Conférence Européenne des Directeurs des Routes

Conference of European Directors of Roads

MANTRA

MANTRA: Making full use of Automation for National Transport and Road Authorities – NRA Core Business

Impacts of connected and automated vehicles – State of the art

Deliverable D3.1

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MANTRA

MANTRA: Making full use of Automation for National Transport and Road Authorities – NRA Core Business

Deliverable D3.1 – D3.1 Impacts of connected and automated vehicles – State of the art

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Executive summary

This deliverable is the first MANTRA deliverable concerning the impacts of connected and automated driving functions on NRA Policy targets. The main purpose of this document is to conduct and summarize a comprehensive state of the art on the impacts of connected and automated driving on travel demand, travel behaviour, traffic flow, safety and energy. The review is based on ongoing and recently completed EU- and national projects, and a comprehensive literature review of key publications and articles on the topic.

The variety of impacts and impacts mechanisms of connected and automated driving, and the related key performance indicators (KPIs) are presented and the most relevant for MANTRA work selected. The later chapters present the main findings of the review of the CAD impacts on mobility and travel behaviour, driver behaviour and traffic flow, traffic safety, user acceptance, energy and environment.

Most of the impact estimates in the literature are based on either expert evaluation or traffic simulations. The other source for current estimates are available field studies on driver assistance systems. It is hence very important to continue following the studies in this area, to complement the results when on-the-road testing of automation in real traffic with other road users present, and data received from those tests, is available in large scale.

Moreover, even the models to estimate impacts, e.g. traffic microsimulation models, still need adjustment and parameters designed specifically for automated vehicles. The current vehicle behavior models are based on the behaviour of human drivers. In addition, the behavior of human drivers might also change when interacting with automated vehicles. The development of the technology also have great impact on the area and conditions where automation can be used (operational design domain, ODD), and hence can have impacts in. The variety of impact mechanisms need to be kept in mind when considering the potential impacts of connected and automated driving not only to traffic safety, but also other impact areas.

The studies reviewed for this paper give an overview of the expected impacts of the deployment of connected and automated driving. As the reader can see when going through the various impact areas, the expectations of the magnitude of the impacts vary a lot. Where someone is expecting the traffic safety to be improved by 90%, the others are much more conservative and present only one-digit estimates. The same applies for other impact areas, even fully contradicting estimates exist.

As many of the studies summarized in this deliverable also remind: automation is not the only megatrend that affects the road transport in the oncoming years. Shared mobility is one issue, which may have great impact on how people select to move around. In addition, electrification have for sure impact on CO_2 emissions, and maybe even the travelling patterns.

List of Figures

List of Tables

Table of contents

Conférence Européenne des Directeurs des Routes
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1 Introduction

The CEDR Transnational Research Programme was launched by the Conference of European Directors of Roads (CEDR). CEDR is the Road Directors' platform for cooperation and promotion of improvements to the road system and its infrastructure, as an integral part of a sustainable transport system in Europe. Its members represent their respective National Road Authorities (NRA) or equivalents and provide support and advice on decisions concerning the road transport system that are taken at national or international level.

The participating NRAs in the **CEDR Call 2017: Automation** are **Austria, Finland, Germany, Ireland, Netherlands, Norway, Slovenia, Sweden** and **the United Kingdom**. As in previous collaborative research programmes, the participating members have established a Programme Executive Board (PEB) made up of experts in the topics to be covered. The research budget is jointly provided by the NRAs as listed above.

MANTRA is an acronym for "Making full use of Automation for National Transport and Road Authorities – NRA Core Business". MANTRA responds to the questions posed as CEDR Automation Call 2017 Topic A: How will automation change the core business of NRA's, by answering the following questions:

- What are the influences of automation on the core business in relation to road safety, traffic efficiency, the environment, customer service, maintenance and construction processes?
- How will the current core business on operations & services, planning & building and ICT change in the future?

An earlier CEDR project DRAGON (Vermaat et al. 2017) already looked at the impacts of three automated driving use cases in specific sites revealing the need to carry out a comprehensive study on the impacts on the road authorities and operators on the European scale.

MANTRA work started with the analysis of vehicle penetrations and Operational Design Domain (ODD) coverage of NRA-relevant automation functions up to 2040. This part is reported in MANTRA Deliverable D2.1. Work-package 3, for which this D3.1 is the first deliverable, concentrates on the impacts of connected and automated driving, and how the impacts relate to the role and policy targets of NRAs. The following work-packages continue from this, and assess and discuss the consequences of automation functions on infrastructure, and how the deployment of automation changes the core business of road operators.

This deliverable is the first deliverable concerning the impacts of connected and automated driving functions on NRA Policy targets. The main purpose of this document is to conduct and summarize a comprehensive state of the art on the impacts of connected and automated driving on travel demand, travel behaviour, traffic flow, safety and energy. The review is based on ongoing and recently completed EU- and national projects, and a literature review of key publications and articleson the topic. The deliverable starts by introducing the variety of impacts and impact mechanisms in connected and automated driving (CAD), and the related key performance indicators (KPIs). The later chapters present the main findings an extensive review of the CAD impacts on mobility and travel behaviour, driver behaviour and traffic flow, traffic safety and user acceptance, and energy and environment.

