European Commission

TECHNICAL REPORT

AI Watch
AI Uptake in Smart Mobility

EUR 30821 EN

Joint Research Centre

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EU Science Hub
https://ec.europa.eu/jrc

JRC126302

EUR 30821 EN

PDF	ISBN 978-92-76-41403-2	ISSN 1831-9424	doi:10.2760/879190

Luxembourg: Publications Office of the European Union, 2021

How to cite this report: De Nigris S., Hradec J., Craglia M., Nepelski D., AI Watch: AI Uptake in Smart Mobility, EUR 30821 EN, Publications Office of the European Union, Luxembourg, 2021, ISBN 978-92-76-41403-2, doi:10.2760/879190, JRC126302.

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Foreword

This report is published in the context of AI Watch, the European Commission knowledge service to monitor the development, uptake and impact of Artificial Intelligence (AI) for Europe, launched in December 2018.

AI has become an area of strategic importance with potential to be a key driver of economic development. AI also has a wide range of potential social implications. As part of its Digital Single Market Strategy, the European Commission put forward in April 2018 a European strategy on AI in its Communication "Artificial Intelligence for Europe". The aims of the European AI strategy announced in the communication are:

- To boost the EU's technological and industrial capacity and AI uptake across the economy, both by the private and public sectors
- To prepare for socio-economic changes brought about by AI
- To ensure an appropriate ethical and legal framework.

In December 2018, the European Commission and the Member States published a “Coordinated Plan on Artificial Intelligence” on the development of AI in the EU. The Coordinated Plan mentions the role of AI Watch to monitor its implementation.

Subsequently, in February 2020, the Commission unveiled its vision for a digital transformation that works for everyone. The Commission presented a White Paper proposing a framework for trustworthy AI based on excellence and trust.

Furthermore, in April 2021 the European Commission proposed a set of actions to boost excellence in AI, and rules to ensure that the technology is trustworthy. The proposed Regulation on a European Approach for Artificial Intelligence and the update of the Coordinated Plan on AI aim to guarantee the safety and fundamental rights of people and businesses, while strengthening investment and innovation across EU countries. The 2021 review of the Coordinated Plan on AI refers to AI Watch reports and confirms the role of AI Watch to support implementation and monitoring of the Coordinated Plan.

AI Watch monitors European Union’s industrial, technological and research capacity in AI; AI-related policy initiatives in the Member States; uptake and technical developments of AI; and AI impact. AI Watch has a European focus within the global landscape. In the context of AI Watch, the Commission works in coordination with Member States. AI Watch results and analyses are published on the AI Watch Portal (https://ec.europa.eu/knowledge4policy/ai-watch_en).

From AI Watch in-depth analyses we will be able to understand better European Union’s areas of strength and areas where investment is needed. AI Watch will provide an independent assessment of the impacts and benefits of AI on growth, jobs, education, and society.

AI Watch is developed by the Joint Research Centre (JRC) of the European Commission in collaboration with the Directorate General for Communications Networks, Content and Technology (DG CONNECT).

This report presents a sectoral analysis of AI Watch focused on the uptake of AI in the smart mobility sector. Its key aim is to act as a benchmark for future editions to be able to assess the changes in uptake over time in line with the mission of AI Watch. The report is based on the methodology described in Craglia et al. (2020) which centred on four components:

1 Scanning and analytics

2 Partnerships

3 Reviews

4 Longitudinal panel studies.

The restrictions to travel and meetings imposed by COVID-19 limited the ability to establish the longitudinal panel necessary for further studies of impacts. These will be available in future editions of this report. This first edition therefore focuses mainly on the outcome of the first three strands of the methodology, and in particular scanning and analytics and literature reviews.

Acknowledgements

The Authors would like to thank Biagio Ciuffo, Kostantinos Gkoumas and Fabio Marques Dos Santos (JRC Unit C.4) for the continuous and fruitful collaboration, discussion and input which helped shape this report. Furthermore, the Authors thank David Fernandez-Llorca (JRC Unit B.6) and Ramón Compañó (JRC Unit B.7) for kindly reviewing the manuscript and providing valuable comments and feedback.

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Abstract

This AI Watch report analyses AI uptake in smart mobility. It recognizes that AI-driven smart mobility applications hold the potential to improve the management of traffic flows, enhance road safety and extend access to mobility to those who do not possess vehicles. In addition, by triggering changes in user behavior, e.g. in the change from "mobility as ownership" to "mobility as a service", they can improve the use-efficiency of mobility assets and reduce energy consumption and pollution, promoting cleaner forms of mobility. However, uptake of AI in smart mobility depends on overcoming a number of technical as well as systemic challenges, related to governance and stakeholder coordination. Key issues concerning data, e.g. data sharing, protection and standardization, and algorithms, e.g. their fairness and transparency, still require further research. The analysis highlights that AI in the smart mobility domain is experiencing a fast growing trend, albeit relatively recent: for instance, start-ups delivering market-ready AI in smart mobility applications have already reached approximately 30% of the total Venture Capital investments in the mobility sector. In the global context, the analysis shows that European automotive and ICT companies play only a minor role in the domain of AI in smart mobility, while the major part of enabling technologies and applications in this domain is being developed and deployed in China and the U.S..

Executive summary

This document presents the sectoral analysis of AI in smart mobility carried out by AI Watch.

Its main aim is to act as a baseline for future editions of the report to be able to assess the changes in uptake and impact of AI in mobility over time, in line with the mission of AI Watch to monitor the development, uptake and impact of Artificial Intelligence in Europe.

AI in smart mobility: Enablers, Applications and Benefits

Both hardware and software technologies are the fundamental building blocks (or *enablers*) of smart mobility solutions: sensors, advanced central and graphics processing units, connectivity technologies and IoT provide the hardware backbone for smart mobility, while AI algorithms mostly from the computer vision, machine learning and, more recently, deep learning, domains compose the software component. Building on these technologies, AI-driven smart mobility applications can be deployed at several scales: at vehicle level, with connected and autonomous vehicles (CAVs) or at the city level, with mobility as a service (MaaS) and smart city solutions.

Further uptake of AI in smart mobility depends on overcoming a number of technical challenges. The key issues concerning data, e.g. data sharing, protection and standardization, and algorithms, e.g. algorithm training, avoiding statistical biases and increasing fairness, still require further research.

AI-driven smart mobility applications hold the potential to improve the management of traffic flows, enhance road safety and extend access to mobility to those who do not possess vehicles. In addition, by triggering changes in user behavior, e.g. in the change from “mobility as ownership” to “mobility as a service”, they can improve the use-efficiency of mobility assets and reduce energy consumption and pollution. In this way, they can promote cleaner forms of mobility. Against this background, AI-based solutions can support the transition to more sustainable mobility. However, sustainability does not directly stem from smart mobility solutions per se, since their deployment is also likely to increase consumer demand and generate rebound effects, offsetting a part of the efficiency benefits.

AI in smart mobility research, innovation and start-up activity: What is Europe’s position?

AI in smart mobility research: The analysis of scientific publications shows a strong increase of research activities in smart mobility after 2017. This increase is correlated with the emergence of concepts linked to AI in transportation, such as “Intelligent vehicles” and, in 2020, “Shared mobility” was among the most cited concepts. Smart mobility accounts for approximatively 9% of total projects funded under the Horizon2020 framework programme. Since 2015, the number of projects per year and respective EU contribution has remained roughly constant, with approximatively 200 projects and EUR 600-700 million per year in EU funding, demonstrating the strong interest for AI in smart mobility initiatives from the EC.

AI in smart mobility innovation: An analysis using patents as a proxy of innovative activity shows that the intensity of innovation in smart mobility experienced an almost exponential increase since 2013. Organizations based in China and the U.S. are filing the largest number of patents. EU is third, together with Japan and South Korea, with approximately 2000 patent filed per year. In Europe, German companies hold more than half of patents, mostly registered by companies from the automotive sector.

AI in smart mobility start-ups and venture capital funding: Venture Capital (VC) investments for startups in smart mobility almost doubled in the last five years. Today, AI and mobility start-ups account approximatively for 30% of the total VC investments in the mobility sector. Although the COVID-19 pandemic led to a 30% drop in 2020 in the mobility sector, the share of VC investments in AI and mobility start-ups increased in 2020. The U.S. and China attract the largest share of investments and Chinese start-ups are the ones receiving most funding per firm. European start-ups account for 6.4% of the global VC investments in the mobility sector.

Key conclusions

We highlight, in conclusion, three fronts susceptible to acquire relevance and require intervention in the coming years:

Policy initiatives to allow the collection and sharing of data are of paramount importance for the deployment of smart mobility solutions. Furthermore, to enable flawless data sharing between devices, standards for data and communication are likely to become increasingly critical.

Secondly, road testing for autonomous vehicles will be pivotal for their take-up as it will allow for a better understanding of their behaviour and a more solid assessment of their potential benefits on safety and efficiency.

Lastly, in the long run, reaping the sustainability benefits from smart mobility will also necessitate, beyond technological advances, new mobility behaviours. To this end, the deployment of MaaS solutions should be sustained, as they ensure a fairer access to mobility, including groups who do not own vehicles, while using more efficiently the existing fleets.

1 Introduction

Smart mobility solutions represent a core part of the Sustainable and Smart Mobility Strategy (European Commission, 2020). Indeed, applications such as Mobility-as-a-Service (MaaS) or the deployment of connected and autonomous vehicles can benefit the environment by lowering pollutant emissions, and can benefit citizens by allowing a fairer access to mobility for all and by improving safety in urban environments.

The positive potential of smart mobility was also established in the Strategic Transport Research and Innovation Agenda (STRIA) roadmap, adopted by the European Commission (EC), first in 2017, as part of the 'Europe on the Move' package (European Commission, 2017a, 2017b), which highlights key transport R&I areas and priorities for clean, connected and competitive mobility, under seven roadmaps. The STRIA roadmaps set out common priorities to support and speed up the research, innovation and deployment process leading to technology changes in transport.

The STRIA roadmaps set out common priorities to support and speed up the research, innovation and deployment process leading to technology changes in transport. In May 2018, the EC announced the third Mobility Package (European Commission, 2018a) with the objective of allowing citizens to benefit from safer traffic, less polluting vehicles and more advanced technological solutions, while supporting the competitiveness of EU industry. Autonomous and smart mobility has a central role, since it has the potential to make transport safer, more accessible, inclusive and sustainable (European Commission, 2018b).

In the STRIA, three thematic areas revolve around smart mobility:

- Connected and automated transport (CAT)
- Network and traffic management systems (NTM)
- Smart mobility and services (SMO)

The STRIA CAT and SMO roadmaps were further updated in 2019 to refine the research and innovation strategy initially developed within the STRIA (European Commission, 2019a, 2019b).

Information and Communication Technologies (ICT) and information technologies, with Artificial Intelligence (AI) among the key technologies underpinning smart mobility solutions and services, are recognized to be the backbone of every smart mobility application. In the Sustainable and Smart Mobility Strategy (European Commission, 2020) the Commission sets goals for upgrading the digital infrastructure, for creating a Common European Mobility Data Space and for ensuring ecosystems of trust and excellence around AI.

In this context, this report provides an overview of the current uptake of AI technologies in the mobility sector. It takes a comprehensive approach and analyses the uptake of AI in smart mobility along the entire value chain from the lab to the market. It starts by taking a scientific research perspective, leveraging data on scientific publications and H2020 projects, in order to analyze the current development of AI technologies for smart mobility. Then, it looks at the uptake of AI for smart mobility through the analysis of AI and smart mobility start-ups and innovation activities proxied by patent applications in this domain.

The "mobility" concept represents the demand satisfied by different transport modes, including the modes of road, rail, air and ship. However, "Smart mobility" is strongly connected to smart cities and to urban mobility, largely by road and by private or public transport.

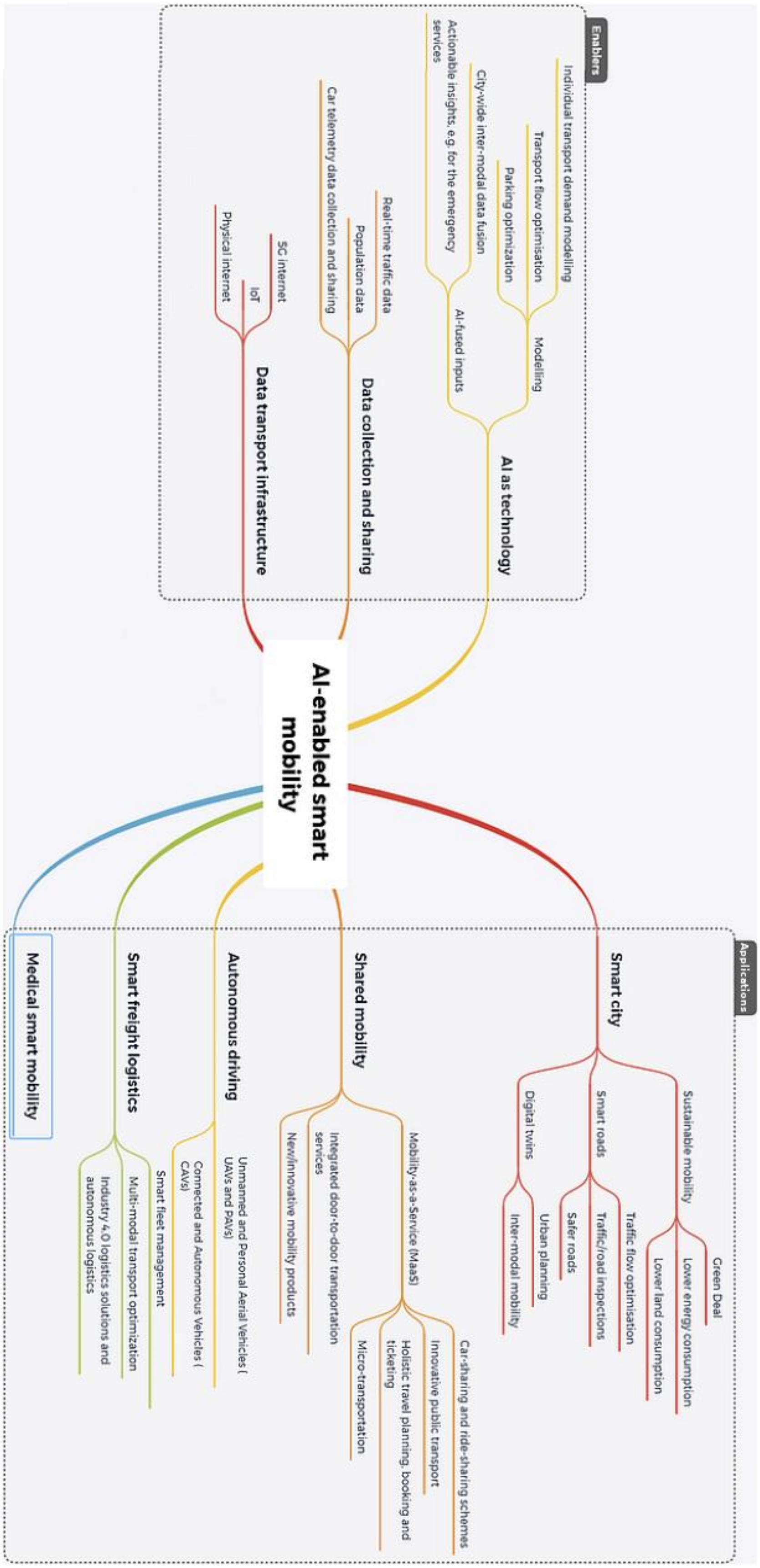
In the scope of this report, we therefore decided to focus on the mobility of people in urban environments, deferring logistics, the design of smart engines and other applications of smart mobility, such as the specific case of transport within the health sector, for further research. More specifically, we focus on the role of AI as a fundamental enabler of connected and smart mobility, delving into the opportunities and challenges stemming from the use of both data and algorithms.

