / GPS Data

Strava is a social network that allows users to share their physical activities with friends. Since its launch in 2009, 100 million users have signed up. They track their activities, mainly biking and running, via GPS with their smartphone in the app and then share their routes publicly with their friends. The data collected includes activity profiles with time of activity, distance, route, and speed. Strava allows research programs to use the data collected through the "Metro for Academic Researchers" program. The processed and anonymized data is available in an online dashboard, or raw data can be provided for specific applications. Data is available for recent years. The data includes origin-destination relationships, travel times, and the number of trips on individual segments. (Strava, 2025)

The data is collected continuously and is permanently available. There are also a few geographic limitations; wherever Strava users have been, there is data. The main uncertainty in using this data for transportation research is the representativeness of the user base (Lee and Sener, 2021).

Venter et al. studied the selectivity of Strava users in Oslo, Norway. They found that young men with high economic status were disproportionately likely to use Strava (Venter et al., 2023). This means that vulnerable groups such as children and the elderly may be neglected in planning. They suggest that to address this imbalance, either a separate GPS tracking survey should be conducted that explicitly asks about these groups, or the data should be weighted using secondary data sources (e.g., census data, counting stations). There have also been attempts to extrapolate the number of bicycle trips and traffic volume from Strava (Roll, 2018; Hochmair et al., 2019). They compared the number of Strava users at a cross-section of a road with the counts from PCS at that cross-section. In principle, they consider this method to be applicable, but several things should be kept in mind:

- The sociodemographic bias differs from neighborhood to neighborhood.
- Increasing numbers of users require regular reweighting.
- Recreational activities are overrepresented in Strava data, but activities are difficult to identify.
- Data accuracy varies between summer and winter.

All reviewed studies conclude that Strava data can be used for transportation planning and modeling. It is a rich data source that can meaningfully complement surveys due to the large number of data points. However, it is imperative to merge Strava data with other data sources to obtain meaningful results.

Sharing Data (e.g., Bike, E-Scooter)

The boom in micromobility is driven by two distinct factors. On the one hand, significant advances in smartphones and mobile internet allow for constant connectivity, which is essential for many micromobility services, especially sharing applications. On the other hand, a shift in attitudes towards environmental awareness and urban mobility is driving changes in mobility. Therefore, many cities and individuals are trying to reduce car use. A combination of public transportation and the use of private bicycles or shared vehicles, such as bicycles or e-scooters, often serves as an alternative form of mobility.(Abduljabbar et al., 2021; Kagerbauer, 2022)

The patterns and motives for using shared e-scooters and free-floating bike sharing are different (Bieliński and Ważna, 2020; Chicco and Diana, 2022; Krauss et al., 2022; Reck, 2021). Therefore, they should be considered separately when modeling these modes. However, since the data collection process is similar, they are discussed together here. To collect e-scooter data, a query is made at a fixed interval to determine which e-scooters are currently available for rent, and their position and ID are stored. If the position of a vehicle has changed by the next query, it means that there was a trip during that time. This makes it possible to determine the number of rentals and the distance traveled using a routing algorithm (McKenzie, 2019; Porojkow and Lißner, 2024). A similar approach can also be used for bike-sharing data (Kaiser et al., 2023; Radzimski and Dzięcielski, 2021). This data is sometimes provided by the providers, sometimes for free (Gehrke et al., 2021; Willberg et al., 2021), and sometimes as a business model (Zhou, 2024).

Data from shared micromobility can be collected continuously without time gaps. Spatially, the data is limited to the service area of the respective provider. Often, these services are available in the inner city and neighboring districts. Cities have an interest in expanding the service area to cover the entire city, if possible, while providers only want to serve the city center for cost reasons (Hirsch et al., 2019). E-scooter and bike sharing users are predominantly young people, most of whom live in the city where the service is offered (Bieliński and Ważna, 2020; Willberg et al., 2021). However, there are also differences between users of bike-sharing services and those who use private bicycles. (Buck et al., 2013) found that women in Washington DC use bike sharing more than private bicycles, while men use private bicycles more than bike sharing. Younger people are more likely to use bike sharing, whereas older people tend to prefer private bicycles. In general, however, there is little research on how private bicycle users differ from bike sharing users (Fishman, 2016). There are also differences between owners and users of shared e-scooters (Petzoldt et al., 2023). For both bicycles and e-scooters, the use of sharing services is not representative of the use of private vehicles. Therefore, sharing data needs to be enriched with additional data to fully represent the use of these modes.