The next steps in WP3 is to assess the implications of selected (see deliverable D2.1) automated driving functions on mobility, travel behaviour, and energy with existing models and the literature review presented in this deliverable. The findings of the review and the next steps in WP3 will be discussed in a mini workshop with CEDR in September 2019.

In addition, simulation models will be utilised to assess the impacts of connected and automated driving on traffic flow and safety. Finally, impacts of automation on efficiency in operational processes and maintenance will be assessed and all the assessments will be summarized as impacts of automation on NRA key policy targets, based on the literature review, models, and expert interviews and expert evaluation.

2 Impact mechanisms and KPIs for automated driving

2.1 Impacts of automated driving - a framework

2.1.1 Introduction

Trilateral Impact Assessment Sub-Group for ART introduced a high-level framework for assessment of the impacts of road traffic automation. The framework included new material, but was partly based on the frameworks presented earlier by US DOT (Smith et. al. 2015) and FESTA (FOTNet, 2014). The main purpose of the presented framework was to support governments in their policy analysis and long-range scenario-based planning. Additionally, manufacturers can use the document to better understand the potential benefits of new automated systems. Moreover, both designers of Field Operational Tests (FOTs) and impact assessment experts can use the document as a starting point for their evaluation work. (Innamaa et. al. 2018).

2.1.2 Classification of impacts

The basic classification of AV impacts is to divide the impacts into two large groups: direct and indirect impacts. Direct impacts are those which have a relatively clear cause-effect relationship with the primary activity or action. They are generally easier to measure and assess, and are often immediate to short-term in nature. In Figure 1 direct impacts are the ones in upper left-corner, highlighted with red circle (Innamaa et. al. 2018).

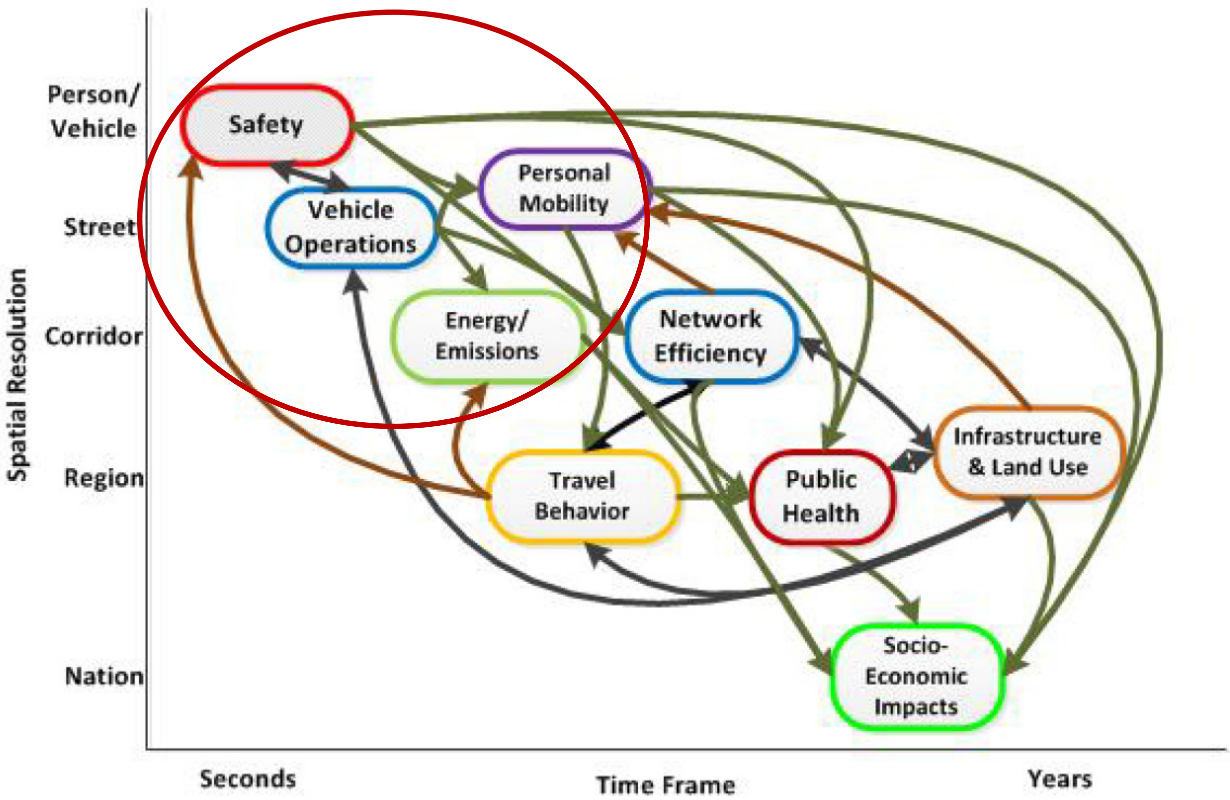

Figure 1. Impact areas by Trilateral Impact assessment sub-group. Direct impacts highlighted with the red circle. (Innamaa et. al. 2018)

Indirect impacts are the second group of impacts. Indirect impacts summarize the broader effects of the individual direct impacts. They are typically harder to measure and have a longer time horizon, (Innamaa et. al. 2018).