The report is organized as follows: in Section 2.1 we outline the fundamental enablers for smart mobility, such as connectivity, data and algorithms relevant for transport. Then, in Section 2.2, we present three applications of smart mobility: autonomous driving, MaaS and smart cities, also reviewing technical obstacles related to each of them. In Section 3, we investigate the presence of AI in transport-related research, analyzing scientific literature and H2020 projects. Then, in Section 4, we analyse the industrial strand of AI uptake for smart mobility, by considering innovation, through the use of patent data, and investments in AI in smart mobility start-ups, using venture capital data. We close the report in Section 5.

2 Defining smart mobility

Smart mobility is a sprawling topic, encompassing solutions from the city-wide level down to the level of the individual vehicle. Thus, we organized the concepts related to AI-enabled smart mobility in a mind map, depicted in Figure 2.1, elaborated based on a review of the literature. This literature review builds on the use of social media data (Twitter) for scoping and on the input from experts from JRC Unit C.4 – Sustainable Transport (see Annex 1 for the methodological details).

Figure 2.1. Conceptual map of enablers and applications of AI in smart mobility.



Source: JRC

The mind map presented above features two broad categories: Enablers and Applications.

According to Figure 2.1, at the core of AI-driven smart mobility products and services are the following Enablers:

- Data collection and sharing,
- Data transport infrastructure,
- AI as a technology,

The three Enablers are described in Section 2.1.

The set of AI in smart mobility Applications, depicted in Figure 2.1, described in detail in Section 2.2, includes:

- Autonomous driving,
- Shared mobility,
- Smart city.

As mentioned in the introduction, we leave an in-depth analysis of smart freight logistics and medical smart mobility for further research.

2.1 Enablers

2.1.1 Data collection and sharing

Data is the foundation of every AI application and, in the context of smart mobility, applications can feed on several data sources: at the individual vehicle level, a primary data source is telemetry data collected by smart sensors; while, at the city level, real-time traffic data and, also, population data can be useful for smart-city applications.

Smart sensors can provide georeferenced information on the internal state of the vehicle, controlling engine and safety parameters, and, most importantly for connected and automated vehicles, they can monitor the surroundings via cameras, radio or LIDARs (Schroten, 2020). These three classes of sensors have very different performances in terms of field of view, range, accuracy, resolution, cost, sensitivity to weather and lighting conditions. Radars have a good sensitivity to speed and they are not affected by the weather, but they have poor lateral resolution; cameras, on the other hand, are suitable for object identification but sensitive to weather and lighting conditions and poor in detecting speed and depth. Finally, LIDARs, which measure distances using the reflections of lasers beams, can perform object detection and also obtain the spatial structure of the surroundings; however, they can pick up spurious reflections in rainy and foggy conditions and they are, at least for the moment, expensive.

Because of those differences, different driving environments may require a specific combination of devices: for instance, in the highway setting, a narrow field of view radar might suffice; while, in an urban environment, because of the lower speed of the vehicles and the presence of pedestrians, the ability to identify them from visual information is needed, therefore cameras are more suitable (Schroten, 2020).

As those sensors have some complementarity, their output data can be combined (sensor fusion), also via AI techniques, in order to perform object detection, suppress noise and construct a more accurate three-dimensional map of a vehicle's environment. Furthermore, in the case of connected vehicles, the sensors can be 'extended' by integrating the data flow from surrounding vehicles, thus enhancing the vehicle's decision-making capacity.

Connectivity also enables the harvesting of **real-time traffic data**: platforms such as SharedStreets, HERE[1] and Open Traffic Data (ITF, 2019c, ITF, 2016) are able to collect data from the location of smartphones, vehicle sensors, GPS and transport operators for mapping city streets or for developing new mobility products. Data from hard-braking events or the use of hazard lights, which can also be integrated in these platforms, can provide further feedback on emergency situations and help improve traffic management.

In the context of smart cities and urban planning, another data source is **population data**, such as age, income, and mobility patterns (ITF, 2019c, ITF 2016). Correlations have been found, for instance, between the presence of sidewalks and the average neighborhood income (Vision Zero Network, 2018b, Gibbs, 2012). Furthermore, traffic-related injuries disproportionately affect low-income communities and some ethnic groups have systematically been excluded from transport planning (Vision Zero Network, 2018b, Winner, 1980). Therefore, population data can be used to improve the design of fairer smart mobility solutions that also cope with social inequalities; we shall return to this point in the smart cities paragraph in Section 2.2.

2.1.2 Data transport infrastructure

Connectivity is a crucial enabler for smart mobility, allowing short range communication between vehicles (V2V), the infrastructure (V2I) or Vulnerable Road Users (V2VRU), as well as long range communication – vehicle to network (V2N) - between vehicles and cloud backend servers (Schroten, 2020, ITF 2019c).

From a technical standpoint, short-range connectivity can use one of two communication standards, ITS-G5 and Cellular V2X (C-V2X). However, the two standards ITS-G5 and C-V2X are not interoperable. Furthermore, they share the same operating frequencies, since they both operate around 5.9 GHz. Thus, the competition between these two standards stands as a challenge for effective deployment of autonomous vehicles (Schroten, 2020, ITF, 2019c).

Long-range communication – vehicle-to-network (V2N) – uses either the 4G (LTE) or 5G mobile network. The latter will allow lower latency and greater bandwidth, and is expected to act as a booster for autonomous vehicles. Several European projects are being carried out to explore its potential (e.g. 5G-MOBIX, 5G-CARMEN, 5G-CROCO, 5G-Blueprint, 5G-MED, 5G-HEART) (Schroten, 2020). Long-range communication can support the connection to central servers in order to transmit traffic information or software updates, beyond which edge-servers can also be deployed closer to the transport infrastructure, further decreasing the latency of critical communications. Furthermore, the ensemble of V2V and vehicle-to-roadside (V2R) connections can sustain a new type of mobile-ad-hoc-network called VANet (vehicular-ad-hoc-network), which exploit vehicles as mobile nodes, thus being decentralized and self-organizing.

The **Internet of Things** (IoT) is an ecosystem of connected devices, such as the telemetry sensors mentioned above, and its defining characteristic is the capacity of such devices to share data over a network without requiring human intervention.

[1] See also Section 4.1

In the mobility context, smart sensors on vehicles and infrastructure but also smartphones can collect data and share it for MaaS services or to provide information to surrounding vehicles, as further discussed in Section 2.2.

2.1.3 AI as a technology

Several AI approaches and algorithms can leverage the aforementioned data sources to enable smart mobility applications, mostly from the **machine learning** and **computer vision** domains.

At the vehicle level, AI can efficiently fuse the data flow from several sensors and, through computer vision and object-recognition algorithms, it can interpret the input from cameras, radars and LIDARs to recognize the surrounding vehicles, road objects and pedestrians. Furthermore, sensor fusion can, as previously mentioned, overcome the shortcomings of each individual sensor, increasing safety and accuracy (Lim, 2019).

Machine learning techniques can also be deployed with optimization and modelling purposes: traffic monitoring and management can be improved by forecasting congestion and other traffic situations from training on historical data. For instance, machine learning algorithms such as Random Forest and Decision Trees, combined with ensemble methods, have been leveraged to predict traffic flow regimes an hour in advance (Vasudevan, 2020).

Beyond the flow of vehicles, pedestrian crossings and traffic signal timings can also be optimized using machine learning, improving safety for pedestrians, especially in the case of disabilities, and preventing queues and bottlenecks.

Finally, **natural language processing** (NLP) algorithms can also find deployment in the mobility context, for instance for emergency and incident management (Vasudevan, 2020): NLP-powered applications can warn citizens of approaching threats and calamities, automatically mining information from messages on social media.

As also happens in other sectors, the deployment of AI for mobility applications faces challenges concerning both data and algorithms. Since such challenges can be application-specific, we will delve into them in Sec. 2.2, focusing on autonomous driving, shared mobility and smart cities.

2.2 Applications

2.2.1 Autonomous driving

One embodiment of the previously outlined AI technologies, in combination with sensors and connectivity, are **Unmanned Aerial Vehicles (UAVs)** or drones, which can be either remotely piloted or autonomous. It is expected that these devices can be used for surveying remote locations, parcel delivery, to enhance asset management and to detect accidents, vehicles and roadway features (Vasudevan, 2020, Cohen, 2020, Gettman, 2019).

At this stage, however, most of the applications are in the test phase and practical examples of their use are scarce.

A second embodiment for the combination of AI software, sensors and connectivity are **Connected and autonomous vehicles (CAVs).** CAV can be conceptualized in three layers (ACEA, 2019, Lim, 2019):

- **Perception.** Sensors and connectivity, as described above, provide the CAV with a representation of reality which is enhanced by object detection and classification algorithms and whose input can be fused through artificial intelligence to further increase its accuracy and robustness to noise.
- **Decision-making.** It comprises the algorithms and software meant to achieve "high-level objectives" such as route planning, and "local objectives" such as changing lane.
- **Control.** Algorithms that control the lateral and longitudinal movement of the vehicle execute the decisions from the decision-making layer, by controlling the autonomous vehicle's actuators (steering wheel, brakes, and accelerator) so that parameters such as the steering angle and vehicle speed enable the CAV to follow a given trajectory.

Whilst automated driving is not necessarily subject to communication with the surrounding vehicles or the infrastructure; there is nonetheless evidence that the viability of autonomous vehicles is dependent on their connectivity (Cohen, 2020, Makridis, 2018). Indeed, CAVs improve the traffic flow since they allow for smaller gaps between the vehicles, which is not the case for purely autonomous vehicles; in addition, thanks to connectivity, they can allow for coordination with other vehicles, further easing the traffic flow.

A useful scale to rank the degree of automation of the driving task has been developed by the International Society of Automotive Engineers (SAE), articulated in six different levels (SAE, 2018):

Table 1. Levels of automation of the driving task.

Level (0-5)	**Driving task automation**
Levels 0-2	Control is retained by the driver, albeit assisted by support systems, such as cruise control, emergency braking and lane-keeping systems.
Level 3	Conditional automation: the vehicle drives itself under limited conditions and the driver has to resume control if such conditions are not fulfilled.
Levels 4-5	The driving task is meant to be fully automated in most (level 4) or all (level 5) driving conditions.

The target for autonomous vehicles are levels 4 and 5, with some deployment already in place in non-road modes sectors, such as for ships and some branches of the rail sector like the underground train (or subway) and airport shuttles. For example, in Paris, France, a driverless underground train is already operational, and pilot projects in the railway sector have been started with remote train driving and highly automated and autonomous trains (from levels 2 to 4) in mixed railway traffic environments (EC, 2019).

In contrast, deployment of autonomous vehicles for road mobility is mostly in the pilot testing phase. Although cars are increasingly equipped with partial automation technologies assisting the driver, autonomous vehicles able to drive from door-to-door (SAE level 5) in any traffic conditions are not expected to be available before 2030, except for testing (GEAR, 2020). For instance, in Europe, automated trucks and truck platooning are tested on highways and, in urban environments, some examples of autonomous shuttles on fixed trajectories can be found in some cities, e.g. in Lyon[2] and Brussels[3].

CAVs are extremely complex and, in order to attain levels 4 and 5 of automation, AI algorithms and data used in the context of autonomous vehicles face hurdles regarding technical, ethical and safety issues (Lim, 2019), that we outline below.

From the technical standpoint, concerns refer to all of the layers of the autonomous vehicle as discussed above: perception, decision-making and control (Lim, 2019; ITF, 2019a).

In the **perception layer**, errors can occur when sensing the environment: as mentioned in Section 2.1.1, each type of sensor, cameras, radars and LIDARs, display specific weaknesses with respect to driving parameters, such as speed, depth, and meteorological conditions. Furthermore, GPS and Global Navigation Satellite Systems (GNSS) are often inaccurate in urban surroundings and GPS can suffer from multi-path interference caused by the signal reflection on obstacles. Adversarial attacks have also been proven to disrupt sensors: for example, modifying, even slightly, road signs led to misclassification errors. Sensing errors and inaccuracies can later be propagated downstream to the processing software, diminishing its accuracy as a result and possibly leading to unsafe behaviours. Tesla's fatal accident in 2016 was partly caused by such a faulty chain reaction starting from the perception layer (see Box 1, below). Hence, mitigation strategies should be envisaged, such as using a Bayesian probability framework, to assess the degree of uncertainty from the perception layer, so that it is adequately considered by the subsequent decision-making layer. Lastly, from a hardware point of view, the high computational demand of the perception layer can be a limit to overall system performance.

