Modelling Emerging Transport Solutions for Urban Mobility

State-of-the-art and future challenges

December 2019

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1. Introduction

The acceleration of technology evolution and societal transformations is changing urban mobility at a much faster pace than we have seen in previous decades, leading to an **increasingly uncertain future**. New mobility solutions hold great promise for moving towards a more sustainable and resilient mobility system, but they also raise concerns such as the induction of new trips, the switch from public transport to less sustainable modes, and the exclusion of vulnerable groups. Planners and decision-makers need to understand these disruptive changes and evaluate the impact of different policies under a range of possible alternative futures, or they risk being unprepared as they were for the likes of Uber. A **deep understanding of the success factors, opportunities and challenges of emerging mobility solutions** is needed for improving and updating the techniques and tools that transport planners use to promote sustainability in urban mobility.

1.1 Urban mobility: the European policy context

The quest for **sustainable urban mobility** is a common and urgent challenge for European cities. Urban mobility is vital to the economic functioning of cities through the provision of accessibility for goods and commuters, as well to the welfare of the population by providing accessibility for all social activities. At the same time, urban transport generates a number of negative externalities, such as congestion, greenhouse gases (GHG) emissions, air and noise pollution, and traffic accidents.

The European Commission (EC) has actively promoted the concept of sustainable urban mobility planning for several years, and different EU-funded initiatives have brought together stakeholders and experts to discuss problem areas and identify best planning practices. The EC's first policy proposal in the area of urban mobility was the Green Paper 'The Citizens' Network - Fulfilling the potential of public passenger transport in Europe' (European Commission 1995), which launched a series of initiatives based on a best practice approach. In 2007, the Green Paper 'Towards a New Culture for Urban Mobility' (EC, 2007) opened a broad consultation on the key issues of urban mobility whose results led to the Action Plan on Urban Mobility (EC, 2009), which proposed 20 measures to help local, regional, and national authorities to achieve their goals for sustainable urban mobility. In December 2013, the EC adopted the Urban Mobility Package (EC, 2013), which sets out a concept for **Sustainable Urban Mobility Plans (SUMPs)** as the strategic transport policy documents which would operate as the basic guideline for transport planning in urban areas. Among other proposals and recommendations for relevant action at local, Member State and EU level, the Urban Mobility Package:

- stresses the potential of smart transport technologies and new mobility concepts to help promote a better integration of the different urban (passenger and freight) transport modes, foster new patterns for car use and ownership, and stimulate a shift towards more sustainable modes;
- highlights the need to improve the quality and availability of data and statistics for decision making in urban mobility planning.

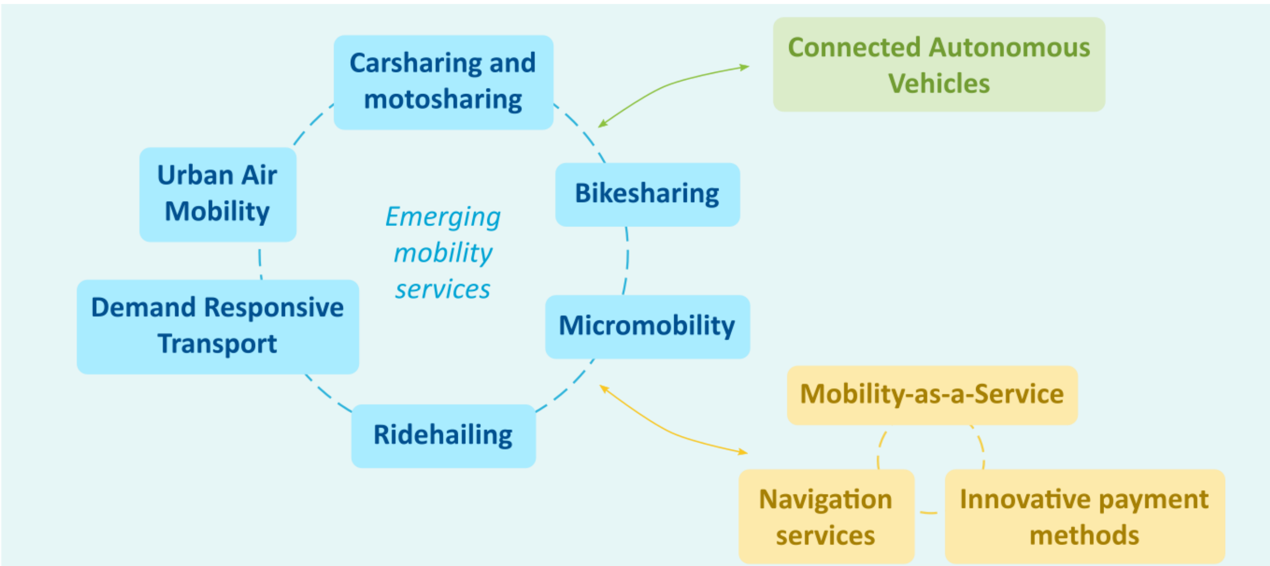
In recent years, the idea that **the rapid technological developments due to automation and digitalisation are opening new opportunities for transport services** (by reducing the number of accidents, energy consumption and pollution, as well as by cutting costs associated with congestion) has gained traction, and it has been reflected more and more explicitly in different EU policy documents (EC, 2016, 2017, 2018a, 2018b). The European Commission has also promoted a consultation process about the effectiveness of the last Urban Mobility Package in coping with latest challenges (EC, 2019). These initiatives suggest that policy-makers require enhanced tools and techniques that allow them to cope with emerging mobility options.