2.2 Overview of the recognized impact mechanisms and impact paths for automated driving

2.2.1 General impact mechanisms for assessment

The trilateral working group (Innamaa et. al. 2018) proposed the nine basic impact mechanisms for road transport automation related studies. These originated from Kulmala's (2010) nine safety impact mechanisms. The main idea of the impact mechanisms list is to ensure that all impacts, no matter if intended or unintended, direct or indirect, short-term or long-term, are covered in the impact assessment. Trilateral group recommends using these mechanisms for all impact areas of AD studies (Innamaa et. al. 2018).

1. Direct modifications of the driving tasks, driver behavior or travel experience
2. Direct influence by physical and/or digital infrastructure
3. Indirect modification of AV user behavior
4. Indirect modification of non-AV user behavior
5. Modification of interaction between AVs and other road users
6. Modification of exposure/amount of travel
7. Modification of modal choice
8. Modification of route choice
9. Modification of consequences due to different vehicle design

These mechanisms are intended to be non-overlapping and all-inclusive, i.e. all impacts fall under some, and preferably only one mechanism to avoid double counting. Innamaa et. al. (2018) also present a comprehensive list of supporting questions that help to understand what is meant by each mechanism.

2.2.2 Impact paths for automated driving

Innamaa et. al. (2018) introduced impact paths for automated driving for all impact areas (safety, network efficiency, environment, mobility, and quality of life). These were later updated for the workshop on Automated Vehicles impact pathways workshop held in Leeds on April 2019. The latest version of these pathways is presented in Figure 2.