Box. 1: Tesla's fatal incident in 2016.

On May 7, 2016, a collision between a 2015 Tesla Model S and a tractor trailer, crossing an uncontrolled intersection on a highway in Florida, resulted in fatal injuries to the Tesla driver.

The vehicle's data showed that it was on Autopilot mode and the Automatic Emergency Braking (AEB) system neither raised warnings nor braked to avoid collision. Furthermore, the driver did not engage in any actions to avoid the crash.

2 https://thelastdriverlicenseholder.com/2019/11/15/navya-shuttles-start-worlds-first-regular-autonomous-bus-line/

3 https://www.2getthere.eu/news/brussels-airport-autonomous-shuttle/

The National Highway Traffic Security Administration (NHTSA) subsequently opened an investigation to assess the “design and performance of any automated driving systems in use at the time of the crash”. The investigation did not identify defects in the AEB or Autopilot systems; however it recognized that the AEB system may fail to brake in certain conditions, since it is designed to avoid rear-end collisions. More specifically, crossing path collisions are outside its expected performance: in the case of Tesla’s incident, its object classification algorithm failed to recognize the side of the tractor trailer as a target because it is trained on rear images of vehicles (NHTSA, 2017).

Furthermore, the Autopilot mode in Tesla is a technology intended to be, at best, SAE Level 2, thus the driver is expected to control the environment at all times. In the Tesla fatal crash, a period of extended distraction (at least 7 seconds) appears to have also played a role in the collision (NHTSA, 2017).

The **decision-making layer** is also fraught with challenges, including those stemming from the human component within the autonomous vehicle. For instance, at level 3 automation (Conditional automation), the driver is expected to resume control when needed, but handover may fail if signs of fatigue or distraction of the driver are not recognized. This failure in passing control to the human drive was another of the causes leading to the mentioned Tesla car incident (see Box 1). Understanding human-machine interaction also impacts the task of driving itself: driving often relies on some amount of negotiation between road users, often via social cues, to achieve coordination. The autonomous vehicle may fail to correctly interpret such signals and, similarly, other users may fail to correctly anticipate the behaviour of the autonomous machine; this mismatch has contributed to collisions in autonomous vehicle trials. From the computational point of view, the decision-making layer must handle uncertainty originating from the perception layer, as it acts as a bridge to the control layer. Conversely, it must also consider the constraints of the control layer, in order to tailor trajectories that can be safely implemented in terms of speed and acceleration - the coordination of which is computationally heavy.

Finally, regarding the **control layer**, different types of controllers display different weaknesses, as is the case with sensors discussed above. Geometric and kinematic controllers are relatively light in computational terms, but they ignore vehicle dynamics, such as friction, so their approximations can lead to vehicle instability. These controllers however are relatively lightweight computationally, which is not the case of nonn-linear, dynamic, adaptive and model predictive controllers. Adaptive controllers are advantageous for their robustness to environmental variations, but are much more computationally intensive. For this reason, similarly to sensor fusion, a solution proposed in the literature has been an adaptive geometric controller, combining the advantages of the two types of controllers (Amer, 2017).

Autonomous vehicles still lack the extensive road testing usually applied to their non-autonomous counterparts and, thus, rely on a significant volume of simulated travel (ITF, 2020). Furthermore, when testing an autonomous vehicle, its responses can vary even in identical conditions because of the non-deterministic feature of its algorithms and this is a challenge also for the design of safety specifications. Rare events that occur outside the normal range of parameters but which humans are nevertheless capable of handling, called ‘corner cases’, are another source of safety hazard in the autonomous driving context: such cases are difficult and costly to input manually in the test data and, if they are simulated in order to train the algorithms they can lead to overfitting. This discrepancy is called the “sim-to-real gap” (simulation-to-real gap) since the system trained in simulation does not perform well in real environments, due to underlying differences between the two contexts.

Bias in the data could also lead to faulty decisions by the autonomous vehicle: statistical bias can be introduced by under/overrepresented groups and the presence of personal characteristics can lead the system to systematically allocate risk to some groups of users. Furthermore, this risk imbalance could become systemic if the algorithm is deployed in fleet of autonomous vehicle.

Finally, another matter of strong concern is how to incorporate ethics into autonomous vehicle algorithms. Top-down approaches, requiring the vehicle to maximise or minimise a given utility function, such as minimising total harm, are adaptable but may lead to biased decisions depending on the function design of the algorithm. On the other hand, a more deontological approach, implemented by enforcing rules in a hierarchical manner, lacks flexibility and may clash with the ambiguities of traffic rules or unforeseen scenarios (Lim, 2019).

Taking the bottom-up route, using algorithms that learn from past experience and build their own rules could provide a flexible and adaptive approach. However, in this case, the decision-making process is more opaque and there are challenges in the implementation of high-level goals of ethical conduct.

2.2.2 Shared mobility

Shared mobility can be defined, in broad terms, as an innovative transportation strategy which allows users to have short-term access to transportation modes on an “as-needed” basis.

Within this context of shared mobility, the **Mobility as a Service (MaaS)** concept has gained traction in recent years with several examples entering the market, such as Blablacar in Europe or Uber in the U.S. and in certain European countries.

In general terms, MaaS shifts the focus from “mobility as a commodity” (e.g. possessing a vehicle to travel) to “mobility as a service” (e.g. purchasing a ride to move around) (Araghi, 2020). It encompasses a wide range of mobility services from journey-planning tools to a more holistic form of planning, booking and ticketing, which allows the customer to organize and purchase door-to-door travel from a single provider (Cohen, 2020, Schroten, 2020, MaaS Alliance, 2017).

In spite of a certain fuzziness in its definition, the building blocks of MaaS can be pinned down to:

- **A platform** to allow interoperability between mobility services and modes.
- **Transportation services**, such as public transport, ride-/car-/bike and scooter-sharing, taxi, car rental or lease, or a combination of the above. Autonomous vehicles (colloquially named “robotaxis”) can also be deployed in MaaS services, with examples from Waymo (up to SAE level 4), and Uber (SAE level 3). MaaS is not limited to road transport, rail or flight transport options can also be part of a MaaS solution.

- **Integration** between transport services, information, payment.

MaaS is, to a wide extent, overlapping with the concept of shared mobility, but its specificity lies in using platforms, such as websites and mobile apps, to operate.

In terms of environmental and social impact, MaaS holds the potential to reduce the use of private cars and promote more sustainable travel solutions. Indeed, several H2020 and FP7 projects, such as SocialCar and 2MOVE2 demonstrated the use case for shared mobility solutions, like carpooling, in European cities and provided useful insights on the acceptance of sustainable urban mobility initiatives (Tsakalidis, 2020).

Social exclusion may also be positively impacted, as population groups without access to a car could improve their mobility. (Cohen, 2020, Araghi, 2020).

It is worth noting, however, that access to MaaS services implies some prerequisites that, if not met, could entail social exclusion:

- connectivity, which may exclude rural areas, less covered by internet and mobile providers;
- a certain amount of digital skills, which may penalize groups with low digital literacy;
- the possession of or access to a connected device, typically a smartphone or a computer, which may be a barrier for low-income households.

MaaS typically deploys AI for a variety of functions. The platform layer deploys machine learning algorithms to, e.g., find optimal routes, dynamically assign prices to rides in correspondence to demand (as in the case of Uber or Ola Cabs) and predict traffic flow, congestion and users' preferences.

The technical challenges and complexity in the case of MaaS primarily lie with the data rather than with the algorithmic component.

Firstly, a vast amount of data is required, often in real-time, to carry out the abovementioned optimization and design of travel solutions. Adding another layer of complexity, the data can come from several sources (see Section 2.1.1 – Data), creating problems of interoperability, and it can be of diverse nature, such as user behaviour data or timetables and routing from various transport services. Common data standards and syntaxes, such as the Mobility Data Specification (MDS) (ITF, 2020), are thus required in order to facilitate the communication between different transport operators and, also, with regulators and public authorities.

Finally, data privacy and security are also relevant challenges for the development of MaaS services. Data sharing can open the door to data misuse and hacking (Cohen, 2020); furthermore, the aforementioned process of profiling users' preferences can lead to breach their privacy, e.g. singling them out by correlating mobility patterns with the location of healthcare facilities, cult temples or political parties (Costantini, 2019). In order to provide the appropriate protection in those cases, (Costantini, 2019) suggested that an update of the GDPR could be envisaged as location data and mobility patterns are not currently regarded as sensitive data, which therefore entails a lower degree of protection afforded to this type of data (Costantini, 2019, Schroten, 2020).

Beyond data sharing, other more privacy preserving approaches exist as an alternative to directly share raw data. One possible route is to have the data stored by a trusted third party, such as a dedicated public agency: the third party would receive the code and execute the analysis, returning trusted responses from its remotely-held data. The OpenTraffic project is one example of this approach (ITF, 2020).

Another approach, more radically transformative, is the creation of synthetic datasets reproducing the statistical properties of the original data (Hradec, 2021, Floridi, 2020). Such datasets, carrying the relevant information at the chosen granularity, render the re-identification and biased 'singling out' impossible, since there is no link between a physical person and the corresponding synthetic counterpart. Therefore, they stand as a formidable tool for smart mobility providers and stakeholders.

2.2.3 Smart city

At the city level, the term "**smart city**" encompasses initiatives and approaches using ICT to improve competitiveness and operational efficiency but, also, to increase social and environmental sustainability (ITF, 2020, Lim, 2019).

A smart city agenda is enabled by the use of connected devices, such as sensors and wearables, that collect and transmit data through the Internet, e.g. the IoT concept, which provides the pillar of smart infrastructure in smart cities. These devices can interact and synchronise their actions across multiple smart applications, enhancing transportation but also grid distribution and community development (Lim, 2019).

Smart mobility is often a major chapter of smart cities agendas, aiming to blend IoT and smart vehicle technologies into the transportation system, with autonomous vehicles often being given a prominent role in these agendas (Yigitcanlar, 2019).

Improved safety and traffic management are among the expected impacts of smart mobility solutions at city scale, enhanced by the efficiency and accuracy of autonomous vehicle decision-making capabilities and intelligent traffic control systems (see Section 2.1.3).

AI technologies can sustain a **more efficient use of road capacity** using advanced and adaptive signalling systems, monitoring traffic flow and synchronizing accordingly the traffic lights or nudging users to take alternative routes (ITF, 2020). These traffic mitigation strategies indicate substantial cost-benefit ratio returns, sometimes as high as 60:1 (ITF, 2019b), because of reductions in travel times. Smart roads applications can go beyond traffic optimization: for instance, parking space can be dynamically allotted and, by suggesting alternate travel modes, as mentioned above with MaaS, crowding and congestion could be avoided (ITF, 2020).

There are some challenges in scaling up the management of traffic flows at the city level: the individual traveller's perception may be sub-optimal when centralized traffic control optimizes road traffic and overall travel fluxes. On the other hand, distributed and crowd-sourced navigation systems can tailor routing solutions to meet individual needs, but this flexibility comes at the expense of overall efficiency (ITF, 2020)

Furthermore, even if platforms exist to exploit data to gain insights for policy and operational processes, a key barrier to their uptake are their operational costs and lack of data scientist and analysts with expertise (ITF, 2019b). Therefore, there is a need for data scientists to team up with transport practitioners and researchers to develop synergies beneficial to the transport sector.

A crucial impact stemming from smart mobility solutions is on **sustainability**. The load on the environment caused by traffic congestion and inefficiency is likely to decrease, all other factors held equal; in addition, improvements in public-transport usage and shifts towards lower-emission vehicles, such as electric vehicles, may lead to a reduction of the environmental impact related to transport.

However, it is important to note that feedback loops and induced travel effects have to be considered to assess the positive outcomes of smart mobility solutions. For instance, consumer demand is increased by smart mobility services as a result of improved efficiency and this extra demand can cancel out the benefits of increased efficiency over time. There is also strong evidence that induced travel effects follow closely infrastructural and operational improvements: roadway expansion – either by new road capacity or freeing the existing one - generates rebound effects, which may also offset the beneficial impacts (ITF, 2020b).

3 Scientific uptake

3.1 Insights from scientific literature

Key messages of this section

Our analysis of the scientific and policy literature from Elsevier's SCOPUS database yielded the following conclusions

1. *Time evolution*: Scientific publications on smart mobility have tripled since 2017, peaking in 2019 with more than 300 yearly publications. Furthermore, the publication increase since 2017 correlates with the emergence of AI related concepts, such as "Intelligent vehicles", "Demand responsive transportation" and, in 2020, "Shared mobility".

2. *Topics:* Papers on smart mobility can be clustered into five super-classes that follow closely the categories outlined in Section 2 (Figure 2.1). The following super-classes were identified: one revolving around IoT and network technologies; three concerning smart mobility applications outlined in Section 2.2 (Autonomous driving, MaaS and Smart cities); and finally one super-class, concerning smart mobility solutions to assist the impaired, represented about 10% of the results.

3. *Keyword co-occurrence:* Keywords co-occurrence allowed to pair smart mobility applications with their enabling technologies. Data mining, big data and AI algorithms are thus connected to urban and human mobility. Furthermore, mobility management is entangled with IoT, cloud/fog computing and 5G technologies. Lastly, sustainability is linked with electric vehicles and mobility.

We investigated the presence of smart mobility topics in the scientific literature by analysing both scientific and policy papers containing the phrase "smart mobility". In this way, we obtain a better understanding of the domains which smart mobility includes.

To this end, we used two bibliographic sources: Elsevier's SCOPUS database, which is the largest abstract and citations database for peer-reviewed literature, and TRID (Transport Research International Documentation)[4], which is the world's largest and most comprehensive bibliographic resource on transportation research information.