Permanent Counting Stations

In this section, we focus on data from bicycle counting stations. Car counting stations have already been discussed in chapter 2.1. There are many different methods to count cyclists automatically. (Ohlms et al., 2019) lists several techniques. The most common methods are Infrared or thermal cameras, computer vision or automated video recognition, and inductive loops. We will not discuss the advantages and disadvantages of each method in this paper; these can be found in the literature (Kothuri et al., 2017; Ohlms et al., 2019; Kędziorek et al., 2023).

The use of counting data in transport planning is diverse. On the one hand, they are used to generate daily, weekly and annual load curves and thus to obtain information on the temporal use of bicycles (Berlin, 2024). Kraus and Koch used PCS to monitor the increase in bicycle use during the COVID-19 pandemic (Kraus and Koch, 2021). Orvin et al. used data from counting stations in New Zealand and Canada to study the effects of weather on cycling (Orvin et al., 2021). The data are also used to calibrate travel demand models, see (Bhowmick et al., 2023). Counting station data is often freely available, with local authorities making it publicly available on various data platforms.

PCS can record traffic volumes twenty-four hours a day. Today, optical sensors can detect various modes of transportation even in darkness and bad weather (Ozan et al., 2021). However, a weakness of counting stations is that they only monitor bike traffic at selected counting stations, not the entire network. Unlike Strava or sharing data, they record all traffic at these intersections. Therefore, these data are often combined to get an overall picture of the amount of bicycle traffic in a city (Roll, 2018; Hochmair et al., 2019). Some optical counting stations can also distinguish e-scooters from bicycles and pedestrians (Ozan et al., 2021).

2.3. Public Transport

Automatic Passenger Counting (APC)

Automatic Passenger Counting (APC) is used to accurately count the number of public transport (PT) passengers. This information is used to distribute ticket revenue and to plan the size of vehicles (FGSV, 2012). Transport companies, therefore, need the data primarily on a long-term basis. However, the data is also used live to inform passengers at the station about the utilization of the individual carriages to achieve balanced occupancy and shorter train stopping times (Deutsche Bahn, 2023).

There are several systems for counting passengers. An overview is given by (Radovan et al., 2024). The systems share similarities in their operation, but they also have distinct advantages and disadvantages. In this paper, we examine the results and accuracies of selected counting methods; for the technical background, we refer to the literature (McCarthy et al., 2021; Radovan et al., 2024). The most common systems are weight sensors, CCTV with image processing, infrared sensors and WiFi Tracking. These systems all provide similarly good accuracy between 90% and 100%. Depending on the situation, they perform better or worse in some cases, but all systems provide reliable results in normal operation (McCarthy et al., 2021).

APC data are used in a variety of research applications. (Lanza and Durand, 2021) used APC to study the effects of heat on bus ridership, (Rasca et al., 2021) studied the effects of the COVID-19 pandemic on public transit ridership, while (Halyal et al., 2022) attempted to predict ridership using a deep learning algorithm.

Local transit agencies can provide raw APC data, which is usually free of cost for research purposes. If all vehicles are equipped with APC, both traffic volume and traffic performance can be accurately calculated from the raw data. It should be noted that passengers with transfers are counted multiple times in the traffic volume (Galliani et al., 2024). The data cannot be compared with the number of trips recorded in surveys, but can only explain individual stages of trips. In some cases, aggregated data, such as passengers per day or passengers per line, are provided. This can be used to calculate the traffic volume, but not the traffic performance, as the length of each trip is unknown.