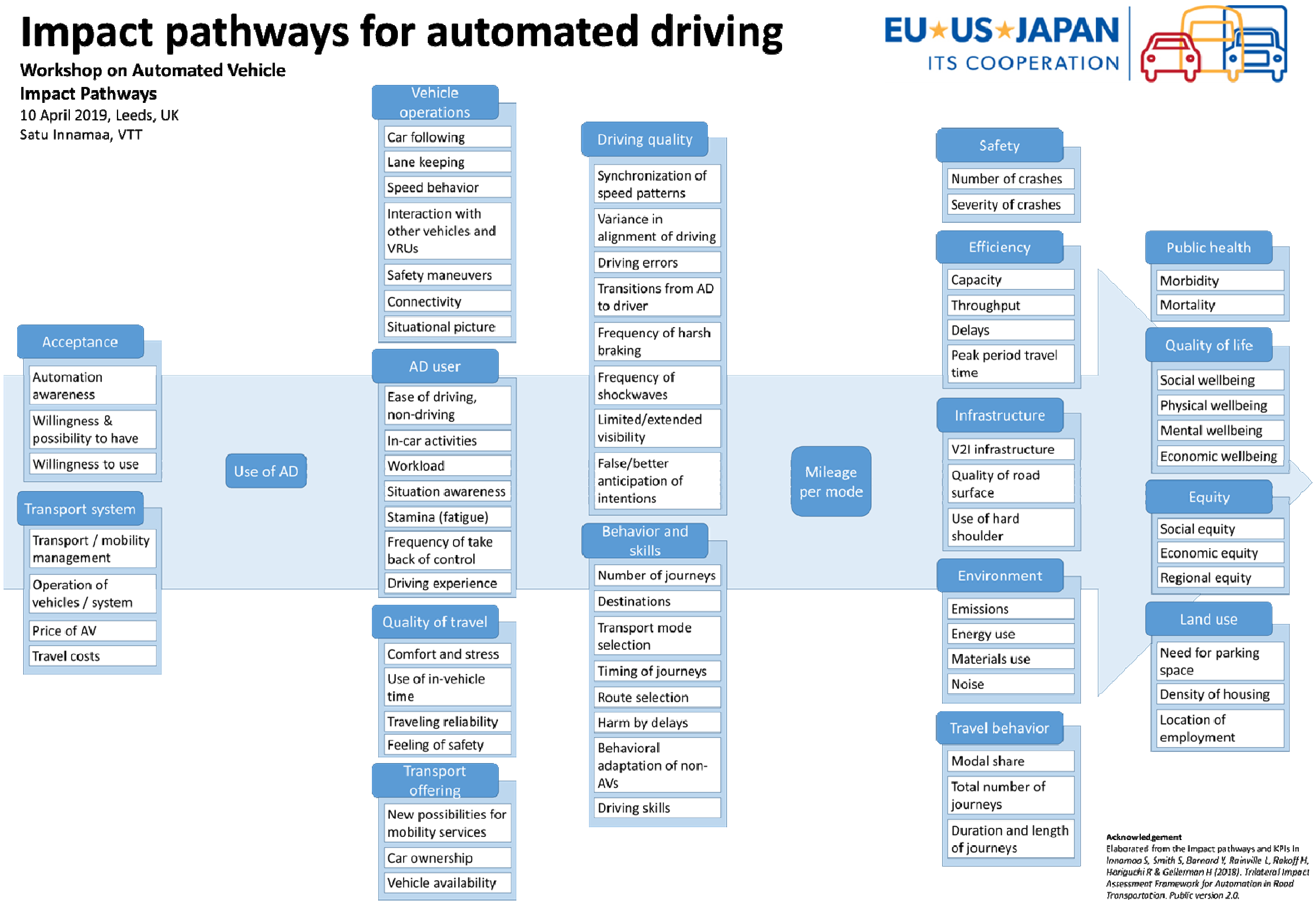

Figure 2. Impact pathways for automated driving (Originally Innamaa et. al. 2018, updated 2019).

2.3 Key Performance Indicators (KPIs) for automated driving

2.3.1 Introduction

Innamaa & Kuisma (2018) reported the results of Trilateral group's KPI survey i.e. selected KPIs for assessing the impacts of automation in road transport. It is important to notice, that these KPIs are mainly in societal level, and hence such, which will be often taken into account when calculating the cost-benefit -analysis for investments. The furher work in MANTRA will however, concentrate more into the KPIs most relevant to NRAs policy targets.

The selected KPIs are based on an expert survey conducted during the second half of 2017. Altogether 77 experts from EU, US and Japan participated the survey. The impact areas included into the survey were the following:

Vehicle operations/automated vehicles

Vehicle operations is one of the four direct impact areas of automated driving. It includes acceleration, deceleration, lane keeping, car following, lane changing, and merging in adjacent lane (Innamaa & Kuisma, 2018). In MANTRA, this area is of interest due to planned simulations and the parameters to be selected for simulations.

The listed KPIs were rated with the scale 0 = not at all important to 6 = extremely important. The following KPIs were rated most important (average > 4.5) for vehicle operations impact assessment (Innamaa & Kuisma, 2018):

- Number of instances where the driver must take manual control / 1000 km
- Mean and maximum duration of the transfer of control between operator/driver and vehicle (when requested by the vehicle)
- Mean and maximum duration of the transfer of control between operator/driver and vehicle (manual overrule)
- Number of emergency decelerations per 1000 km
- Mean and minimum time-headway to the vehicle in front in car following situations
- Minimum accepted gap at intersections or in lane changes
- Mean and minimum distance (m) to the vehicle in front in car following situations (headway 5 s or less)

When applying these to the MANTRA use cases, the take-overs may not be as important as for L3, but of course, L4 may require take-overs, too.

Use of automated driving

Use of automated driving is highly relevant in especially lower levels of automation, where driver can still select to activate (or not to activate) automated driving functions when within defined ODD. For scaling up the impacts, it is a key factor. The following KPIs were rated as 3 most important ones concerning the use of automated driving functions (Innamaa & Kuisma, 2018).

- Number of instances where the driver must take manual control / 1000 km
- Use of automated driving functions (% of km within ODD)
- Comprehensibility of user interface, subjective scale

In mixed traffic situations, the following were highlighted important, too:

- Inappropriate use of automated driving functions in lower automation levels i.e. driver not monitoring the environment and traffic, even if he is supposed to do so (number of events per 100 km)

The actual use of the AD functions is very important to be included in impact evaluation. Even if we assume a certain penetration level for automated vehicles in the fleet, we cannot assume the usage of the automated driving functions being 100% of the time or distance for those vehicles.

On one hand, use of automated driving functions can be approached by careful analysis of ODDs - and only include impacts on those parts of the network (and those environmental conditions) within each ODD. On the other hand, if the user has the option of selecting whether to activate automated driving functions within ODD, this is an additional issue to be taken into account, and not just assuming 100% usage within ODD. These will be further elaborated in chapter 5.4.

Safety

Safety is typically measured as a number of fatalities, injuries, or property damage for vehicle occupants or other road users. Other road users may include pedestrians, bicyclists, slow-moving vehicles, construction workers, and first respondents. The following KPIs were rated as most important ones (Innamaa & Kuisma, 2018).

- Number of crashes (distinguishing property damage, and crashes with injuries and fatalities) in total, and per 100 million km
- Numbers of conflicts encountered where time-to-collision (TTC) is less than a pre-determined threshold / 100 million km
- Number of instances with hard braking (high deceleration) / 1000 km

In addition, the number of take-overs was rated high in importance, but it is not as unambiguous KPI as the previously listed. Especially in L3 and L4 the take-overs may and will happen, but some of them may be driver initiated, and some of them expected and planned, when approaching the end of ODD. Hence, more elaboration is needed for this KPI, and potentially more accurate KPIs would be e.g. “unplanned take-over per driven distance” or if taking the position of the driver “unexpected take-overs per driven distance”.