TRID is a database maintained by the National Academies of Science and Engineering. It contains over 1.25 million records of transportation research worldwide, and it combines two other databases: TRB[5]'s Transportation Research Information Services (TRIS) Database and the OECD's Joint Transport Research Centre's International Transport Research Documentation (ITRD) Database. Furthermore, TRID records are indexed with standardized vocabularies related to transport, which is a very useful tool to investigate concepts in the database.

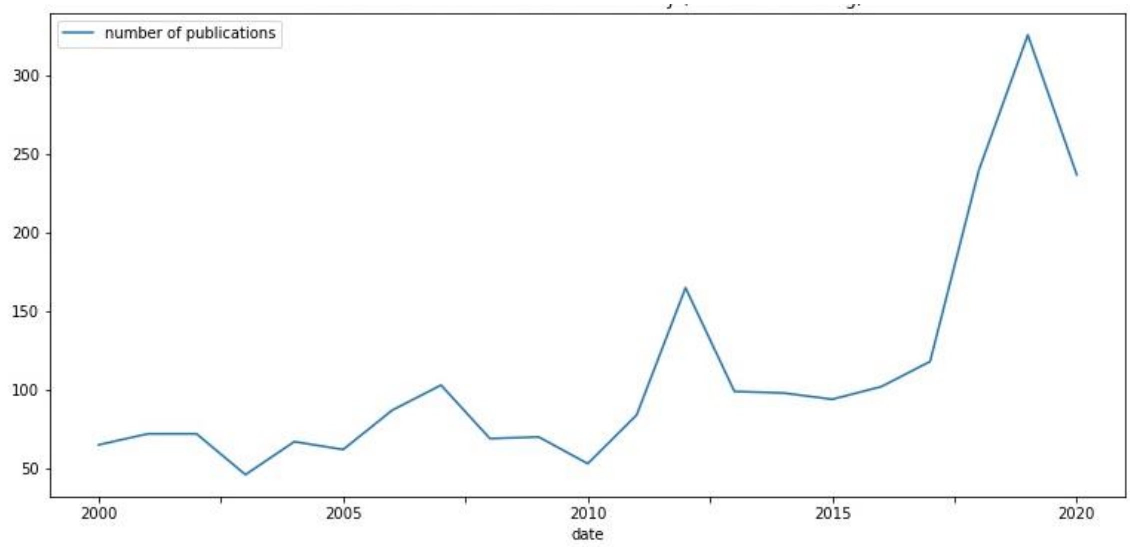
This very comprehensive bibliographical resource allowed us to investigate the time evolution of smart mobility related publications. In Figure 3.1.1, we can observe that the corpus of documents related to smart mobility has grown steadily, with yearly publications

4 http://www.trb.org/InformationServices/AboutTRID.aspx

5 Transportation Research Board: https://www.nationalacademies.org/trb/transportation-research-board

increasing from around 50 in 2000 to 120 in 2017, with a steep rise in publications after 2017, almost tripling the publication output.

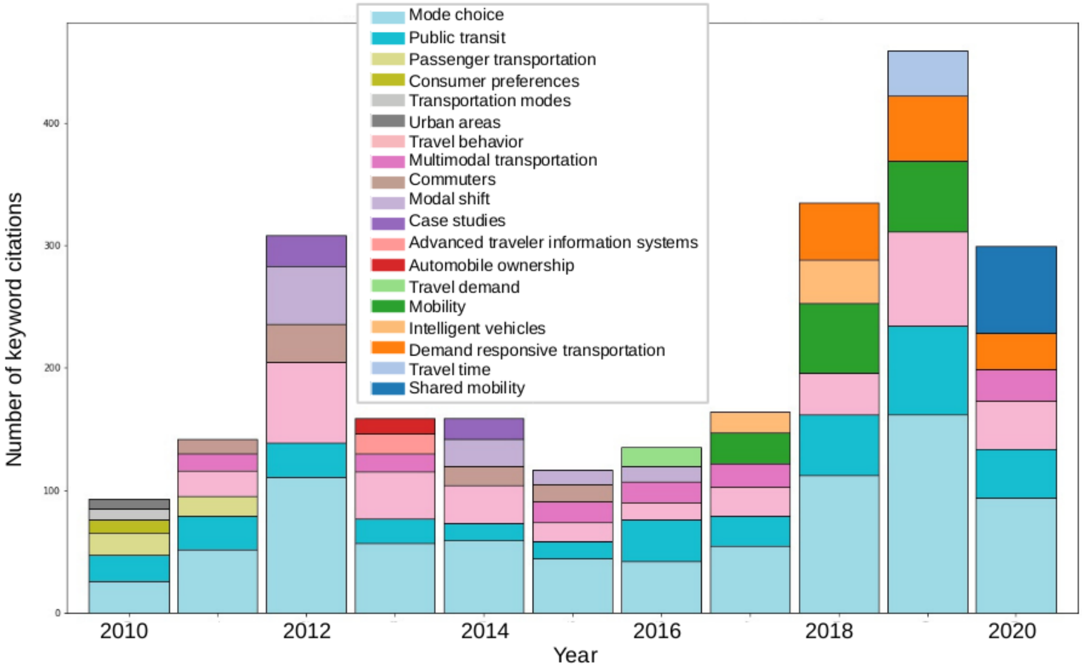
Figure 3.1.1. Number of smart mobility articles per year



Source: JRC, TRID data

Using the keywords indexing TRID records, we were also able to observe the most important topics in transport publications and their evolution over time. . In Figure 3.1.2 the six most cited keywords per year are displayed: some keywords, like “Mode choice” and “Public transit”, are among the most cited for all the timespan considered; on the other hand, other concepts, such as the ones related to smart mobility, started appearing later on. More specifically, we observe in 2017 a significant number of works on “Intelligent vehicles” appear along with another smart mobility concept, “Demand responsive transportation”. Also, “Shared mobility” appears in 2020, confirming the trend away from car ownership signalled by the increasing offer of MaaS services.

Figure 3.1.2. Most cited TRID keywords per year



Source: JRC, TRID data

Coming to our second bibliographic source, Elsevier provides an API search through its SCOPUS database that we have used to get the relevant metadata of the papers. While the phrase "smart mobility" got us 7,072 results from 2015-2020, the search term "smart mobility AND artificial intelligence" provided only 231, and machine learning 244. This is obviously an unexpected drop in the number of results, which needed detailed scrutiny.

We have obtained the complete metadata for the "smart mobility" articles (N= 7,072) from Elsevier and we clustered them according to their similarity (see Annex 2 for methodological details of the clustering). The clusters were then manually interpreted and, in Table 2, we display the clusters organized into five super-classes:

Table 2. Clusters emerging from the Elsevier literature analysis.

Super-classes	**Clusters**
IoT and networks	5G networks; IoT analytics applications; IoT and mobile ad-hoc networks (MANET); vehicular ad-hoc networks (VANET); IoT network; IoT network routing; IoT software architecture; IoT standardization; IoT, smart card data; ad hoc networks security; crowdsensing; service centric IoT, mobile service-oriented networks;
Assistive technology	assistive technology; assistive technology, mHealth; assistive technology, robotics, task offloading; assistive technology, smart wheelchair; assistive technology, visually impaired;

	assistive technology, wearables;
Smart Cities: Urban planning and sustainability	smart grid modelling; smart grids, energy storage; smart living; smart mobility for prosperity; smart mobility services; smart urban mobility; smart urban mobility: sustainable development; supply chain vehicle management; sustainable multimodal transport; traffic modelling and management; urban planning, urban planning, decision support systems; urban planning, digital transformation; urban planning, smart parking; urban planning, transport planning;
Autonomous driving	automated driving, vehicle-to-everything (v2x); automated driving, vision based transportation, materials; autonomous driving; autonomous vehicles; behaviour analysis; autonomous driving; business model design; demand responsive transit system; edge computing; electric vehicles, smart charging;
MaaS	intelligent transportation system (ITS) routing; intelligent transportation system (ITS), traffic and emission modelling; mobility as a service (MaaS); mobility as a service (MaaS), education, innovation; human mobility, location prediction; sharing economy;

More than 10% of the papers were not strictly about smart mobility but about e.g. medical systems mentioning smart mobility and well as climate and environmental studies citing smart mobility as a possible solution to reduce carbon footprint. Practically, it was not possible to clearly distinguish when smart wheel chair is actually more a medical device or a smart mobility system and thus all these papers were included in our analysis.

In total we may assess that the smart mobility scientific papers are spread equally into the five super-classes below (Table 2):

1. IoT technologies, networks, edge computing, mobile-ad-hoc-networks (MANET) and vehicular-ad-hoc-networks (VANET), crowdsensing
2. Assistive technologies, including smart wheel chairs and support to elderly and visually impaired
3. Smart city: urban and traffic planning, sustainability
4. Mobility as a service (MaaS)
5. Autonomous driving, UAVs, and intelligent transport systems (ITS)

Although these categories are to a large extent overlapping with the Twitter-based taxonomy defined above, they nevertheless help to shed light and better contextualize the use of AI methods within the scientific literature.

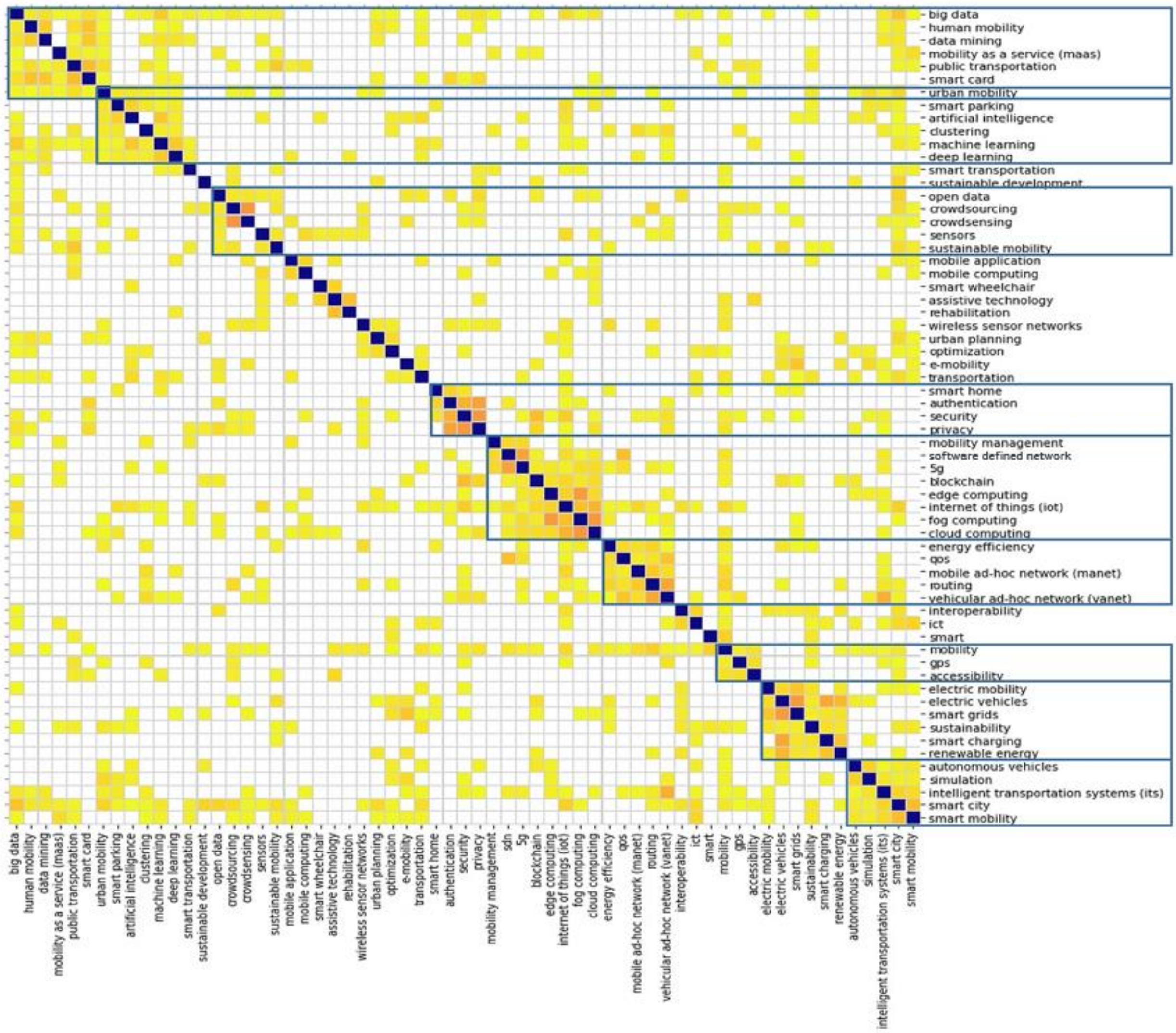
The co-occurrence of keywords in the papers allows the identification of connected concepts. This is depicted in Figure 3.1.3: the most frequently co-occurring keywords are visible as they form denser squares along the diagonal.

The bottom right corner contains a cluster encompassing smart mobility, with “autonomous vehicles”, “intelligent transportation systems” and “smart city”. Then, moving up along the diagonal, another cluster links “sustainability” with electric mobility concepts: “smart grid”, “electric mobility/vehicles”, “smart charging”.

Other clusters link smart mobility applications with their respective enabling technologies: “mobility management” with “5G”, “edge/cloud computing” and “internet of things”. Interestingly, “smart home” is clustered with “security”, “privacy” and “authentication”, highlighting how cybersecurity and privacy protection are of paramount importance for domotics applications.

Lastly, in the top left corner we observe a cluster connecting “big data” and “data mining” to “human mobility”, “mobility as a service” and “urban mobility”. The latter concept, “urban mobility”, shows up as deeply entangled with several AI technologies: “machine learning”, “deep learning” and “clustering”.

Figure 3.1.3. Co-occurrence of keywords.



Source: JRC

3.2 EU-funded Research and innovation projects

Key messages of the section

1. *Topics:* Analysis of H2020 projects yielded the same broad classes discovered in the scientific literature analysis (Section 3.1). Smart city is the largest group, followed by Intelligent transport systems (which includes MaaS) and Automated driving. Assistive technologies are also present, accounting for around 10% of projects.