APC records all public transport passengers for an unlimited period of time. If all vehicles in a region are equipped with them, the traffic volume of the entire area is recorded. Sometimes, only certain vehicles are equipped with APC devices, in which case the validity is limited. However, there are ways to treat missing values (Dib et al., 2023). All passengers are counted regardless of their ticket type. Therefore, if the vehicles are fully equipped, it can be considered a complete census; there is no selectivity of the sample.

2.4. Floating Phone Data

Floating phone data is generated by the movement of cell phones in the cellular network. Cell phones are always connected to a cell tower (in case they are turned on and have coverage). The cell towers keep track of which phones are connected to them at any given time. As a cell phone moves through the network, it regularly connects to new cell towers. This creates movement profiles known as floating phone data. This data is collected and anonymized by mobile network operators. It can then be shared with customers. Customers are, for example, transport planners, media agencies, and property developers (Telefonica, 2025).

In Germany, over 90 % of the population now owns a mobile phone (Statistisches Bundesamt, 2025), which offers a near-complete census of travel movements. However, there are three major network operators in Germany: Telekom, Vodafone, and Telefonica. All three distribute floating phone data, but to the authors' knowledge, no platform currently aggregates this data to provide a comprehensive view of all floating phones in Germany. Therefore, when working with floating phone data, not all people in an area are usually recorded, but only those who have a cell phone contract with the provider whose data is being used. The data is available without temporal or geographical restrictions. It is also available ex-post. There are currently no studies examining differences in travel behavior of the three providers' customers. The providers do not disclose sociodemographic differences among customers.

The main challenge in using mobile data for travel modeling is that the mode of transport used on a trip is unknown. Huang et al. reviewed several studies and approaches on this topic. They found that mode detection is difficult to implement due to the coarse spatial resolution of the data compared to GPS data. For example, reliable mode detection would require the exact route, speeds, or accelerations. These are not available in floating phone data. Furthermore, there is no ground truth data for the detected modes of transport, which makes it difficult to evaluate the approaches and prevents the training of machine learning algorithms (Huang et al., 2019). Wischer et al. were able to link the GPS trajectories of the study participants with their cell phone data. This allowed for the training of a random forest algorithm. The accuracy of mode detection was 80%, although their data set consisted of only 600 trips. They suspect that mode detection will be significantly better with a larger sample size (Wischer et al., 2023).

2.5. Travel Survey Data

For decades, travel surveys have been the standard approach for generating travel data. They are a crucial source for calculating key performance indicators (KPIs), particularly for estimating both travel demand and transport performance across all modes. In research, they are widely used to analyze travel behavior and as a basis for travel demand models. Most surveys are designed for a specific purpose. Therefore, most surveys differ in the methods used and the results obtained. For an overview of the different options, please refer to the literature (Richardson et al., 1995; Morency and Verreault, 2023; FGSV, 2012). E.g., in Germany, the survey *Mobilität in Deutschland* (MiD) offers a wide range of representative data on the mobility behavior of Germans, whereas the *System of Representative Travel Surveys* (SrV) collects data on mobility in urban areas.

The surveys typically rely on one-day or multi-day travel trip diaries, conducted as either cross-sectional or longitudinal studies, supplemented by sociodemographic questionnaires. Participants are randomly selected and invited to report details about their trips, including departure time, mode of transport, trip purpose, and distance. In recent years, GPS tracking has increasingly been integrated into survey methodologies, improving data accuracy. Sociodemographic information enables the weighting of the sample.

Despite their advantages, travel surveys face several challenges. They are costly and require significant time for data collection and processing. As a result, they are only available for specific survey periods rather than continuously. Some large-scale surveys, such as Mobility in Germany (MiD), extend over an entire year, allowing for a more comprehensive analysis of seasonal effects but it is only carried out about every five years, which means that it is not possible to monitor travel behavior and KPIs continuously (Nobis and Kuhnimhof, 2018).