Energy and environment

This category includes both the energy consumption of the vehicle through a driving cycle, and tailpipe emissions of pollutants including greenhouse gases. The direct energy/emissions impacts come from the change in the driving cycle. It is important to notice that changes in vehicle propulsion (e.g. electric vehicles) may also have a significant effect on tailpipe emissions. The following KPIs were rated most important (Innamaa & Kuisma, 2018):

- Energy consumption of a vehicle (liters/100 km or miles per gallon or electric equivalent)
- Tailpipe carbon dioxide (CO_2) emissions in total per year and per vehicle-km or mile
- Tailpipe criteria pollutant emissions (NO_X, CO, PM10, PM2.5, VOC) in total per year and per vehicle-km or mile.

Automation may have effect on the above mentioned by speed selection, speed variance, and other driving style factors. Additionally, platooning of heavy vehicles is expected to have great impact on energy consumption and emissions. Note that noise was not listed as a KPI in the original work of CARTRE or Trilateral WG. It was, however, added later, as shown in Figure 3.

Personal mobility

Personal mobility is mobility from individual user's point of view, and it includes journey quality (comfort, use of in-vehicle time), travel cost, and whether the option is overall available for someone. It also includes equity and accessibility considerations. The following KPIs were selected as the most important ones overall (Innamaa & Kuisma, 2018):

- Mean distance travelled per day
- Total time spent travelling per day per person
- Type and duration of in-vehicle activities when not operating the vehicle (high automation levels)
- User perception of travelling quality & User perception of travelling reliability

Travel behavior

A traveler may change his/her travel behavior due to automated transport options. There may be more or fewer trips. In addition, modes, routes and destinations may change. Especially the high level of automation is expected to have significant effect on personal mobility and travel behavior. The following KPIs were rated as most important ones overall (Innamaa & Kuisma, 2018):

- Share of transport modes (modal split) per week (based on the total number of trips)
- Number and type of trips per week (in total and per inhabitant)
- Total duration of trips per week by mode (in total and per inhabitant)
- Network-level journey time by mode per week.

Network efficiency

Network efficiency refers to lane, link or intersection capacity and throughput in a selected network level, e.g. regional. It also refers to travel time and reliability of travel time. The following KPIs were rated highest (Innamaa & Kuisma, 2018):

- Throughput, i.e. number of vehicles per hour through a particular road section or intersection approach, normalized to number of lanes and proportion of green time (if relevant)
- Maximum road capacity (for a given road section)
- Road capacity at design speed (for a given road section).

These KPIs are of particular interest for MANTRA as they touch the core business of NRAs and hence the objectives of the MANTRA project directly.

Asset management

Asset management refers to management of physical and digital infrastructure for road transport. The following KPIs were selected as the most important ones (Innamaa & Kuisma, 2018):

- Availability and coverage of V2I infrastructure for automation
- Frequency of pothole occurrence (number of potholes per 100 km), In MANTRA it is proposed to widen this KPI to "severe road damages on the main carriageway" rather than limit it to potholes only

- Use of hard shoulder (for hard-shoulder running or as an emergency stop area for automated vehicles)

In addition to the above mentioned, road markings and their visibility is seen as important and may differ within/beyond ODD stretches of the roads.

The focus of the Trilateral group's KPI survey (Innamaa & Kuisma, 2018) was the users perspective rather than the road operator perspective which becomes particularly clear in the category Asset management. Therefore the selection within the categorie Asset management, which is key to NRAs, needs to be considered with caution and looked into with more detail. From the perspective of NRAs critical KPIs to be added should be, at least:

- Pavement deterioration (rutting measurement results in mm each year)
- Road marking renewal cycles (average renewal period following ODD requirements for retroreflectivity and luminance)
- Winter maintenance (necessary maximum duration for clearing of roads)
- Required satellite positioning land stations (max. distance between them in m)
- Required safe harbours and emergency lanes (max. distance between them in m)

In addition KPIs of traditional road asset management can still be relevant when evaluating impacts of AVs.

Costs

Costs typically include capital, maintenance and operating costs. The most important KPIs for automated road transport overall were the following (Innamaa & Kuisma, 2018):

- Capital cost per vehicle for the deployed system (infrastructure, monetary value)
- Cost of purchased automated vehicle (market price, monetary value)
- Operating costs for the deployed system (per vehicle-hour or per vehicle-km, monetary value)

For the higher level of automation (L4 - L5) the following costs were the most important ones (Innamaa & Kuisma, 2018):

- Cost per trip (for user, monetary value)
- Operation and maintenance cost for digital infrastructure (per road km, monetary value)
- Investment cost for connectivity network (per road km, monetary value)

In addition to the ones selected by Innamaa & Kuisma (2018), at least the following costs are important from MANTRA perspective:

- Cost for infrastructure renewal (if e.g. extra lanes, geofencing, safe harbours, etc. is required for automated vehicles to be able to operate on the road).
- Cost of additional maintenance (mentioned also under asset management above)

Public health

Automation may also impact public health (physical and mental) of individuals and entire communities via safety, air pollution, amount of walking and biking, as well as access to the needed destinations, such as medical care, employment, education, recreation and services. The following KPIs were selected to be the most important ones (Innamaa & Kuisma, 2018):

- Modal share (%) and total mileage travelled (km) by active modes of transportation
- Number of (traffic related) fatalities and injuries per year per million inhabitants
- Proportion of people with improved access to health services.