2. *Time evolution:* H2020 projects received significant funding, which kept increasing along the years: from slightly less than EUR 800 million in 2015, accounting for 7.6% of the total funding for H2020 projects, to peak in 2019 with EUR 1.1 billion, the 9.6% of total funding for H2020 projects for that year.

3. *Participant countries*: The network of collaboration between the countries displays a tightly knit cluster formed by Germany, Spain, Italy, France, UK and Belgium. Countries such as Sweden and Greece have also strong links with this cluster. Out of Europe, Israel and Turkey are the countries collaborating the most with European countries in H2020 projects.

The analysis of H2020 data found 2970 out of total 31116 projects containing the keywords mined from the Elsevier analysis (Section 3.1). This search was further refined by weighting whether the overall context of the project leans towards mobility or towards other domains such as nanomaterials, cell biology, and medical devices (see Annex 3 for the methodological details).

Pure ICT projects were further investigated to assess whenever they have smart mobility as the use case (e.g. routing of data from sensors to central processing server) or just mentioned smart mobility among its applications (e.g. generic sensor data collection). This approach yielded 1615 projects, approximately the 5% of the total.

The analysis of the clusters for the prevalent keywords gives the following distribution:

Table 3. Clusters in the H2020 projects

Cluster	**Number of projects**
Smart city	750
Intelligent transport systems (ITS)	437
Assistive technologies	308
Automated driving	199
AI	8

The clusters are characterised by the following most frequent keywords (edited for readability, e.g. city/cities):

Smart city: smart city, smart card, intermodal, energy storage, smart grid, smart infrastructure, smart cycling, urban mobility

Intelligent transport systems: predictive maintenance, intelligent transportation system, drone, mobile service-oriented networks, mobility as a service, MaaS, smart transportation, traffic management

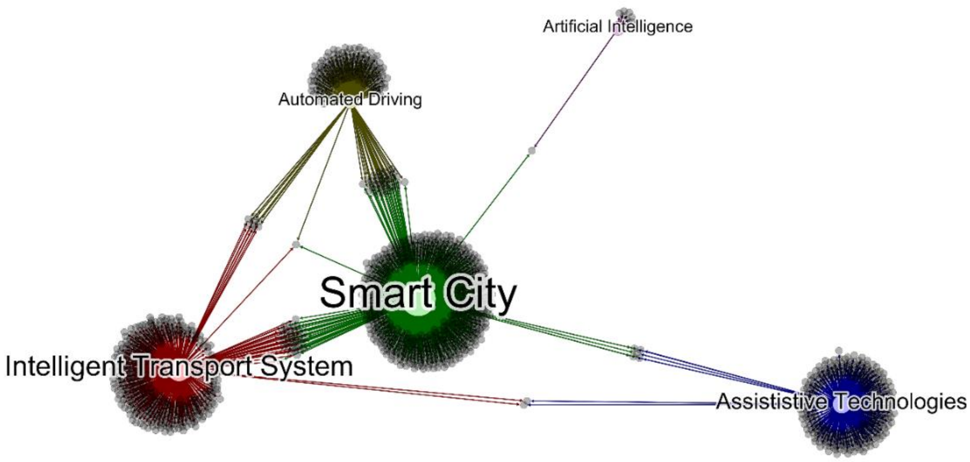
Assistive technologies: assistive, smart wheelchair, impaired

Automated driving: automated driving, vehicle-to-everything, v2x, electric vehicles, vehicular ad-hoc networks (VANET), mobile ad-hoc network (MANET)

AI: mobility patterns prediction, destination prediction, next trip prediction, parking availability predictions, flow prediction, charging behaviour prediction, route prediction, road-traffic prediction, next-place prediction, individual-level choice prediction, real-time prediction, trajectory prediction.

In Table 3, we observe that the “AI” cluster features 8 projects: this relatively small number of projects was most probably caused by the more extensive use of specialized language, from the mathematical realm, than in other more practical projects; hence the keywords from Elsevier triggered a small number of results. Furthermore, several H2020 projects lie at the intersection of the clusters since they simultaneously belong to two or more clusters: in Figure 3.2.1, we depict the different clusters and, within them, the projects that are connected to two or more clusters. Thus, we can see that the Smart city cluster is the most central and it is strongly connected to the clusters for Automated driving cluster and Intelligent Transport System, which also show a strong interconnection between them. The aforementioned difference in language also entails the small number of connections between the "pure" AI projects cluster and the other clusters, which feature more practical applications of AI.

Figure 3.2.1 Network of smart mobility H2020 projects

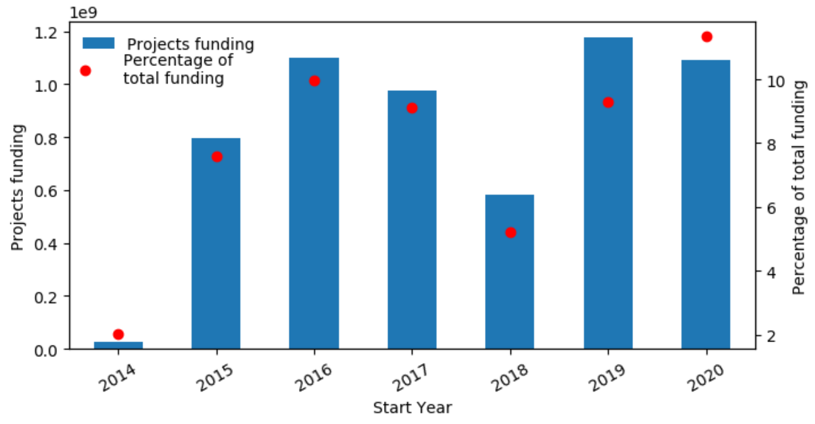


Source: Cordis data, calculations JRC

H2020 projects received significant funding, which progressively increased over the duration of this framework programme (Figure 3.2.2): from slightly less than EUR 800 million in 2015, accounting for 7.6% of the total funding for H2020 projects, to peak in 2019 with EUR 1.1 billion, the 9.6% of total funding for H2020 projects for that year. Overall, AI-enhanced mobility-related H2020 projects received between 7% and 11% of the total funding each year, confirming the strong interest for smart mobility initiatives in Europe. As a comparison, smart health initiatives received approximately EUR 100 million in 2019, a tenth of the funding for smart mobility initiatives.

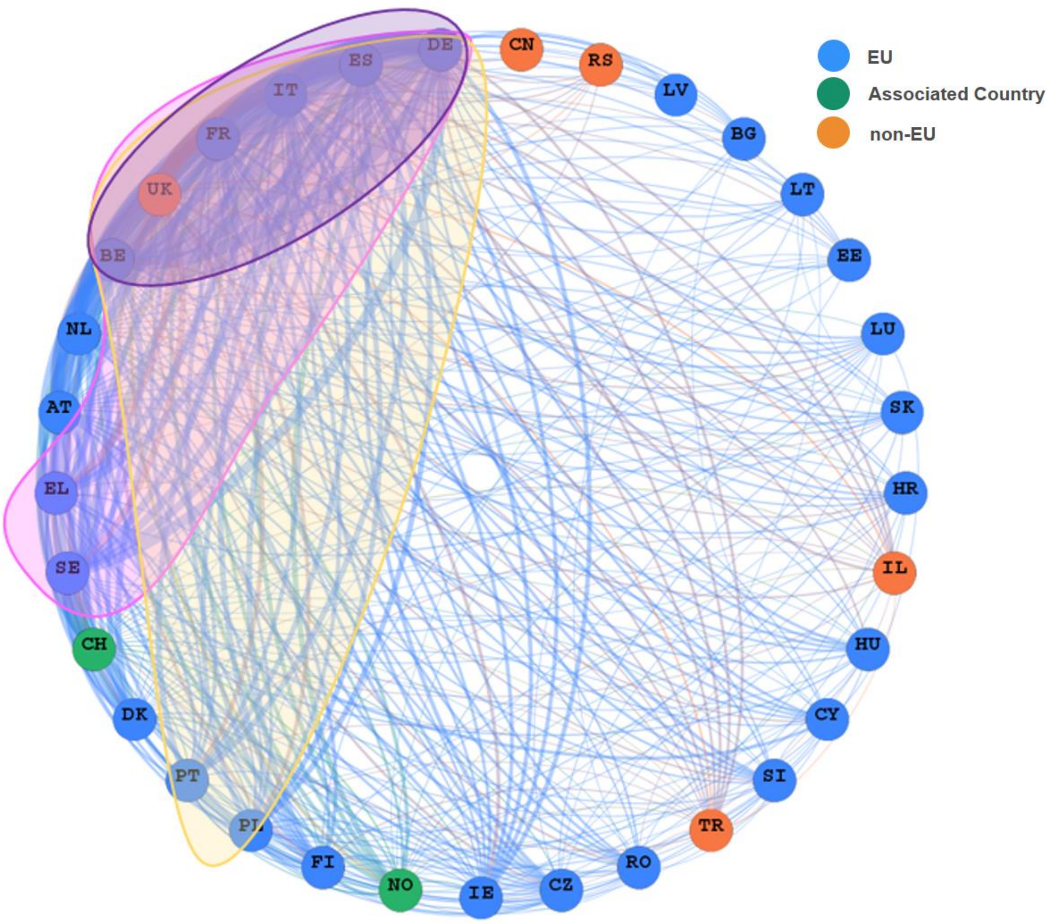
Coming to the countries involved in H2020 projects, we display in Figure 3.2.3 the network of collaboration between the countries: the more tightly knit cluster is the one formed by Germany, Spain, Italy, France, UK and Belgium, in the upper left corner of the network (in purple in the figure). Greece and Sweden also have several projects and, hence, strong links with the first cluster (highlighted in pink), together with Portugal and Poland (highlighted in yellow). Out of Europe, Israel collaborates with countries mainly from the first cluster and also Turkey has a wide collaboration network with European countries.

Figure 3.2.2. Total funding of smart mobility H2020 projects per start year (billion EUR).



Source: Cordis data, calculations JRC

Figure 3.2.3. Network of countries involved in smart mobility H2020 projects.



Source: Cordis data, calculations JRC.
Blue dots are for EU countries, green for EFTA and red for extra-EU countries.

4 Industrial take up

4.1 Technological innovation from patenting activity

Key messages of the section

From our analysis of the AI and mobility patents data, we can draw the following conclusion

1. *Patent content*: The patents were clustered into two cohorts: “Enabler” for patents featuring AI keywords that could also, but not exclusively, be used for smart mobility and “Application” for patents where AI concepts and keywords explicitly concerned a smart mobility application. Their content, explored using IPC and CPC codes, sees data as crucial: both Enabler and Application patents most cited codes concern data handling, processing and storing. In the Application most cited codes, however, transport related codes are also present, concerning traffic or vehicle sub-unit control and navigation

2. Geographical distribution: The geographical distribution marks a strong Asian presence in the first five positions of the ranking, together with the U.S..
China is, by far, the most active in filing Application patents, with more than 13,000 patent requests in AI and mobility. The U.S. is in second place with more than 7,000 Application patents. South Korea, Japan and Europe follow with more than 2,000 patents each. For the Enabler patents, the distribution follows closely the one of Application patents: China and the U.S. are leaders with approximately 2,600 patents each, South Korea and Europe hold 509 and 349 patents respectively.

3. *Time evolution:* The number of patent filings increased almost exponentially since 2013, with a 10-fold increase both for Application and Enabler patents.

4. *Top patent holders:* The top fifteen ranking is dominated by Chinese, U.S. and South Korean companies. For Applications patents, companies from the Automotive and ICT sectors are present. The German company Bosch is featured in the top fifteen, with 172 Application patents. The Enabler patent ranking is composed mostly of companies in the ICT sector, with U.S. companies being the most numerous (N=8), then China (N=5) and South Korea (N=2). Within Europe, the Application patent ranking is dominated by German companies in the automotive sector, while German, Dutch, Swedish and French ICT companies compose the Enabler patent ranking.

In order to quantify the degree of technological innovation, we mined a comprehensive patents database using Orbit Intelligence software by Questel. This database comprehends the World Intellectual Property Organization (WIPO), the European Patent Office (EPO) and the national authorities in UK, Canada, France, Germany, China, Japan, South Korea and India, totalling over 100 patents authorities.

The database records come in the form of ‘FamPat family numbers’: such families of patents are invention-based, so that all the publication stages of an invention as well as documents from different patenting authorities are associated to only one FamPat number.

In the database, we isolated patents featuring both AI-related and mobility-related keywords (see Annex 4 for methodological details), obtaining 38,687 hits[6].

Among our selected patents, we distinguished two cohorts:

- Enabler: patents mostly featuring AI related concepts and keywords, but which could be used in the context of mobility, albeit sometimes not exclusively. It is often the case, for instance, of smart sensors (N=7,230).
- Application: patents where AI and mobility keywords and concepts appeared with equal weight (N=31,484).

In order to explore the patents' contents, we turned to the International Patent Classification codes (IPC) characterizing each patent family (Figure 4.1.1). We chose, in this case, IPC codes over the Cooperative Patent Classification (CPC) because the CPC has recently been introduced in China and Korea[7] and, therefore, many patents families from those countries miss the CPC codes, while they do have IPC codes.
Application patents and Enabler patents feature similarities and some notable differences in the IPC frequency distribution: in both cases, codes concerning data processing and handling occupy the first three positions; however, for Application patents many transport-oriented codes are present, such as conjoint control of vehicle sub-units and traffic control in fourth and fifth place. Conversely, for the Enabler patents, the higher ranked codes are all geared towards data, in various forms such as speech or images, and its processing and transmission:

Table 4. Most frequent IPC codes Application patents.

IPC Codes	**Number of patent families**	**% of all**
Data recognition and presentation	12236	14.4%
Electric digital data processing	10909	12.8%
Data processing systems or methods	9598	11.3%
Conjoint control of vehicle sub-units	9077	10.6%
Traffic control systems	9016	10.6%
Computer systems based on specific computational models	7983	9.4%
Image data processing	7974	9.4%
Wireless communication networks	6740	7.9%
Radio direction-finding and navigation	5924	6.9%
Systems for controlling non-electric variables	5784	6.8%
Total	**85241**	**100.0%**

Source: JRC, Orbit data.