A key limitation of travel surveys is their selectivity. Response rates have been declining, partly due to difficulties in reaching households via traditional means like telephone surveys (Chlond et al., 2024; Morency and Verreault, 2023). There are also other unconventional forms of data collection. One example is the *Klimataler* (climate coin) project. In this project, participants install an app to record their trips. They get coins for climate-friendly mobility. They can then use the coin to receive discounts at local businesses, such as museums and cafés. Participating cities pay the incentive and, in return, receive the participants' mobility data. Currently, around 15.000 people are using the *Klimataler* app across selected cities in Germany. However, due to the incentive for climate-friendly mobility, the sample is skewed towards climate-aware people (Canzler et al., 2024). Precise studies on this are still pending.

3. Comparison and Evaluation of Transport Data

In this chapter, we compare the data types and highlight their advantages and disadvantages. We focus on classifying the data according to its suitability for calculating emissions based on the territorial principle and the polluter pays principle. In addition, we also rank the data according to its representativeness in terms of spatial and personal coverage, as these are sometimes very different.

Table 1: Types of Transport Data

Mode of Transport	Data Type	Traffic Volume	Traffic Performance	Territorial Principle	Polluter Pays Principle
Car	Permanent Counting Stations	X		X	
	Floating Car Data (FCD)	X	X	X	
Bike/Walking/E-Scooter	Counting Stations	X		X	
	Sharing (Bike, E-Scooter)	X	X	X	
	Strava / GPS Data	X	X	X	
Public Transport	Passenger Counting Systems (APC)	X	X	X	
All Modes	Floating Phone Data	X	X	X	X
	Travel Survey	X	X	(X)	X

Error! Reference source not found. displays various data sources. All data provide information on traffic volume. Counting stations count vehicles at cross-sections, indicating the number of trips at that location. However, information on traffic performance is not recorded because the length of the trips is unknown. Information on trip lengths can only be added through data fusion in combination with GPS data, i.e., FCD, bike-sharing, e-scooter-sharing, or Strava data. This allows traffic performance to be calculated. APC counts the number of people getting on and off public transportation. Since this information is available permanently, it is always known how many people are inside a vehicle. Therefore, both the number of trips and the total distance traveled are known. However, the distances of individual trips are unknown. Floating phone data provides information on traffic volume and performance if trips are long enough for the phone to log into a new cell tower.

Since users collect most data at a specific location, it only provides information about travel behavior based on the territorial principle. In theory, FCD, shared data, and Strava data could be used to record users' home locations. However, for data protection reasons, this information cannot be shared. Floating phone data can contain the home addresses of mobile phones, and this information may also be used on an aggregated level. Surveys are an exception to this. With traditional travel diaries, the home location is known. However, information about the starting point, destination, and places traveled through is not always included in surveys. We have placed this information in brackets. **Error! Reference source not found.** categorizes the presented data sources based on their representativeness. The x-axis represents spatial coverage: data points further to the right cover people and vehicles floating through the area, while those on the left are station-based and therefore limited to a few locations. The y-axis represents personal representativeness: data points at the top capture travel behavior across a large share of the people traveling in the area, while those at the bottom reflect only a small subset of people. The colors indicate the transport mode that can be measured with each type of data.