As for the cost KPIs, public health part also had very few respondents, and the results should hence be taken as indicative.

Land use

Automation may affect the use of land for transport functions. Longer-term land-use changes may include community planning. The most important KPIs for land use were the following (Innamaa & Kuisma, 2018):

- Number of parking slots
- Density of housing
- Location of parking.

In addition, at higher automation levels, especially for robo-taxis the passenger pick-up and drop-of locations and accessibility to those locations are essential.

Economic impacts

Improved safety, use of travel time, freight movement, travel options, public health, land use and effects of changes emissions will have longer-term economic impacts. Automation may also have substantial impact on labor markets and industries. For economic impacts, the following KPIs were rated as most important ones for both overall, and for higher automation levels L4 - L5 (Innamaa & Kuisma, 2018):

- Work time gained due to ability to multitask while travelling (hours per year, overall and per capita; monetary value)
- Socio-economic cost benefit ratio
- Work time lost from traffic crashes (hours per year, overall and per capita; monetary value).

It is good to notice that the participants of the survey were free to select what kind of vehicles they are considering when answering. 49% of the respondents selected passenger car, 4% automated shuttle bus/pod, 4% automated truck and 42% mixed traffic, which included also vulnerable road users.

In addition, the participants were asked to select themselves the SAE level they are considering when selecting the most important KPIs ; 22% selected level “assist”, i.e. level 1 - 2, 29% SAE 3 and 49% SAE 4 - 5. (Innamaa & Kuisma, 2018). If there were remarkable differences between the lower and higher level of automation and related KPIs, those are specifically mentioned in the text above. Additionally, a few KPIs highly relevant to MANTRA work and NRAs are added and specifically highlighted.

Within the CARTRE project (Rämä & Kuisma, 2018) a comprehensive list of KPIs was defined based on the work of the Trilateral ART Working Group. The impact areas and the KPIs within each area are summarized in Table 1.

Table 1. Impact areas and KPIs from CARTRE project (Rämä & Kuisma, 2018).

Impact area	KPIs	
Use & acceptance	• Use of automated driving functions • Requirement of attention and concentration (for driving) • General feeling/acceptance of general public • Trust (for CAD users) • Perception of reliability • Perceived usefulness	• Perceived comfort • Feeling of safety (from the perspective of vehicle users) • Feeling of control of the overall situation (from the perspective of vehicle user) • Intended use
Driver behavior	• Maximum speed v95 • Average speed • Eco-driving • Unnecessary decelerations/low speed due to VRU	• Time headway • Post encroachment time (PET) • Adaptability to traffic conditions • Reaction time.
Mobility & travel behavior	• Number of trips • Total travel time • Total kilometres travelled • Share of each transport mode (car) • Share of each transport mode (public transport) • Share of each transport mode (bicycle)	• Travelling on peak hours (timing) • Travelling reliability • Travelling comfort • Accessibility of lower density areas.
Network efficiency	• Road capacity • Total or average travel • time per road-km	• Intersection capacity
Energy and environment	• Energy savings due to reduced air resistance	• Energy use for in-car IT technology
Public health and safety	• Total mileage travelled by active modes of transportation (walking and bicycle) • Proportion of people with improved access to health services • Improved access to recreation and other services	• Social isolation • Number of fatalities • Number of injuries
Land use	• Underground parking space in city centre areas • Street parking space in city centre areas	• Location of employment (distance from city centre) • Number of lanes
Economic analysis	• Growth of the automotive industry (manufacturing) • Growth of transport services sector • New established businesses	• Total factor productivity / multi-factor productivity estimates • Several additional costs and investments related KPIs

2.3.2 Selected MANTRA KPIs

The selection of the KPIs for MANTRA work and for this deliverable is a subset of the comprehensive list of KPIs defined by the Trilateral WG and CARTRE, while considering the importance of the KPIs to road operators and their relevance for the following work that would involve traffic simulation analysis. Namely, we have selected those KPIs that could be assessed with simulation, or could be useful as input to simulation (Table 2).

Table 2. Selected KPIs for MANTRA work.

Impact area	KPIs	
Mobility and travel behaviour	• Number of trips • Value of travel time • Total kilometers travelled • Share of car and public transport	• Travelling on peak hour (timing) • Travelling reliability • Travelling comfort • Accessibility
Driver behavior and traffic flow	• Driving speed and speed variability • Time headway • Capacity	• Traffic stability • Travel time
Traffic safety	• Number of injuries • Number of fatalities • Number and severity of conflicts	• Surrogate safety measures • User acceptance
Energy and environment	• Energy • Carbon	• Noise

All the impact areas and KPIs in Table 2 will be further elaborated in the Chapters 3 - 7. The futher work in MANTRA will target the KPIs most relevant to NRAs policy targets. These will be reported later in MANTRA deliverable D3.2.