6 As of 13/11/2020.

7 China and Korea agreed to start introducing the CPC system from 2013.

Table 5. Most frequent IPC codes for Enabler patents.

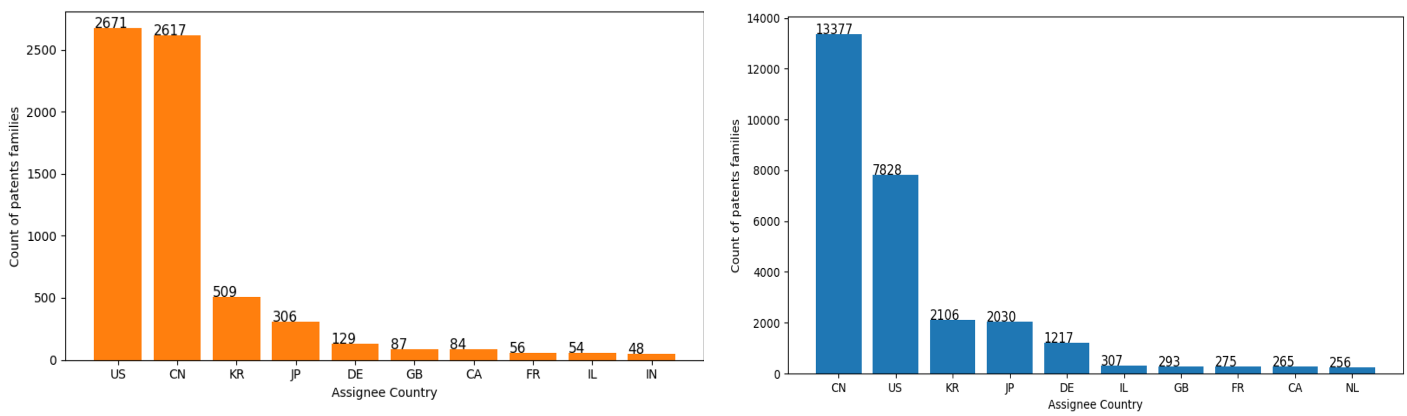
IPC Codes	Number of patent families	% of all
Electric digital data processing	6711	26.5%
Computer systems based on specific computational models	4955	19.6%
Data recognition and presentation	3274	12.9%
Data processing systems or methods	2875	11.4%
Image data processing	2193	8.7%
Transmission of digital information	1779	7.0%
Pictorial communication	1204	4.8%
Speech analysis and synthesis	1141	4.5%
Wireless communication networks	841	3.3%
Control or regulating systems	345	1.4%
Total	**25318**	**100%**

Source: JRC, Orbit data.

In terms of geographical distribution of the patent assignees (Figure 4.1.1), China's companies are the most active in filing AI and mobility Applications patents (Figure 4.1.1 right), followed by the U.S.. South Korea and Japan are respectively in third and fourth position, albeit with a very small difference. As for Enabler patents (Figure 4.1.1 left), U.S. and China lead with a very close number of patent families, followed again by South Korea and Japan. In both rankings, we see Germany in the 6th position and France in the 9th. As a whole, the EU27 filed over 2,000 Application patents and over 300 Enabler patents, marking a strong European presence in the global (geographical) patent landscape.

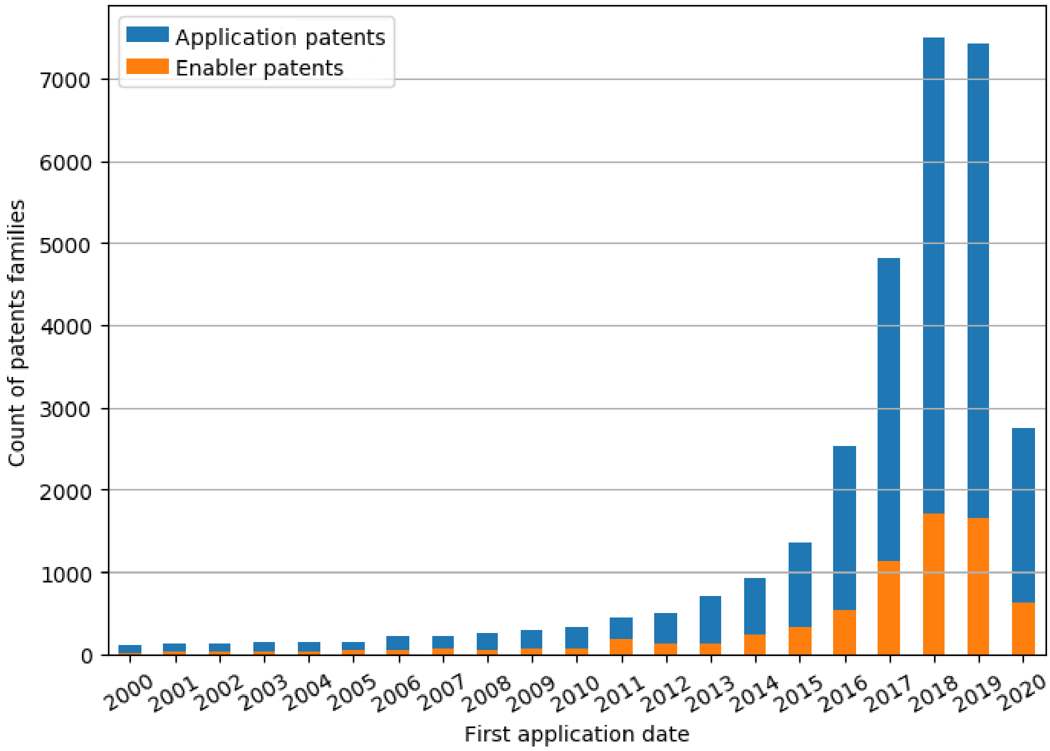
The number of filings (Figure 4.1.2) of Application patents has seen an almost exponential rise since approximately 2013, passing from 706 in 2013 to 7510 in 2018, more than a 10-fold increase in five years. Enabler patents have seen an even bigger increase (12-fold), albeit with smaller absolute numbers, rising from 131 in 2013 to 1702 in 2018.

Figure 4.1.1. Geographical distribution of assignee countries for Enabler patents (left) and Application patents (right).



Source: JRC, Orbit data

Figure 4.1.2. Year of first application for Enabler and Application patents.

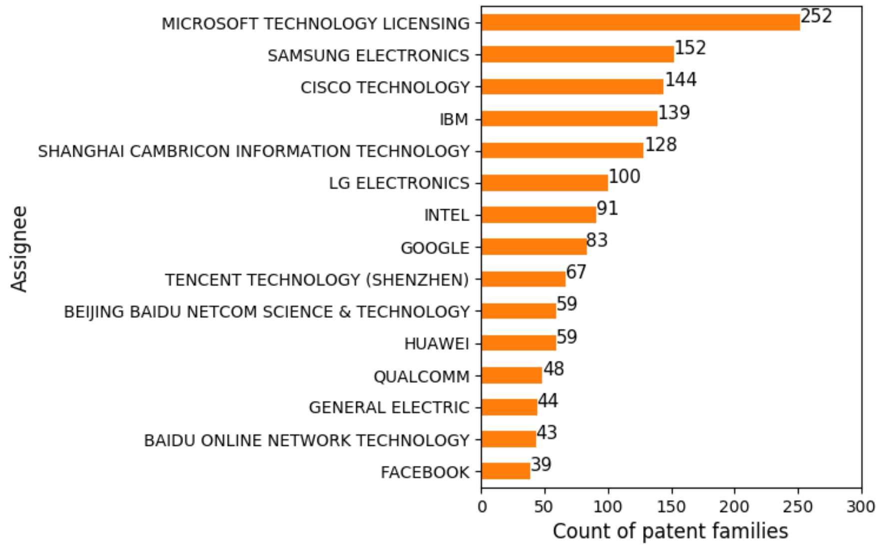


Source: JRC, Orbit data.

Note: The data for 2019 and 2020 are to be considered provisional because of the 18-months gap between the filing of an application and its publication.

Analysing individual patent holders, the top assignees for Application and Enabler patents are significantly different: the ranking of top Enabler patent-holders (Figure 4.1.3) sees almost exclusively companies in the ICT sector: Microsoft leads with 252 patents, followed by Samsung Electronics, with 166, and Cisco Technology (151). In this case, U.S. companies are the most numerous (N=8), followed by China (N=5) and South Korea (N=2).

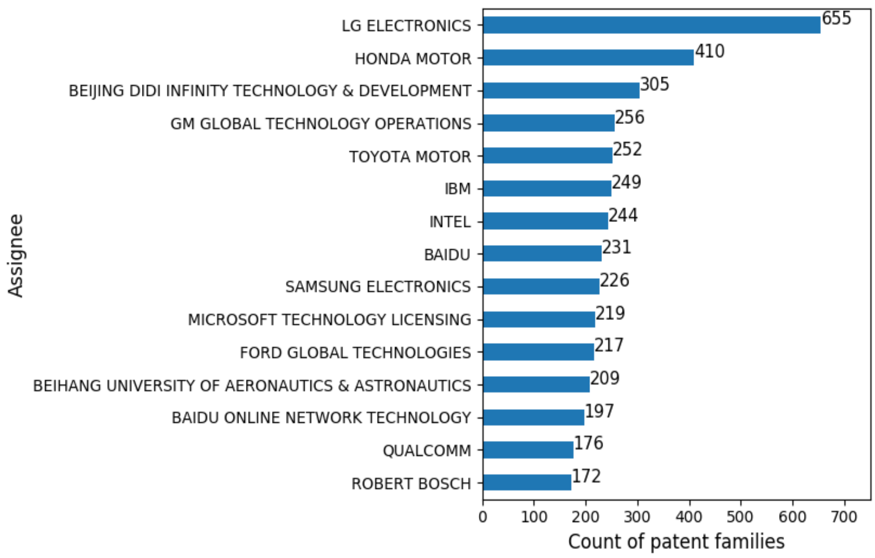
Figure 4.1.3. Top patents assignees for Enabler patents



Source: JRC, Orbit data

On the other hand, the ranking for top Application patent-holders comprises both companies in the automotive industry, such as Honda Motor, Ford and Toyota, and companies in the ICT realm, as IBM, Microsoft and Baidu. In the raking for Application patents, LG Electronics holds the biggest share of patents (655), followed by Honda Motor (410) and Didi (305). Overall the raking is mostly composed by U.S. and Chinese companies, together with some Japanese and South Korean ones that rank very high (Figure 4.1.4).

Figure 4.1.4. Top patents assignees for Application patents.



Source: JRC, Orbit data

Focusing on Europe, for Application patents (Table 6), German companies related to the automotive sector dominate the ranking, with the notable exception of HERE, a Dutch company working on real-time traffic data (see Section 2.1.1), which ranks second. Similarly to the global ranking, the European Enabler patents ranking (Table 7) is composed by companies in the ICT sector. It is led by an Irish-American company, Accenture Global Solutions, working in logistics. Furthermore, Swedish ICT companies Ericsson and Nokia are present along with the Dutch HERE and Philips.

Table 6. Top European Application patents assignees

Name	Country	Patents
Robert Bosch	DE	172
HERE	NL	167
BMW	DE	114
Audi	DE	113
Siemens	DE	104.5
Volkswagen	DE	75
Daimler	DE	68
ZF Friedrichshafen	DE	62
Ericsson	SE	50
Accenture Global Solutions	IE	34

Source: JRC, Orbit data

Table 7. Top European Enabler patents holders.

Name	Country	Patents
Accenture Global Solutions	IE	37
Robert Bosch	DE	28.5
Siemens	DE	28
Ericsson	SE	17
SAP	DE	14
HERE	NL	9
Dassault Systèmes	FR	9
Philips	NL	7
Amadeus	FR	6
Nokia	FI	3

Source: JRC, Orbit data
The fractional count is due to shared patents.

4.2 Venture Capital investments in AI mobility start-ups

Key Messages of the section.

The analysis of start-ups applying AI in the mobility sector allows to make the following conclusions:

1. In the last five years, the total VC investment in mobility start-ups nearly doubled from EUR 17.1 billion in 2014 to EUR 31 billion in 2019. Following the COVID-19 crisis, the level of funding dropped to EUR 18.1 billion in 2020.
2. AI mobility start-ups account for approximately 30% of total VC investment in the mobility sector.
3. While the total level of VC investment in the mobility sector dropped significantly in 2020, the share of total funding going to AI mobility start-ups increased. This reflects the overall impact of COVID-19 crisis on the increasing level of digitalisation of economic activities.
4. The U.S. and China together attract over 85% of the global VC investment in mobility start-ups and in start-ups applying AI in the mobility sector. European start-ups account for 6.4% of the global VC investment in the mobility sector.5. Chinese start-ups attract the largest amount of VC funding per firm. For example, WM Motor, NIO and Xiaopeng Motors received over EUR 2 billion of VC funding each. In comparison, Lilium, the start-up with the largest amount of total VC funding in Europe, received EUR 334 million.
6. Chinese and U.S. AI mobility start-ups with the largest amounts of the total VC funding are mainly active in the field of autonomous electric vehicles**.** With the exception of Lilium, European AI mobility start-ups are targeting the technologies enabling connectivity and IoT.

Entrepreneurs and start-ups are one of the main vehicles by which the potential of new technologies is converted into economic benefits. Start-ups are more likely than existing businesses to pursue opportunities associated with radical innovations that may have transformative consequences for society and economy. In the last two decades, we have seen such newcomers as Skype, Uber or Airbnb quickly disrupt traditional industries. Similarly, the mobility sector has already attracted many entrepreneurs and large venture capital investments. It includes such companies as Uber, Tesla or BlaBlaCar disrupting the mobility sector. Many of these companies blend a number of digital technologies, including Artificial Intelligence.