1.2 Disruptive changes in urban mobility

Cities are an extraordinarily dynamic context. Urban mobility is permanently subject to changes and adaptations to the **evolving nature of cities** and urban societies. For instance, phenomena like teleworking and e-shopping may lead to less commuting and shopping trips while increasing leisure and freight trips, thus modifying temporal demand patterns and modal split. Moreover, urban mobility is a field prone to the **development of innovative solutions** through the application of technological advancements. An example is the evolution of vehicle propulsion systems along history, from the use of horse-drawn trams to the electrification of many urban transport fleets. In addition, the footprint of urban mobility in the public space has an impact on the value of places, which explains that policy-makers use urban mobility as **a tool for urban transformation**.

While the aforementioned aspects are common to present and past changes, the ongoing transformations, which are extensively interpreted as *disruptive*, have two salient drivers that explain their speed and intensity. First, **Information and Communication Technologies (ICTs)** have multiplied the possibilities in terms of transport services operation, opening the door for new services based on vehicles and management procedures that were not attainable just a few decades ago. Second, the spread of the so-called **shared economy** has reached the field of urban mobility, increasing the acceptability and attractiveness of mobility options that constitute an alternative to private car ownership. These enablers do not act independently, but rather interact with each other fostering the emergence of new mobility options. Some shared mobility solutions that were already in place some decades ago have been recently boosted by GPS positioning and smartphone applications (e.g., carsharing and bikesharing), while some of the most prominent vehicle innovations are applied faster to shared mobility schemes than to classical private fleets (e.g., use of autonomous cars in ridehailing services).

All these transformations are often grouped under the banner of **smart mobility** or intelligent mobility. It involves many solutions that revolutionise urban transport: **emerging mobility services**, such as carsharing, micromobility, ridehailing or Urban Air Mobility; **vehicle automation** technologies, which have an impact both in traditional and new transport options; and several innovations in transport services management, of which **Mobility-as-a-Service** stands out as a powerful tool to integrate the present and the future of urban mobility from a user-centric perspective.



Emerging mobility services

In recent times, many new alternatives to private vehicles have emerged. These mobility options are heterogeneous in terms of vehicles, ownership models and market niches. However, all rely on **enhanced connectivity** and **GPS positioning** to provide an attractive user experience. The following services are part of this group of innovative solutions:

- Shared vehicles, including **carsharing**, **motosharing**, **bikesharing** and **micromobility** services, based on the provision of a fleet of vehicles that is made available to the public to meet their punctual mobility needs. The fleet operator provides the energy supply of the vehicles and the maintenance, while users pay a fee for using them (Cohen & Shaheen 2018).

- **Ridehailing** services, which are based on mobile applications that match costumer demand for a ride with private drivers or drivers of vehicles for hire through GPS tracking (UITP 2019).

- **Demand Responsive Transport (DRT)**, which are transport services operated by a company with professional drivers with no fixed schedule, not necessarily fixed stops, and dynamic routing. DRT serves multiple passengers independent from each other using dynamically generated routes (Mageean & Nelson 2003).

- **Urban Air Mobility**, which intends to use unmanned aerial systems and electric propulsion for operating an on-demand basis service for urban air transportation (Shaheen et al. 2018).

Vehicle automation

The application of **communication technologies** and **artificial intelligence systems** to urban vehicles changes the way these are driven. By equipping both the vehicles and the infrastructure with multiple sensors, the vehicle is capable of performing part or all of the driving tasks by itself. Interestingly, this is not only behind the conception of Connected and Autonomous Vehicles (CAVs), but to can be applied to any road transport fleet (e.g., buses).

Mobility-as-a-Service (MaaS)

In the complex reality of cities, multimodal mobility solutions are often the most efficient manner to attend the wide range of transport needs. Mobility-as-a-Service (MaaS) emerges as a model for the provision of transportation services based on the **integration of various forms of transport** into a single package accessible by end users on demand (MaaS Alliance 2017). The user does not have to worry about who is operating each service, facilitating the use of multimodal trip combinations. MaaS platforms provide a **navigation application** with multimodal functionalities covering the entire trip chain, and a **platform that centralises end user interaction with the booking and ticketing procedures** of the different service providers.

1.3 Smart mobility: challenges and opportunities for cities

Expectations about smart mobility are high. Many stakeholders promote new solutions as a powerful tool to achieve policy objectives related to sustainable urban mobility. At the same time, the short history of these transport options makes it difficult to evaluate their actual contribution to the sustainability of urban transport. As a consequence, several challenges related to these innovative solutions remain open.

Opportunities

Smart mobility holds a number of opportunities for improving the sustainability of urban mobility:

- Shared mobility services can provide a solution for the challenging provision of public transport in suburban areas. Most contemporary cities are experiencing the spread of low density developments in their outskirts. These areas fail to generate enough trips for reaching viable public transport demand levels. In this context, **shared vehicles and DRT systems can complement scheduled public transport** by covering the first and last mile legs of the trips to/from these areas (Mounce and Nelson 2019). This can improve the accessibility of peripherical districts and suburban towns, reducing their characteristic car dependency.

- By providing an **alternative to car ownership**, emerging mobility services can avoid or limit many of the externalities that the use of private car induces in cities (Arndt et al. 2019).

- It can be said that the use of shared vehicles has boosted **road transport electrification** within cities. Many carsharing and motosharing service operators have electric vehicles in their fleets, contributing to the reduction of GHG emissions, local air pollution and noise levels (Mounce & Nelson 2019).