3 Impacts of connected and automated driving on Mobility & Travel Behaviour

Even if there is a lot of work done in defining the impact areas, impact paths and key performance indicators (Chapter 2) for automated driving, lot of uncertainties still remain. In the following chapters, the potential impacts on the selected impact areas relevant to MANTRA are discussed in detail. It is important to keep in mind, that most of the impacts listed and discussed in the following sections are based on either simulations, expert analysis, or field tests of lower automation levels (i.e. driver assistance systems). The results presented below are based on carefully selected set of reviewed literature in the area. The authors, however, recognize the need to update this knowledge when real-word evaluations of higher automation levels become available.

It must be noted that there are large uncertainties in the potential impacts of connected and automated driving, which does not depend on the technology only, rather on how the technology is adopted for various purposes. Especially, there is little understanding on whether these vehicles will be owned or leased by users following the current model, or whether automated mobility services will make ownership obsolete, as claimed in some non-academic literature. As Wadud et al. (2016) suggest the share of ownership vs. mobility services in an automated future is possibly the largest uncertainty in impact modelling, as these affect nearly all of the impacts mentioned in this section.

3.1 Value of travel time

Travel time is traditionally counted as a ‘waste’ of time or cost to the traveller during the traveller decision-making process and in travel demand modelling. The wasted value of time (Value of Time) or the Value of Travel Time Saved has two important functions in transport modelling and appraisal. Firstly, the choice of modes depends on the relative costs of different modes, including this cost of wasted time; and secondly appraisal of transport project employs this number for benefit calculations given the reduction of travel time is often the aim of major transport projects.

One of the biggest advantages of automated vehicles is the potential for relieving the driver of driving duties and using that time for other worthwhile uses. Any such beneficial use of time has substantial implications for our travel decisions and travel demand modelling through changes in the Value of Travel Time Saved. Citing the literature on multitasking, especially in public transport modes, several authors have suggested that the Value of Time or Value of Travel Time Saved will be smaller in an autonomous vehicle, compared to that for a driver in a manually driven vehicle (Lyons and Wardman 2017, Wadud et al. 2016). The numerical value of the Value of Travel Time Saved thus sits at the centre of the debate on the travel demand impacts of autonomous vehicles and the modelling of it.

Time savings are typically one of the dominating factors in cost–benefit analyses of transport-related investments. In a longer term assessment perspective, with already some penetration of automated vehicles and the related time savings already reaped, one of the most important benefit drivers will likely diminish as the unit cost of an hour spent in traffic shall dramatically decrease (Geissler et. al, 2016).

It is accepted that the Value of Travel Time Saved depends on the ability to engage in other activities during travelling, although a direct relationship with Value of Travel Time Saved and activities has not been established so far. In the context of automated vehicles, there are three – somewhat separate – strands of literature that deal with the travel time use issue. The first, followed by early researchers like Wadud et al. (2016), Brown et al. (2014) simply borrows Value of Travel Time Saved from other studies that might be assumed to mimic the behaviour in an automated car, such as the value of time of a car passenger.

The second, followed by early researchers such Kyriakidis et al. (2015), Schoettle and Sivak (2014), Cyganski et al. (2015), and Bansal and Kockelman (2017) investigate how people might spend their time in autonomous vehicles. These studies use questionnaire surveys asking the respondents about their intended activities. Recently, Wadud and Huda (2019) conducted a stated intention survey similar to previous studies, but substantiate their results by asking chauffeur-driven car users about their time use now, assuming the time use behaviour in chauffeur-driven cars mimic that in autonomous vehicles. The authors find a strong correlation between stated intention about activities to be done in automated vehicles and current activities done in chauffeur-driven cars. Wadud and Huda (2019) also correlates the perceived usefulness of travel time in autonomous vehicles to the activities that people may engage in.

The third stream of literature estimates the Value of Travel Time Saved in autonomous vehicles directly, generally using choice experiments. Despite the importance of this parameter, there are only a few such studies, which are summarized in Table 1. Among these, Steck et al. (2018) estimated Value of Travel Time Saved for commute trips in Germany and find support in favour of a reduced Value of Travel Time Saved in automated vehicles. The authors find that the Value of Travel Time Saved in private automated vehicles is 31% and in exclusive-use on-demand, automated vehicles are 10% smaller than that in manually driven vehicles. Correia et al. (2019) also found similar results in the Netherlands – a 26% reduction of Value of Travel Time Saved for commute trips in an automated vehicle with an interior layout of a mobile workspace. They also found that a leisure-oriented design does not reduce the value of travel time. In Switzerland, Horl et al. (2018) Switzerland report a reduction of Value of Travel Time Saved of 31% for exclusive use on-demand automated vehicles, which is substantially larger than Steck et al. (2018). Although Steck et al. (2018) could not find any substantial differences between Value of Travel Time Saved in exclusive-use and shared-use automated on-demand mobility services, Horl et al. (2018) indeed report a smaller reduction in the shared-use case, which is expected.