In order to look at the level of AI uptake among start-ups in the mobility sector, venture capital (VC) investment was analysed using a dataset provided by Dealroom[8]. Dealroom is a data and software platform providing worldwide intelligence on startups, innovation and VC activities. Dealroom data has been extensively used for monitoring the developments of the European start-up landscape. For example, funded in 2020 with the support of the European Commission and European Parliament, European Startups[9] relies on Dealroom data and is a project aimed at facilitating informed conversation and collaboration among European tech ecosystem stakeholders to help to develop Europe's startup economy.

For our analysis, we filtered in the dataset the mobility related records, giving a first cohort of 5,560 companies worldwide. This selection was made by filtering the companies that are

8 https://app.dealroom.co/
9 https://europeanstartups.com

either in the "Transportation" industry or that feature smart mobility related keywords[10] in the "Tags" field and whose funding is compatible with being a start-up[11].

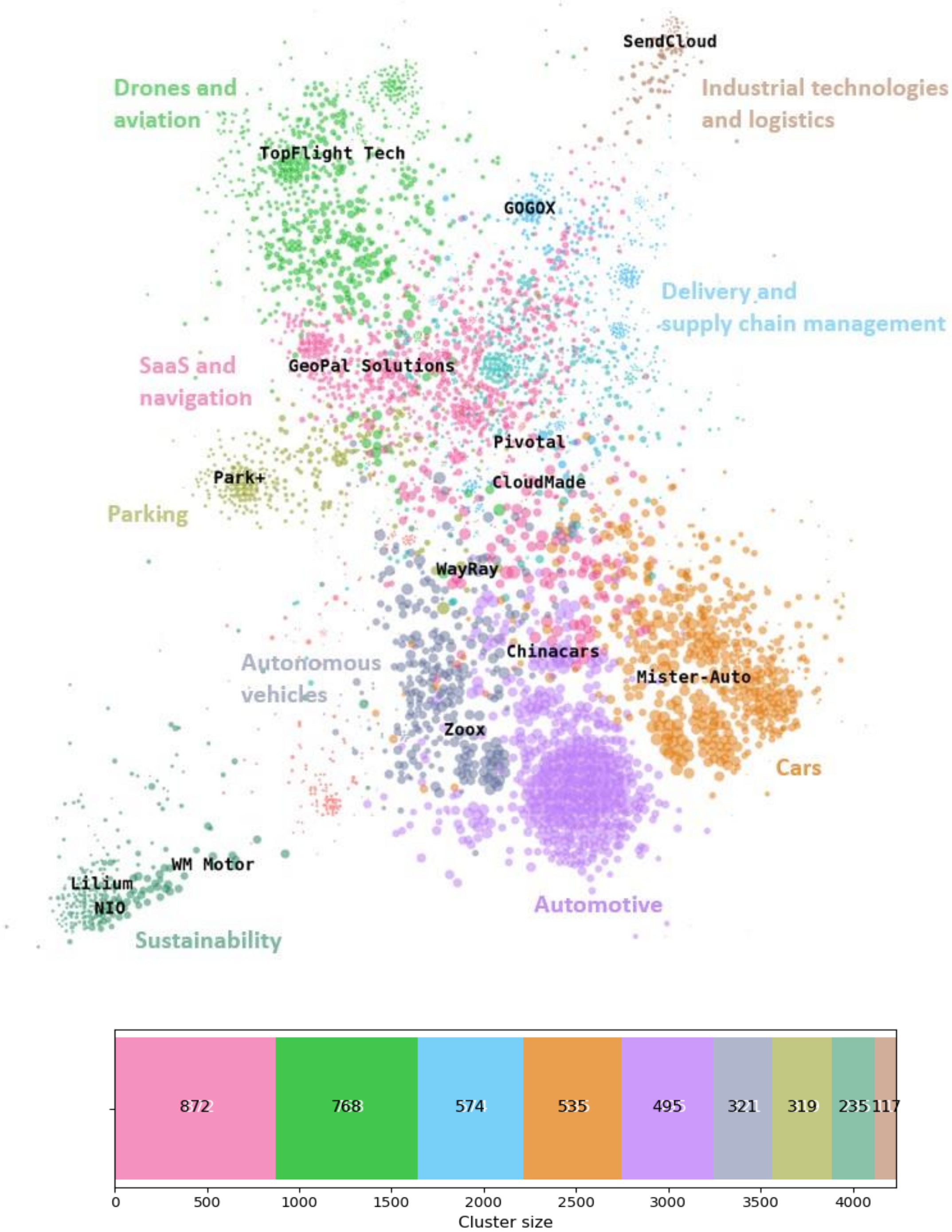
Furthermore, we mined the companies featuring AI-related keywords in their description to isolate a subset of **1,808 AI-related mobility start-ups** that were backed by VC between 2000 and 2020, either by angel investors or by venture capital funds.

To have a deeper understanding of the different specializations in mobility start-ups, we linked every company to similar ones, according to the similarity in their description and we then clustered the resulting network. Figure 4.2.1 displays the result of the clustering analysis: it is possible to observe clusters pertaining to a specific transportation mode, e.g. automotive, drones and logistics, lying at the rim of the network, while the cluster focusing on SaaS (Software as a Service), navigation and ICT solutions for transportation lies at the centre and is deeply intermeshed with the other clusters. This entanglement between the SaaS and ICT-related cluster and the ones specializing in a given transportation mode is natural as software and ICT are enablers for smart mobility solutions.

10 The keywords considered were: 'transport', 'mobility', 'vehicle', 'car', 'drive', 'air traffic', 'drone', 'route optimization', 'parking', 'maritime', 'ride sharing', "sharing e-bikes", 'scooter sharing', 'ridesharing', 'road safety', 'electric motor', 'automotive', 'ride hailing', 'fleet management'.

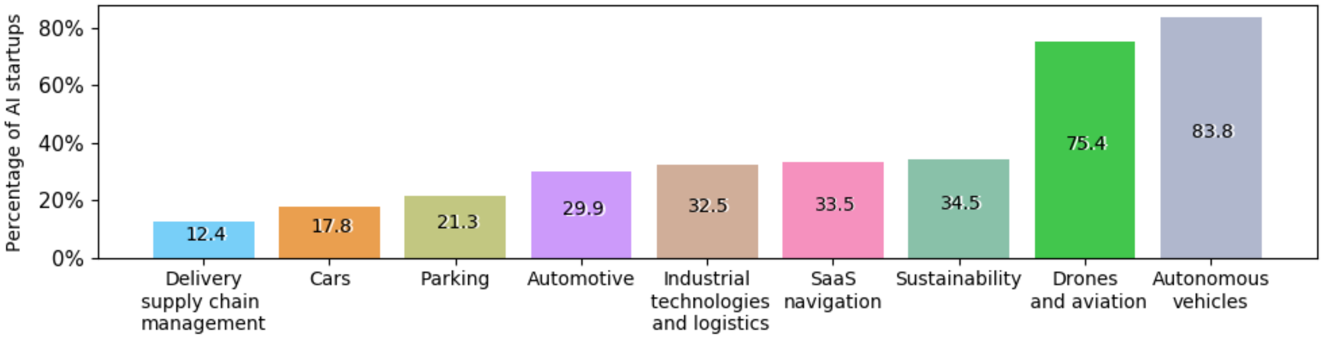
11 Specifically, companies whose funding rounds were of the type: 'angel', 'seed', 'early VC', 'series a-i' and 'late VC'.

Figure 4.2.1. Clusters formed by the mobility start-ups.



Source: based on data by Dealroom. Calculations JRC
In the figure, we highlighted companies receiving the highest share of VC funding (as in Figure 4.2.6) or the companies with the highest degree (i.e. number of connections) in the cluster as examples.

Figure 4.2.2. Percentage of AI and mobility start-ups in the clusters



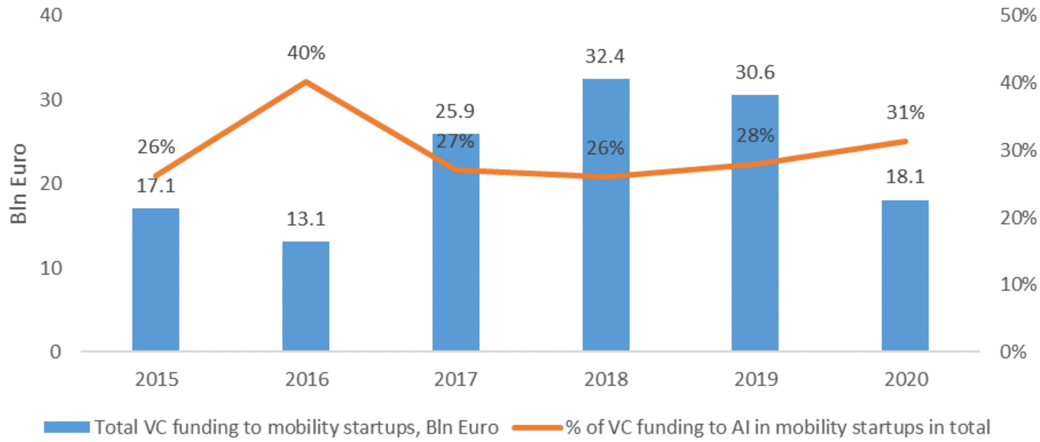
Source: Calculations JRC, data: Dealroom

The percentage of mobility start-ups whose products and services incorporate AI widely varies in the clusters, as shown in Figure 4.2.2: a vast majority of the companies in the "Drones and aviation" and "Autonomous vehicles" clusters are AI companies; while in the "Automotive", "Industrial technologies", "SaaS and navigation" and "Sustainability" the percentage of AI companies is roughly about 30%.

Figure 4.2.3 presents the total number VC funding to mobility start-ups and the percentage of total funding in the mobility sector received by AI-related start-ups between 2015 and 2020. In this period, the total investments in mobility of start-ups were between EUR 13.1 billion in 2016 and EUR 32.4 billion in 2018. The share of investments in AI-related start-ups in the total investments in mobility start-ups was between 26% in 2015 and 40% in 2016. On average, between 2015 and 2020, AI-related start-ups received 30% of VC investments in mobility.

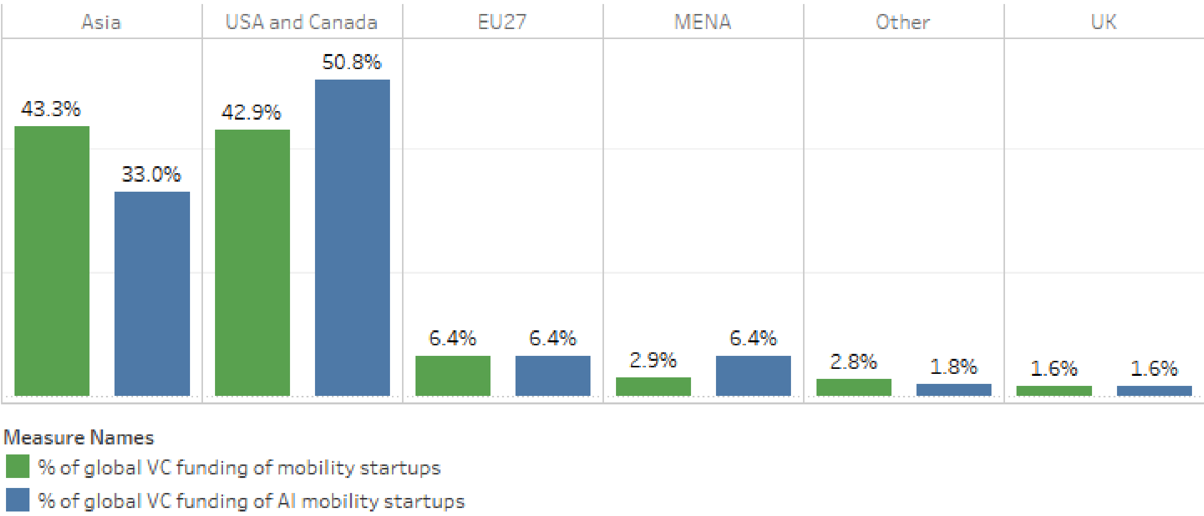
Concerning the impact of the COVID-19 crisis on VC investment in mobility, one can observe that it dropped considerably. While the total VC funding in mobility start-ups in 2019 reached over EUR 30 billion, in 2020, it decreased to EUR 18.1 billion. At the same time, however, the share of AI-related start-ups back by venture capitalists increased. This is in line with the overall trend of investments in digitalisation in the economy.

Figure 4.2.3. Global VC investments on mobility start-ups aggregated over the years and percentage of investments in AI related mobility start-ups



Source: JRC, data: Dealroom

Figure 4.2.4. Global VC investments on mobility and AI mobility start-ups per region, 2000-2020.



Source: based on data by Dealroom. Calculations JRC

Figure 4.2.4 shows the geographical distribution of total VC investment in mobility and AI-related mobility start-ups between 2000 and 2020. With over 43% of total VC capital directed to non-AI mobility start-ups, Asia leads the rank, followed by the U.S. European mobility start-ups attracted much smaller figures, accounting for 6.4% of total VC investment in this sector.

Regarding the share of VC investment in AI-related mobility start-ups, the U.S. accounts for over half of the global funding in this sector between 2000 and 2020. It is then followed by Asia, which attracted one third of such investment. Start-ups based in Europe and in the Middle East and North Africa attracted 6.4% of the global VC investments in AI-related mobility start-ups in the same period.

Figure 4.2.5 lists the top five AI-related mobility start-ups ranked by total VC funding received between 2000 and 2020 per each region. According to the data, Asian companies attracted the largest amount of VC funding per company. For example, WM Motor, NIO and Xiaopeng Motors, the top three Chinese companies, received over EUR 2 billion of funding each. This is double the amount of the total investment in Pivotal, a U.S. AI-related mobility start-up, which received the highest amount of VC funding in the USA and Canada region. European AI mobility start-ups attracted much smaller amounts of VC funding per company compared to their U.S. and Chinese counterparts. Lilium, the developer of the world's first electric vertical take-off and landing (VTOL) jet, or SIGFOX, a service provider for Internet of Things (IoT), received in total EUR 334 million and EUR 280 million of VC funding respectively.