- Vehicle automation can **improve the efficiency of public transport** services by decreasing operational costs and enabling a more dynamic, demand-responsive system (Fraedrich et al. 2019). In addition, vehicle automation will also contribute to the viability of emerging mobility services. For instance, ridehailing will likely become cheaper than current taxi-like services as no driver will be needed.

- Vehicle automation can also **increase urban road safety** for all users. The vehicles can receive and execute specific instructions to achieve this, such as when driving into traffic calming zones. This can facilitate the implementation of safety measures (Millard-Ball 2018). Moreover, a reduction of parking problems can be expected, as the CAVs may be sent to park elsewhere or to serve another user.

- MaaS platforms can **promote sustainable mobility choices**. The availability of information about all transport supply options facilitates multimodal trips. Additionally, the mobility solution provided for each trip can be evaluated by the user from an environmental impact perspective, and not only in terms of time and monetary costs (Geier 2019).

- All the emerging mobility options and the associated technologies collect a **vast amount of data**. Once this is correctly anonymised in order to preserve privacy, the data can be analysed to provide policy-makers with indicators that allow them to better understand mobility patterns within cities.

Challenges

The empirical evidence supporting an effective contribution of these innovations to sustainable mobility is still very limited and often contradictory. The above opportunities are accompanied by several challenges. The following aspects can be highlighted:

- Shared mobility services can **compete with public transport**. Nowadays many of these services operate in the central districts of metropolitan areas, where public transport already provides a competitive alternative to private car. The operating areas rarely cover peripheral districts, where the complementarity with bus and rail networks would be clearer. It is feared that most of the trips using shared mobility services would have been made by public transport and not by car (Martin & Shaheen 2011). This limits the expected impact on car ownership and private car externalities.

- Shared mobility services **compete with active modes**. Once again, the fact that these systems usually cover central districts implies that the proportion of short trips covered by them is very high. This is particularly the case of micromobility services based on e-scooters (Hollingsworth et al. 2019).

- Shared mobility services rely on the availability of their vehicles on the streets, so that they remain visible to potential users. Cities struggle to define **parking regulations applicable to these systems**. Many shared mobility services provide a free-floating fleet, which implies that no special points are designated for leaving the vehicles after a trip. This is especially troublesome in the case of motosharing, bikesharing and e-scooter sharing, since sidewalks are often used to park the vehicles. This puts an additional pressure on public space and complicates pedestrian mobility (Gertheis 2019).

- Some services can **increase the number of vehicle-kilometers travelled** even without an increase in the number of actual trips served. For instance, ridehailing services require a redeployment of the vehicle to serve each customer, leading to empty movements. In those cases where sharing rides is an option, detours are needed in order to pick up and deliver passengers, deviating from the shortest route for individuals.

- The introduction of CAVs may lead to an **increase in car usage**. Some people unable to drive today will be able to use them in the future, so a number of trips can be induced. Also, the in-vehicle time will no longer be wasted, so commuting time will be a weaker deterrent to locating away from the workplace. This means that CAVs may promote urban sprawl, increasing car dependency and congestion issues (Bagloee et al. 2016).

- Even though the progress in **vehicle automation technologies** has been remarkable, there are still some concerns about the **limitations and application of these advancements**. Firstly, the system must be robust against software attacks, since they can seriously affect safety and data privacy (Parkinson et al. 2017). Secondly, a completely autonomous driving process makes it necessary to solve a number of moral dilemmas for defining victim preference in irreversible situations (Awad et al. 2018). Finally, there is a risk that commercial strategies of vehicle manufacturers may increase inequalities in mobility and accessibility, since vehicles from each manufacturer may cooperate among each other to cut their travel times at the expense of others (Millard-Ball 2018).

- While the data produced by all these innovative mobility solutions has a lot of potential for analysing mobility patterns, it is still unclear if cities will have **access to all the datasets generated** by them. Given that shared mobility systems and MaaS platforms are usually privately-owned, companies are reluctant to share data (Docherty et al. 2018). Many cities are currently working on achieving data sharing agreements across all urban mobility stakeholders.

- MaaS platforms and shared mobility systems usually include navigation services that guide drivers in their trips. Depending on how routing algorithms are implemented, there is a risk for a **mismatch between the intended road hierarchy and routing recommendations**. Certain local streets can act as shortcuts, while they are not prepared to be used by many vehicles (van der Graaf 2018).

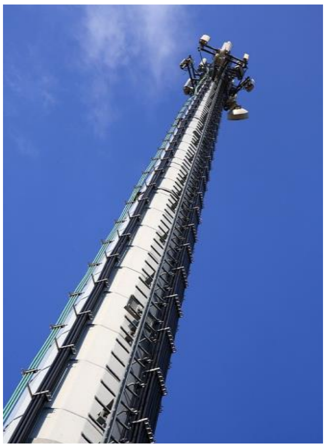
2. Tools and techniques for transport planning

The task of planning urban transport is far from simple. It involves the engagement of a myriad of stakeholders with opposite interests and values, and the design and implementation of measures in a highly uncertain context. As a consequence, transport planners often resort to decision support tools that integrate several techniques useful to conduct this task. Data analysis and simulation techniques are at the heart of these tools.

2.1 Transport data sources and analysis techniques

The availability of high-quality data about transport supply and demand is a basic requirement for conducting an accurate diagnosis of mobility patterns, which is in turn essential for developing an urban transport plan. Data can take several roles: (i) it can substantiate **descriptive** exercises, providing information about how citizens move in the baseline situation; (ii) it is crucial for **calibrating** modelling parameters, allowing models to be applied in different contexts; and (iii) it provides contrast information useful for **validating** the output of the models used by transport planners.