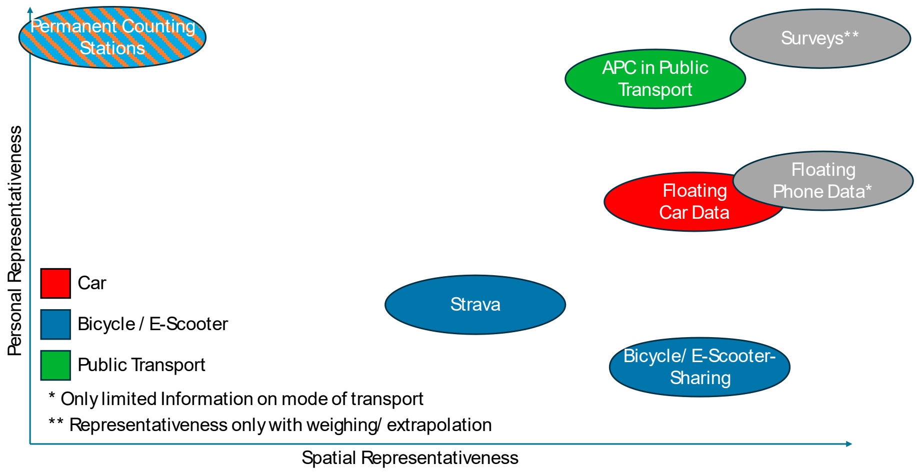

Figure 1: Classification of Data by Representativeness

Travel surveys provide a broad picture of both people and space. However, this is only true if a sufficiently large, representative sample can be recruited. Alternatively, the data must be weighted. Floating phone data provides a good picture of both spatial and personal travel behavior. However, as the use of transport modes for short trips can only be determined to a limited extent, they are only suitable to a limited extent for determining KPIs for individual transport modes. The goal should be to integrate multiple data sources in a way that maximizes both spatial and personal representativeness, ideally placing the combined dataset in the upper right quadrant of the diagram. Studies that have already done this for individual modes were presented in the previous chapter.

The availability of PCS is limited. Since there are only a few counting stations within cities, only a fraction of the traffic is recorded. This data, therefore, needs to be combined with data that covers people throughout the city, while also allowing for comparison with counting stations. This has already been explored by (Roll, 2018; Hochmair et al., 2019) using bicycle data. Both conclude that with a sufficient number of counting stations, bikesharing data or Strava data, it is possible to calculate the volume and performance of bicycle traffic. This method has also been tested for cars (Eisinga and Lorkowski, 2025) and leads to accurate and suitable results.

While individual datasets provide valuable insights, most do not fully capture origin-destination (OD) relationships. Counting stations record only cross-sectional traffic volumes. Bike and e-scooter sharing data provide OD but only for a niche subset of trips, as the behavior of private and shared vehicle users differs significantly. Similarly, FCD and public transport APC data reveal partial movement patterns but do not track complete journeys. Floating phone data, however, can help bridge this gap. Unlike traditional surveys, which rely on self-reported trips, floating phone data is collected passively and continuously, providing a high temporal and spatial resolution of travel behavior.

4. Discussion and Further Research

The presented data sources offer valuable insights into travel patterns but also exhibit fundamental differences, particularly when compared to survey data. One key distinction lies in the principle by which data is collected: while many datasets follow the territorial principle, capturing travel as it occurs within a specific area, travel survey data primarily follows the polluter pays principle, assigning trips to individuals regardless of where they take place. This difference has significant implications for emissions calculations and policy evaluations.

An advantage of travel survey data is its ability to capture micro-level behavioral insights, such as trip purposes, motivations, or detailed multimodal trip chains. None of the presented data sources can fully replace this depth of information. Moreover, surveys are the only dataset that systematically covers all modes of transport. In contrast, other sources tend to focus on specific modes, such as floating car data for motorized traffic or APC data for public transport. In comparison to the other data sources presented, survey data include information on the entire trip, whereas the other sources only cover individual legs of a trip.

However, survey data also have significant drawbacks. It is costly to conduct and requires extensive processing and weighting to ensure representativeness. Additionally, data collection and evaluation often take months, meaning that survey results quickly become outdated, for example, during a pandemic or a spike in gas prices. In contrast, many of the alternative data sources discussed here, such as floating phone data or public transport APC systems, are available in (near) real-time. This allows for much faster assessments of travel developments and enables dynamic mobility analyses that would not be feasible with traditional survey data.

Future research should focus on integrating multiple data types to leverage their respective strengths. A challenge remains the combination of datasets across different transport modes, ensuring consistency in methodology and comparability. Travel surveys can play an important role in calibrating these models, as they provide a complete picture of mode use of individuals. Developing robust data fusion techniques will be essential to achieving a comprehensive and reliable understanding of urban mobility.

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