The description of activity of the AI mobility start-ups shows that firms in each region focus on different aspects of applying AI to the mobility sector. For example, most of the top five Asian and U.S. start-ups by amount of funding are involved in the development of self-driving electric cars. With the exception of Lilium, European top five start-ups by amount of funding are targeting enabler technologies such as connectivity and IoT.

Figure 4.2.5. Top five AI-related mobility start-ups by total VC funding (2000 and 2020) per region (in millions of EUR).

Region	Name	Description	Total Funding
Asia	WM Motor	Electric vehicles	2,664
	NIO	Designing and developing electric autonomous vehicles	2,180
	Xiaopeng Motors	Integrating autonomous driving and internet technologies	2,162
	BYTON	Turning cars into a next-generation smart device	1,052
	Mobike	A fully station-less bicycle-sharing system	855
USA and Canada	Pivotal	Providing digital transformation technology and services	1,304
	Zoox	Autonomous vehicle fleet and supporting ecosystem	914
	Nuro.ai	Robotics for everyday life	904
	Pony.ai	Building autonomous driving technology	647
	Joby Aviation	Electric motor development and battery pack design	641
EU27	Lilium	Fully electric vertical take-off and landing jet	334
	SIGFOX	A service provider for Internet of Things	280
	Volocopter	An urban air mobility service provider	161
	Advanced Manufacturing Control..	Integrated software and vehicle technology	84
	DiBcom	Integrated circuits for broadband wireless solutions	71
MENA	Gett (GetTaxi)	A global ridesharing app	674
	Souq	Leading e-commerce store in the Arab world	387
	Innoviz Technologies	High-performance solid-state LiDAR & perception software	220
	Vayyar	Developing mobile, low cost 3D imaging sensors	167
	Fabric	Robotic micro-fulfillment centers for online grocery shopping	121
Other	Heptagon	Micro-optics products for OEM suppliers	180
	WayRay	Augmented Reality for the automotive industry	93
	Neoway	Big Data and AI company	40
	Myriota	Communication and monitoring services for remote locations	30
	Baraja	3D machine vision systems manufacturer	29
UK	Arrival	Making smart and electric vans	101
	Envisics	Developing in-car holographic display using augmented reality	85
	Five AI	AI and ML-based navigation systems for autonomous cars	69
	Secondmind	A cloud-based decision-making platform powered by AI	34
	CloudMade	AI solutions for automitive	27

0K 2K 4K

Total Funding

Source: based on data by Dealroom. Calculations JRC

Box. 2: Tesla vs Volkswagen

The history of digital transformation shows us that assets that were sources of competitive advantage in the traditional industries are becoming obstacles in the digital world. As a result, Europe has repeatedly seen that it is losing against digital newcomers in sectors in which it enjoyed an unchallenged position in the past. The current race to build electric autonomous vehicles illustrates this well. In spite of its leading position in the car sector, Europe finds it difficult to keep up with Tesla, the newcomer and trendsetter in this new market niche.

With twice as many software developers as Tesla, the biggest challenge for Volkswagen, the world's largest car manufacturer, is to integrate digital technologies into its products that would transform them from a means of transport into digital devices embedded in a large mobility data platform enabling the provision of high-value products and services. The market valuations of Tesla and Volkswagen reflect these capabilities to seize the emerging opportunities. With only 3% of Volkswagen's car sales, Tesla's current market capitalisation already exceeds that of Volkswagen by 10%.

5 Conclusions

Building blocks of AI in smart mobility

Smart mobility is a sprawling topic, encompassing applications from the city-wide level down to the level of the individual vehicle. These applications hold the potential to improve the management of traffic flows, enhance road safety and extend access to mobility to those who do not possess vehicles. In addition, by allowing for new forms of mobility and triggering changes in user behaviour, they can improve the use-efficiency of mobility assets, reduce energy consumption and pollution. Although they can promote more sustainable forms of mobility, their deployment is also likely to increase consumer demand and generate rebound effects, offsetting a part of the efficiency benefits.

AI is at the core of smart mobility applications. Computer vision, machine learning and deep learning algorithms compose the software component of smart mobility. Sensors, connectivity technologies and IoT provide the hardware backbone for smart city, shared mobility and autonomous driving. Finally, telemetry, real-time traffic data and population data is also an important enabler of any smart mobility application.

The uptake of smart mobility applications depends on the availability of mature technological enablers as well as their integration into safe and viable ecosystems of products and services. Before this happens on a massive scale, a number of technical as well as governance challenges need to be solved. For example, because smart mobility applications rely on vast amounts and diverse types of data coming from various actors, data sharing and integration are necessary conditions for developing and deploying them in real-life environments. Standards will play a key role in securing interoperability between connectivity and IoT infrastructure and data. Similarly, before appearing in cities and on highways, autonomous vehicles will need to go through intensive road testing helping to understand vehicle behaviour, detect corner cases to ensure the safety of automated driving.

AI in smart mobility uptake in research, innovation and market applications

The current analysis shows that AI started to make inroads into the smart mobility domain in the early 2000's. Fuelled by advances in deep learning, research activity in AI in smart mobility experienced a sharp increase after 2017. This change of pace was also accompanied by an increase of research topics in AI in smart mobility, signalled by the emergence of such topics as "Intelligent vehicle" and "Shared mobility". According to the analysis of patent applications, one can observe that the number of inventions in AI in smart mobility has seen an almost exponential growth since 2013. This sharp increase concerns both AI in mobility enabler technologies, mostly patented by ICT companies, as well as AI in mobility applications, which are mostly patented by automotive companies. Start-up activity in the AI and smart mobility domain is also a recent but fast growing phenomenon. The current analysis of Venture Capital investments shows that start-ups delivering market-ready AI in smart mobility applications have already reached approximately 30% of the total investments in the mobility sector.

Europe's position in the global AI in smart mobility technology landscape

Regarding the source of AI in smart mobility technologies, the analysis of patent filings concerning AI in smart mobility enablers shows a strong Asian and U.S. presence in the global ranking. China and the U.S. hold approximately 2,600 patents each, South Korea and

Europe hold 509 and 349 patents respectively. The top fifteen ranking of Enabler patent holders is composed mostly of companies in the ICT sector, with U.S. companies being the most numerous (N=8), then China (N=5) and South Korea (N=2). This ranking does not include any European company.

For the patents concerning the applications of AI in smart mobility, the distribution of patent filings by world's regions follows closely the pattern of the enablers. China is, by far, the most active in filing Application patents in AI and mobility, followed by the U.S. These inventions are developed mainly by companies from the automotive and ICT sector. The ranking of the top fifteen companies holding patents on AI and mobility applications includes only one European company. With 172 Application patents, Bosch, the German automotive supplier holds the last place in the ranking.

The geographic distribution of Venture Capital funding, which reflects investments in market-ready AI in smart mobility applications, confirms the dominance of the U.S. and China observed in research and innovation activities. The U.S. and China account for 51% and 33% of the global VC funding in this sector respectively. European start-ups with AI-enabled smart mobility offerings attract approximately 6% of global VC investments. A company level analysis shows also that Chinese start-ups working on electric and autonomous vehicles are among firms that attracted the largest amount of funding per company. WM Motor, NIO and Xiaopeng Motors received over EUR 2 billion of funding each. This is double the amount of the total investment in Pivotal, a U.S. AI-related mobility start-up, which received the highest amount of VC funding in the U.S. and Canada region. In comparison, European AI mobility start-ups receive significantly smaller amounts of funding: for instance, the top VC funding receiver in Europe, Lilium, the developer of the world's first electric vertical take-off and landing, received in total EUR 334 million.

In conclusion, the current report shows that AI-driven smart mobility applications are ecosystems of complex technologies. Creating viable smart mobility products and services does not only require securing technological interoperability of their enablers, but also an orchestration of a number of different stakeholders. For example, real-life smart city projects show that user-centric innovation requires involving even more people, public sector organizations and technology firms in the co-creation and design of new services and solutions. Creating efficient data sharing, governance and management mechanisms between them is, however, often challenging. With respect to the geography of AI in smart mobility, the analysis shows that the major part of enabling technologies and applications in this domain is being developed and deployed in China and the U.S.. European automotive and ICT companies play only a minor role in the domain of AI in smart mobility.

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Annexes

Annex 1. Methodology for scoping and literature review.

Twitter data was used to understand the relevant sub-concepts encompassed by the intersection between mobility and AI concept. To this end, we started from mining tweets mentioning words related to artificial intelligence and, in this first cohort, we selected tweets mentioning words related to mobility.

This set of words was our initial input set to be further expanded. By analyzing the hashtags and the network created by their co-presence, we were then able to discover concepts connected to the initial input set, thus expanding our ensemble of concepts and vocabulary.

Furthermore we received in this phase input and relevant literature from experts in JRC Unit C.4 - Sustainable Transport in order to build a solid basis for the literature review in Section 2. Lastly, from the literature review and the analysis of the network created by the tweets, we elaborated the mind map in Figure 2.1, which was then discussed with the colleagues in Unit C.4.

Annex 2. Methodology for Elsevier SCOPUS data analysis

We have obtained the complete metadata for the “smart mobility” articles from the Elsevier API. Using SciBERT we have calculated the article embedding into a 768-dimensional latent space, projected the data into 5 dimensions using UMAP algorithm and clustered the articles using HDBSCAN. Iterative optimization to decrease noise (not clustered articles), keep the number of topics between 20 and 100 and avoid creation of huge clusters lead to parameters providing 96 clusters with the largest cluster of 278 papers and 753 unclustered papers (10%).

Annex 3. Methodology for H2020 data analysis

To cluster the projects by content similarity, we have used SciBERT[12] fine-tuned to NLI[13] sentence embedding task to project the text into the latent space. This matrix was projected from 768 to 5 dimensions using UMAP and clustered using HDBSCAN. Iterative hyperparameter search provided best balanced groups for 7 UMAP neighbours and minimum cluster size of 20 for the HDBSCAN, only 13 projects were unassigned as noise.

Annex 4. Methodology for patent data analysis

In order to isolate relevant patents in the Orbit database, we performed the following steps:

1. We first used the advanced search tool of Orbit software, looking for the co-presence of the AI-related and mobility-related keywords listed below:

- **AI Keywords**: artificial intelligence, computer vision, deep learning, machine learning, augmented reality, neural network.

12 I. Beltagy et al, SciBERT: A Pretrained Language Model for Scientific Text https://www.aclweb.org/anthology/D19-1371/

13 https://github.com/gsarti/covid-papers-browser

- **Mobility Keywords**: transport*, smart mobility, automated vehicle, autonomous vehicle, drone, rail, maritime, automotive, airplane, aeroplane, aircraft, smart cit*, traffic flow, self driving car, vehicle, automatic driving car, road, flight, rout*.

As the keyword "rout*" can trigger many results from the telecommunications realm, related for instance to packets routing on a network, we constrained the search for this keyword to results where at least another mobility keyword was present, such as "vehicle" or "aeroplane".

2. We further excluded results in less relevant technological domains:

"SURFACE TECHNOLOGY, COATING" OR "TEXTILE AND PAPER MACHINES" OR "MEDICAL TECHNOLOGY" OR "OTHER SPECIAL MACHINES" OR "FURNITURE, GAMES" OR "MACHINE TOOLS" OR "OTHER CONSUMER GOODS" OR "FOOD CHEMISTRY" OR "CIVIL ENGINEERING" OR "ANALYSIS OF BIOLOGICAL MATERIALS" OR "CHEMICAL ENGINEERING" OR "ENVIRONMENTAL TECHNOLOGY" OR "BIOTECHNOLOGY" OR "SEMICONDUCTORS" OR "ENGINES, PUMPS, TURBINES" OR "PHARMACEUTICALS" OR "MECHANICAL ELEMENTS" OR "THERMAL PROCESSES AND APPARATUS"

3. The above steps of advanced keyword search and removal of technological domains were applied to perform two searches:

- One search, called "Pure", restricting the search to just the most relevant patents fields: Title, Abstract, Claims, Object of Invention.
- The second search, called "Extended", included also the field Concepts, beyond the aforementioned Title, Abstract, Claims and Object of Invention.

4. As the Extended search contained many spurious results, estimated up to one third of the total, we constructed a classifier meant to distinguish the relevance of the keywords in the patent text. The first step of the classifier checks the CPC (or, if missing the IPC[14]) codes of the patent to find hits with the following list of transport related codes, based on input by experts from JRC Unit C.4:

Transport CPC list: 'B60', 'B63', 'B64', 'B61', 'B62D', 'G01S', 'G01C', 'G08G', 'G05D-001/00', 'G08B-005/00', 'G05D-013/00', 'G05D-003/00'

If the patent contains one or more of the above codes list, the classifier then assesses the relevance of the AI keywords. In case the patent codes do not comprehend some of the Transport CPC list, the classifier assesses the relevance of both the AI keywords and the mobility ones.

5. The classifier tags the patent as follows:

- Application: patents where AI and mobility keywords and concepts appear with equal weight.
- Enablers: patents mostly featuring AI related concepts and keywords, but which could we used in the context of mobility, albeit not exclusively. It is often the case, for instance, of smart sensors.

14 We first checked if the Transport CPC list's codes coincided with the corresponding IPCs.

- Spurious: patents where the presence of the AI and mobility keywords is very weak.

6. The resulting dataset is the union of the Pure and Extended dataset, once both have been filtered by the classifier.

Annex 5. Estimation of false positive and false negatives.

False positives: After several cleaning and validation rounds, the share of false positives in our datasets is below 5%.

False negatives: For Scopus and patent data from Orbit having a precise estimation of false negatives is challenging as both datasets are queried via an API; hence, there may be records which are not captured by our queries and, not having access to the entirety of the datasets, their quantification remains imprecise.

Hence, to palliate to this problem, we perform queries to the APIs as general and as comprehensive as possible to circumscribe large swaths of the datasets, which we then clean afterwards to remove the false positives. Furthermore, we adopt a hybrid strategy for curating the queries, both supervised (with experts validating the keywords) and unsupervised (by using topic modelling from different sources, such as Twitter (see Annex I) to further uncover keywords).

KJ-NA-30821-EN-N

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Publications Office of the European Union

doi:10.2760/879190
ISBN 978-92-76-41403-2