The traditional approach for the collection of travel demand information is based on **surveys** (household travel surveys, vehicle intercept surveys, on-board transit surveys, etc.). Surveys provide rich information on mobility patterns and the underlying behavioural drivers (e.g., travellers' sociodemographic characteristics, trip origin and destination, trip purpose, modal choices), but they have intrinsic problems, such as incorrect and imprecise answers, and they are expensive and time-consuming, which limits the size of the sample and the frequency of update. This leads to many urban mobility plans being developed on the basis of incomplete or outdated information. During the last decade, different studies have shown the potential of new, opportunistically collected data sources to overcome some of these limitations. Relevant examples of these new data sources are **mobile phone records** (Iqbal et al. 2014; Picornell et al. 2015; Toole et al. 2015; Wang et al. 2018), **GPS data from mobile apps** (Jurdak et al. 2015; Lenormand et al. 2014), **smart card data from PT systems** (Munizaga et al. 2014; Yuan et al. 2013; Zhao et al. 2018), **GPS vehicle data** (Carrese et al. 2017; Houbraken et al. 2018; Mannini et al. 2017), **Bluetooth beacons** (Aliari & Haghani 2012; Barceló et al. 2010; Crawford et al. 2018) and **credit card data** (Di Clemente et al. 2018; Lenormand et al. 2014; Sobolevsky et al. 2014). These sources pave the way for a continuous collection of large samples of mobility data with a high level of spatio-temporal resolution, in a fraction of the time and cost required by traditional methods. Different validation experiments performed in recent years have shown that origin-destination matrices obtained from non-conventional sources are consistent with those obtained from traditional surveys (Alexander et al. 2015; Lenormand et al. 2014), and transport modellers have begun to integrate the information extracted from these new sources into transport planning practices (Picornell & Willumsen 2016; Tolouei et al. 2017).



The ongoing transformations in the urban mobility field have two complementary impacts on data sources. First, the operation of emerging mobility services **generates an important amount of geolocated data**, which can be used to extract the usage patterns of the users. These datasets often integrate supply and demand data, which constitutes a step forward in comparison with traditional transport services. Second, the analysis of emerging mobility services requires **large scale, high-resolution data sources** to understand their adoption and usage patterns. The elements that define modal choice and therefore the use of these services can only be explored and identified through fine-grained analyses of longitudinal mobility patterns.

2.2 Transport modelling techniques

Transport planning does not only require an accurate description of current mobility patterns, but also to run simulations in a variety of scenarios to make planning decisions resilient enough. Transport models have been used for decades as a powerful tool to **test and evaluate alternative policies, infrastructures, services and transport management solutions under different future supply and demand scenarios**.

Most strategic transport models are based on the classical **4-step transport model**. These models estimate the generation and distribution of the trips depending on sociodemographic variables, simulates the modal and route choice of users among the available options for each trip and assign the movements to the transport network. Nowadays it is frequent to work with static, aggregated trip-based or tour-based models. **Trip-based models** have the disadvantage of not considering trips chains (e.g., they fail to capture the fact that the availability of a carsharing system to travel back home late in the evening may lead a person to leave his/her car at home and use public transport in the morning). **Tour-based models** partially address this limitation by adopting the tour (or trip-chain) as modelling unit, but they still have important limitations, such as neglecting the linkages between different tours (Sivakumar 2007). **Activity-based models** emerged as an alternative to trip-based and tour-based models. In these models, travel demand is the result of individuals performing their daily activities at different locations. All the conditions that activities impose on mobility patterns can be represented, e.g. the fact that the starting time of some activities is particularly rigid, such as work or meetings with other people (Figure 1). By nature, activity-based models provide a more disaggregated, detailed and realistic representation of persons and households and consider the full chain of trips, being better suited to modelling user-centric concepts like MaaS.

Whereas in the US they have seen a wide adoption, in Europe the operational use of activity-based models is rather limited. One of the main reasons is that these models require a huge amount of very detailed input data that are hard to obtain through conventional methods like surveys. The access to large samples of fine-grained mobility data collected through personal mobile devices (e.g., mobile phone data) opens promising avenues to overcome this problem (Anda, Erath, and Fourie 2017; Bassolas et al. 2019).

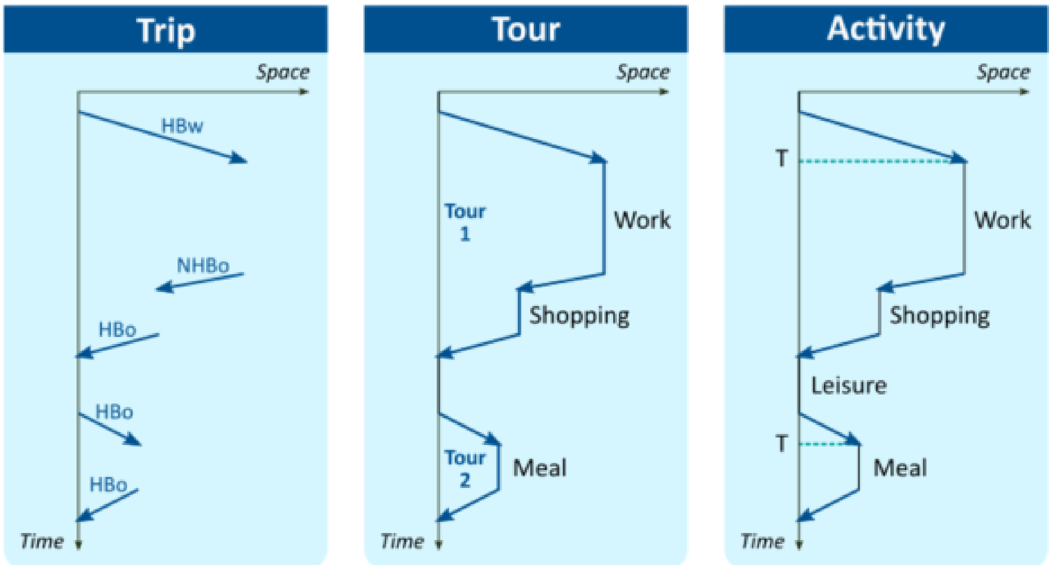


Figure 1 – Transport modelling approaches. Source: adapted from Ortúzar and Willumsen (2011)

As for the modelling of supply, **new transport services also call for more detailed and disaggregated modelling approaches** able to represent the algorithms used to schedule trips by a known fleet of vehicles with the aim to serve a number of dispersed demand requests. The few attempts to model MaaS, CAV and shared mobility technologies are restricted to optimising the scheduling of ridesharing services under pre-assumed demand conditions.

2.3 Transport decision support tools

Data analysis and modelling techniques are usually **embedded in decision support tools** that help policy-makers to define their interventions in urban mobility (Żak 2010). Given the limited resources and the complexity of some of the aforementioned techniques, the availability of usable and tailored tools is essential for releasing all the potential of data and models.

Transport decision support tools are usually composed of a database management system, which interacts with all the available datasets for performing the analyses; a modelling suite; and a user interface, which retrieves the calculated indicators and provides visualisation tools to understand and communicate the results (Figure 2). All these modules are adapted to the requirements associated to the specific transport problem to be addressed. The problems for which decision support tools are commonly used include fleet assignment, vehicle routing and scheduling, fleet composition, crew assignment and scheduling, fleet replacement, fleet maintenance, service portfolio optimisation, and infrastructure maintenance and renovation.

Decision support tools make use of different methodologies to provide outputs for policy-makers. **Multicriteria Analysis (MCA)** addresses the multidimensionality of the decision problems in transportation. It considers several weighted aspects (economic, social, market orientation, technical, environmental etc.), reproducing the variety of interests that have to be reconciled. It is often the case that these tools rely on **Geographic Information Systems (GIS)** to perform spatial calculations and to visualise the output indicators.

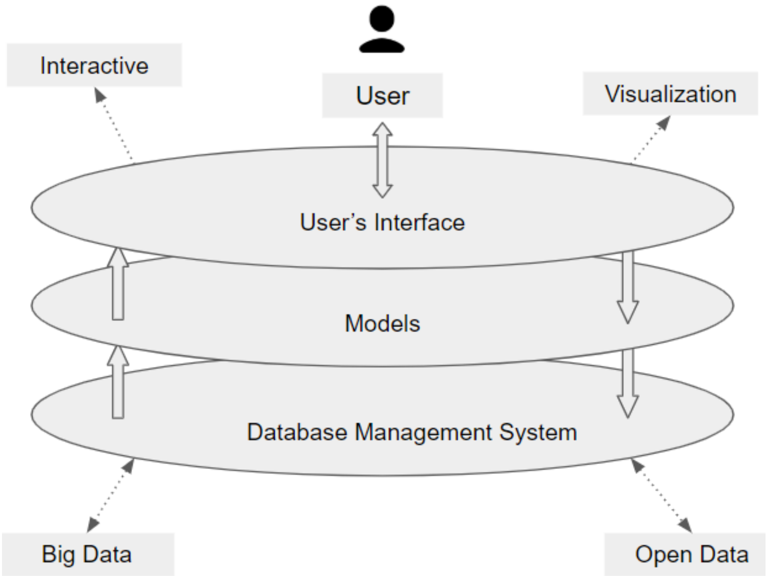


Figure 2 – Main components of a decision support tool

Finally, it is important to note that mobility policies are subject to highly distributed, multi-level decision processes and have a profound impact on a wide variety of stakeholders, often with conflicting objectives. Decision support tools have to take into account that transport planning is a participatory process that incorporates the inputs of a variety of stakeholders, including transport authorities, public transport operators, private businesses and citizens' associations. The SUMPs framework intends to integrate all these views. The outputs and visualisation modules of the tools have therefore to be designed for supporting **participatory planning processes**.

3. Research challenges and opportunities

There is a consensus that current transport planning tools and techniques are not well-suited for the task of evaluating the impact of smart mobility on cities. Transport data analysis and modelling techniques need to be adapted to this new context, and enhanced decision-support tools need to integrate these advances to remain valuable to policy-makers. This situation brings about a number of research challenges and opportunities.

3.1 Transport data sources and analysis techniques

The increasing sensorisation of the built environment and the pervasive use of personal mobile devices is facilitating the **collection of mobility data** with an unprecedented level of detail. A variety of sensors are being deployed in the so-called smart cities to measure parking availability, traffic volumes and speeds, position of public transport vehicles, pollutants in specific zones, etc. In parallel, the digital traces left by personal geolocated devices such as mobile phones and intelligent transport cards allow the reconstruction of mobility patterns for large segments of the population. The availability of these datasets paves the way for a better understanding of the current and future transformations of urban mobility. However, a number of issues are yet to be overcome to exploit the full potential of these emerging data sources (Chen et al. 2016):

- Data are **often noisy and large in size**, so data pre-processing procedures are required to clean, compress and segment the data
- Samples can be **biased or not representative** of the whole population
- Relevant information for travel behaviour analysis, such as **sociodemographic data or behavioural drivers** (e.g., trip purpose), is often limited, completely missing or must be inferred.

There issues lead to three main research challenges:

1. Development of **new data fusion and analysis methods for inferring mobility patterns** from heterogeneous and sparse data sources with different levels of resolution and representativity. Different approaches can be explored, such as stage-based, feature-based and semantic-based data fusion, as well as different machine learning algorithms such as co-training, multi-kernel learning and matrix factorisation, among others.
2. Design of **machine learning algorithms for the classification of mobility patterns** into different categories and the identification of possible explanatory variables. Spatial analysis and unsupervised machine learning techniques (e.g., clustering) can be used to automatically extract these categories by grouping people with similar mobility patterns. Then, interpretable machine learning algorithms (e.g., linear regression, fuzzy rule-based systems, probabilistic graphical models, etc.) can be employed to create models that infer the categories of new mobility patterns. It is also needed to leverage the interpretability of the models provided by these algorithms in order to extract common features and identify possible explanatory variables, with particular focus on the adoption of new mobility services.
3. Development of **new user profiling techniques based on data fusion and machine learning**. The objective of these techniques is to infer missing information about travellers based on their activity-mobility patterns. First, advanced data fusion methods can be developed to join users' explicit profile information extracted from different data sources, eliminating redundant and dependant features. Then, machine learning classification and regression algorithms can be applied to infer implicit or missing information from the users.

3.2 Transport modelling techniques

To understand the need for renewed modelling approaches, it is worth thinking in terms of the high-level questions that policy makers and transport planners will have to ask, such as the impact of MaaS, CAVs and shared mobility on aspects like vehicle ownership, fleet sizes, trip generation and induction, congestion, the use of public transport, the willingness to pay for parking, tolls and congestion charges, and the spatial distribution of activities (e.g., how do we prevent urban sprawl?). Research on the **drivers for the adoption and use of new mobility services is still very limited**. Several studies based on surveys have shown that sociodemographic characteristics such as age, gender and place of residence influence the adoption of e-hailing and carsharing services (Becker et al. 2017; Cervero et al. 2007; Clewlow & Mishra 2017; Prieto et al. 2017). The number of family members and the position in the family, car ownership, commuting distances and accessibility to food and other goods and facilities also seem to have an influence on the adoption of these systems (Becker et al. 2017; Kopp et al. 2015; Prieto et al. 2017). Most adopters are young residents of urban areas with an average to high income. Similar sociodemographic characteristics are found for users of bikesharing systems in North American and Australian cities (Fishman et al. Haworth 2012; Shaheen et al. 2013).

Regarding the influence of new mobility services on the **mobility patterns of their users**, several studies show that users of carsharing are more multimodal, have a lower level of car use, and in general make a better use of the available options (Kopp et al. 2015; Sioui et al. 2013). On average, they make more trips, but travel shorter distances; whether this is a cause or an effect is not clear (Kopp et al. 2015; Martin & Shaheen 2011). Within the variables affecting the use of shared mobility, research points towards trip purpose (Becker et al. 2017), weather (Schmöller et al. 2015), availability or lack of good quality public transport (Becker et al. 2017), parking facilities and, in the case of bikesharing systems, availability of cycling infrastructures (special lanes or paths) near the cycling docks (Rixey 2013; Zhao et al. 2014). None of the studies discussed above is conclusive, and there is even less solid evidence of the potential impacts of MaaS and CAVs.

Modelling this increasingly complex system makes it necessary to go beyond traditional transport models in the representation of both transport supply and travel demand. There are four challenges whose exploration would contribute to advancing the state-of-the-art in this field:

1. Development of **new data-driven predictive models** of the adoption rates and usage patterns of new mobility services. These models would analyse the sensitivity of these travel choices to factors such as changes in prices, payment methods, difficulties in parking search, etc. Different modelling approaches can be explored, from regression models to less conventional approaches based on artificial intelligence and pattern recognition, to investigate how the precursors of these new services influence travel choices.

2. Transport modelling software needs to be evolved to **represent demand in more disaggregated and heterogeneous terms** and include **supply and demand of emerging transport options**. With the new data sources available, the formulation and calibration of activity-based demand models becomes within reach. This will allow this theoretically superior modelling paradigm to become practical, allowing for predictively valid models able to capture travellers' choice behaviour.

3. Model the **impact of new mobility services on the use of different infrastructures**, such as road and parking space, by using dynamic assignment techniques and simulation allowing a better representation of phenomena such as parking restriction policies.

4. Explore in a systematic manner the conditions for the **emergence of synergies and/or competition** with other transport modes, in particular with collective public transport, and the consequences for different population groups, with particular focus on vulnerable users. This can be done through the scenarios managed by the simulation tools.

3.3 Transport decision support tools

Mobility policies are subject to highly distributed, multi-level decision processes and have a profound impact on a wide variety of stakeholders, often with conflicting objectives. Data collection and analysis techniques and transport models need to be accompanied by decision support tools (e.g., for visualisation of modelling results) and methodological approaches allowing their fluent and credible integration into participatory planning processes. SUMPs are a well-established policy instrument for conducting such processes, so **transport decision support tools need to be tailored to SUMPs current and future requirements**. For instance, emerging mobility services are only considered to a limited extent or not considered at all. Moreover, although there are rapid developments in making urban simulation models more visual and in scaling them down to use in the policy context, **many sketch planning tools provide simplicity at the cost of sacrificing theoretical soundness and validity**. Progress is still needed to providing transparency and ease of use without sacrificing the necessary sophistication required for a realistic modelling of urban mobility.

There is a number of research challenges related to decision support tools and their integration into collaborative mobility planning processes that need to be addressed:

1. Development of impact assessment and decision support tools through **interactive learning process** between model developers, planning practitioners and other stakeholders. Urban mobility policy assessment shall necessarily be a multi-criteria and multi-stakeholder process. The knowledge transfer facilitated by this process is expected to ensure the relevance of the modelled scenarios and increase the confidence in the modelling results, but also to provide useful insights on how to achieve a more effective integration of quantitative, evidence-based approaches into participatory planning processes.

2. Development of **user-friendly, interactive dashboards** that facilitate impact assessment and comparison of different alternative policies, with the aim to achieve a common understanding across all concerned stakeholders. This calls for the development of visual interfaces and data representations that ease the interpretation of the modelling results, the analysis of trade-offs between conflicting objectives, uncertainty representation, and multi-criteria evaluation of policy alternatives.

3. Development of **dynamic tools** that capture the need for a paradigm shift in urban mobility planning, moving from traditional static planning to more dynamic planning processes that recognise the intrinsically uncertain and fast-changing environment faced by urban mobility in the years to come. These tools have to integrate innovative data collection methods and models to help cities to adopt this new, much needed vision, empowering them to formulate more flexible and resilient policies that perform well under a range of possible futures.

4. The MOMENTUM project

MOMENTUM - Modelling Emerging Transport Solutions for Urban Mobility (https://h2020-momentum.eu/) is a research project funded under H2020 programme which aims to develop a set of new mobility data analysis methods, transport models, and planning and decision support tools able to capture the impact of new transport options and ICT-driven behavioural changes on urban mobility, in order to support local authorities in the task of designing the right policy mix to exploit the full potential of emerging mobility solutions. The project is conducted by a Consortium led by EMT Madrid (Municipal Transport Company of Madrid) and composed by Nommon Solutions and Technologies, Dimos Thessalonikis, CERTH, Stad Leuven, TML, Stadt Regensburg, Technical University of Munich, University of Deusto, Aimsun, POLIS and UITP.

4.1 Project objectives

MOMENTUM pursues the following objectives:

1. Identify a set of **plausible future scenarios for the next decade** to be taken into account for mobility planning in European cities, considering the introduction of new mobility schemes and disruptive technologies such as CAVs.

2. Characterise **changes in user behaviour and emerging activity-travel patterns**, with special focus on the demand for new forms of transport and the mobility needs of the population, including vulnerable groups, by profiting from the increasing availability of high-resolution spatio-temporal data collected from personal mobile devices and digital sensors.

3. Develop **data-driven predictive models of the adoption and use of new mobility concepts** and transport solutions, and their interaction with public transport.

4. Provide **transport simulation and planning support tools able to cope with the new challenges faced by transport planners**, by enhancing existing state-of-the-art tools with the new data analysis methods and travel demand models developed by the project.

5. Demonstrate the **potential of the newly developed methods and tools** by testing the impact of a variety of policies and innovative transport services in different European cities with heterogeneous sizes and characteristics, namely Madrid, Thessaloniki, Leuven, and Regensburg, and evaluating the contribution of the proposed measures to the strategic policy goals of each city.

6. Provide **guidelines for the practical use of the methods, tools and lessons learnt** delivered by the project in the elaboration and implementation of SUMPs and other planning instruments.

4.2 Approach

The proposed research methodology comprises six main stages:

1. **Conceptual framework and problem definition**. MOMENTUM will identify future scenarios relevant for mobility planning in Europe (demographic trends, irruption of disruptive technologies, etc.), relevant policy objectives and KPIs, and promising policy measures (pricing, parking management, etc.). This will be done through a combination of desk research, a Delphi poll with a panel of experts, and working sessions with city representatives, transport planners, researchers and other stakeholders. This analysis at European level will be used as an input to specify the test cases of Madrid, Thessaloniki, Leuven and Regensburg.

2. **Data collection and analysis**. MOMENTUM will use a wide range of powerful data sources for mobility analysis: (i) passively collected data from mobile devices (e.g., mobile phone records, data from mobile apps, intelligent transport cards, GPS vehicle data); (ii) sensor data (traffic counts, parking data, etc.); (iii) data on the use on new transport services obtained through specific agreements with mobility providers (e.g., carsharing operators), (iv) other, more conventional data, such as mobility surveys. New data fusion and analysis methodologies will be developed to characterise the mobility patterns of different population segments and identify the main behavioural drivers of the observed travel behaviour, with special focus on the adoption of new forms of transport and the mobility needs of vulnerable groups.

3. **Modelling of emerging mobility solutions**. The insights gained from the data analysis work will be used to formulate, calibrate and validate data-driven models of emerging transport systems demand and supply. For the modelling of demand, MOMENTUM will explore classical approaches to discrete choice modelling (e.g., multinomial logistic regression), as well as less conventional machine learning approaches (neural networks, decision trees, random forests, etc.).

4. **Simulation, impact assessment and decision support toolset**. The new data analysis and transport modelling approaches will be used to enhance existing simulation tools (e.g., Aimsun Next transport modelling software). Additionally, MOMENTUM will develop interactive dashboards equipped with visualisation and visual analytics tools for mobility monitoring and management. The new tools will be implemented in the four partner cities involved in the project.

5. **Policy assessment**. The tools and techniques developed in the previous steps will be demonstrated and evaluated through four case studies in the four MOMENTUM cities. A set of collaborative policy assessment exercises will explore the medium and long-term effects of different mobility policies and transport solutions. These exercises will be led by the cities and will involve the participation of transport authorities, public transport operators, private businesses and other stakeholders.

6. **Guidelines and recommendations**. The results of the case studies will be used to derive conclusions on how to maximise the benefits of emerging transport solutions (e.g., increase the resilience of the transport system, reduce the number of car trips) and avoid potentially negative effects (e.g., car trip induction, reduction of public transport users). A set of practical recommendations will be produced for the effective use of the project results in the elaboration of SUMPs, and more generally in participatory mobility planning processes, which will be widely disseminated among European cities using the privileged network of partners and dissemination channels provided by Polis and UITP.

The aforementioned research activities will be developed at two levels:

- a more **general** level, identifying the main challenges and the proposed solutions from a Europe-wide perspective;

- a second level, in which the identified challenges, as well as the data sources, analysis techniques, modelling approaches and planning support tools selected as most suitable to address such challenges, will be particularised to the **local circumstances of the four MOMENTUM cities**.

The proposed approach will provide a representative set of case studies with heterogeneous characteristics in terms of size, morphology, environmental, socioeconomic and cultural factors, mobility issues and policy goals. This **heterogeneity** will allow us to understand how to tailor the project results to the specific context and needs of different types of European cities.

4.3 Target outcomes and expected impact

Project outcomes

The project will deliver the following outcomes:

1. A set of **future scenarios to be considered in the planning and design of urban mobility policies in Europe**. Each scenario will include the expected macroeconomic context (e.g., oil prices), demographic changes and the maturity of disruptive technologies such as CAVs.

2. A detailed analysis of the **activity-travel patterns of different population groups**, according to their sociodemographic characteristics (age, gender, income, etc.), with particular focus on their use of new mobility services and the identification of the main adoption drivers. The analysis will include groups of users often overlooked by traditional survey-based methods, such as tourists and other non-permanent residents, which have however a significant impact on the transport system.

3. A set of **data-driven predictive models** for the estimation of the rate of adoption and the usage patterns of new mobility options, as a function of different sociodemographic and behavioural variables (sociodemographic profile, trip purpose, etc.).

4. New **transport simulation and decision support tools** for urban mobility planning able to properly consider the impact of new transport technologies. State-of-the-art transport modelling software, such as Aimsun Next, will be enhanced with the choice models developed for new transport modes, and new tools for supporting participatory planning processes (e.g., visualisation tools) will be developed.

5. A **prototype of the newly developed tools implemented in the cities of Madrid, Thessaloniki, Leuven and Regensburg**. This will provide the MOMENTUM partner cities with a fully calibrated strategic transport model and a strategic planning dashboard. The toolset will be validated and demonstrated through a set of planning exercises. In each city, the new toolset will be used to forecast the impact of different combinations of policies and innovative transport services, such as MaaS and vehicle sharing systems. The results of this modelling effort will be iteratively refined and assessed in a participatory framework involving public authorities, public transport operators, private businesses and other relevant stakeholders.

6. A set of **guidelines for the use of the solutions developed by the project in the elaboration and implementation of SUMPs**. These guidelines will include recommendations for the collection and analysis of mobility data, the calibration and validation of transport models, and the implementation of participatory policy assessment processes.

Expected impact

The aforementioned outcomes are expected to render a number of benefits for the scientific advancement of transport planning tools and techniques and for transport policy and governance in cities:

- **New methods and tools for mobility data analysis**. MOMENTUM will develop novel techniques for the analysis of travel behaviour and mobility patterns. The new methodologies and algorithms will blend and analyse a variety of conventional and emerging data sources, leading to more accurate and efficient methodologies for the obtention of travel demand information.

- **Enhanced understanding of mobility patterns**. The research performed in MOMENTUM will broaden the knowledge of the ultimate causes underlying mobility patterns in European cities. In particular, the project will shed light on the behavioural drivers behind the adoption of new mobility services by different population segments.

- **Improved transport models and simulation tools**. The knowledge obtained from the analysis of the large and varied datasets available to the project will allow the development of more realistic transport and traffic models. The resulting models will be able to address questions that are still not well understood today, and will be better suited to tackle the challenge of sustainable urban mobility in the presence of disruptive mobility concepts and technologies, such as MaaS, CAVs and shared mobility.

- **Improved decision support tools for urban mobility planning**. The MOMENTUM decision support toolset will integrate the methodological and technological advances of the project with a set of innovative interactive visualisation tools, providing policy makers and transport planners with a state-of-the-art, user-friendly decision support tool.

- **Better and cheaper mobility data**. The data collection and analysis techniques developed by MOMENTUM will result in the availability of better mobility and travel demand information at a fraction of the cost required by traditional methods. As an example, while a traditional household mobility survey targeting 2% of the population for a metropolitan area like Madrid has an estimated cost of 1-2 M€, the estimated cost of a similar study based on the fusion of mobile phone data, smart card data, and other data sources investigated in MOMENTUM is expected to reduce this cost down to 100-200 k€. This will result in important savings for taxpayers, contributing to more sustainable public finances.

- **Faster and more targeted intervention**. Due to their high cost, travel surveys are typically conducted every 5 to 10 years, which results in many urban mobility projects being planned on the basis of obsolete or incomplete information, often at a high cost for society (e.g., bailouts). The possibility to monitor mobility on a continuous basis in an affordable manner will enable the early detection of changes in mobility patterns (due to, for instance, the irruption of new mobility services) and the update and recalibration of transport models on a more frequent basis, leading to more reactive, adaptive, efficient and resilient policies.

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