A factor affecting the possibility of work or leisure activities in a highly automated vehicle is the proneness of vehicle occupants to motion sickness. For example, Wadud and Huda (2019) show that people prone to motion sickness engage in a different type of activities (more thinking and planning than working or studying), which may affect the value of time differently too. Patented measures for motion sickness in automated vehicles have already been developed (Sivak & Schoettle 2018).

The Value of Travel Time Saved in the shared-use case is especially important for mode choice, since it has a role in the choice between owning an automated vehicle and using an automated on-demand mobility service, with knock on effects on travel demand. Interestingly, Gao et al. (2019) find that the Value of Travel Time Saved in automated ride hailing services is higher than the Value of Travel Time Saved in a manually driven private vehicle; this discrepancy is a result of lack of trust in automated vehicles, which was not separated in the study. In summary, although some of the numbers may vary between these studies from three different countries, the qualitative conclusion from all these studies is the same: the Value of Travel Time Saved in automated vehicles is substantially lower compared to that for the current car drivers. For mobility services the reduction should not be as large as for the privately owned vehicles (table 3).

Table 3. Value of time in automated vehicles

	Country	Trip type	value of time manual car	value of time autonomous private	value of time autonomous exclusive-use service	value of time autonomous shared-use service
Steck et al. (2018)	Germany	Commute	€6.60	€4.59	€5.94	-
Correia et al. (2019)	Netherlands	Commute	€7.47	-	€5.50	-

Horl et al. (2018)	Switzerland	-	CHF9.57	-	CHF6.63	CHF7.90
Gao et al. (2019)	USA	-	USD24.47		USD28.03	

3.2 Number of trips

While there are a substantial number of studies that model the effects of vehicle automation on total travel demand, studies that focus on the number of trips are few. Like the Value of Travel Time above, the effects on the number of trips also depend on whether automated vehicles will be owned or used to provide mobility services and their relative share.

Wadud et al. (2016) suggest that there are two types of effects on car trips in an owned-automated vehicle future. Firstly, there could be new car trips from the elderly or the disabled, who are resigned to a reduced-mobility lifestyle now; this is supported by Harper et al. (2016) also. Truong et al. (2018) extend this to include the younger age group (under driving-license age) too. Secondly, there could be larger number of trips from existing car users due to the reduced Value of Travel Time Saved, or from a modal shift toward automated cars. Although a number of researchers focus on the modal shift and increased travel demand (e.g. Wadud et al. (2016), Harper et al. (2016), Milakis et al. (2017), Auld et al. (2018)), often do not provide separate estimates for trips and instead focus on Vehicle Mileage Travelled. Schoettle and Sivak (2015) analyse the time synchronization of households' vehicle trips in the US and find that the vehicle ownership could go down by 43%, with concomitant increase in the rise of empty trips to allow the same trips to take place. Some of the estimates for trips are presented in Table 2, which clearly show the potential to increase the car trips. However, none of these estimates are predictions or forecast, rather than the result of what-if scenarios, e.g. what if all the elderly started to travel as much as the middle-aged group, or what if the household trips can be made by a fewer number of cars.

The net effects of on-demand mobility services, often termed as shared autonomous vehicles collectively, on the number of trips remain uncertain. Nearly every exclusive-use mobility service vehicle (similar to Uber or taxis) is certain to have empty trips between dropping off a passenger and picking up the next one. While this may increase (if the services are cheaper than the current total costs of ownership and use of private vehicles) or not (if the marginal cost nature of the mobility-services become dominant) the total passenger trips in autonomous mobility vehicles, it will almost certainly increase total vehicle trips due to the empty trips (and vehicle miles, Childress et al. 2015, Horl et al. 2016, ITF 2015). On the other hand, shared-use of mobility services, could reduce the number of total car trips since one vehicle trip can replace several car trips. Once again, estimates for the reduction in the number of trips are scarce.

Given the assumptions in the underlying models and the uncertainty in the share between ownership and automated on-demand mobility services in the future, the potential effects of automation on the number of car trips have a large uncertainty, however automation would almost certainly increase the number of car trips if "ride-shared" on-demand mobility services are not realized on a mass scale in future (Table 4).

Table 4. Effect of vehicle automation on total trips

	Country	Timeline	Trip type	Increase in number of trips	Key assumptions
Childress et al. (2015)	Puget Sound, USA		Total person trips	0%-4.9%	Different scenarios
Wadud et al. (2016)	USA		Total car trips	2%-10%	New trips by the elderly and the disabled
Kroger et al. (2018)	Germany	2035	Total car trips	2.2%-8.3%	Owned vehicle scenario
Kroger et al. (2018)	USA	2035	Total car trips	3.1%-7%	
Truong et al. (2018)	Victoria, Australia		Total car trips	7.31%	New trips by elderly, young (follows Wadud et al. 2016) + mode switch

3.3 Total kilometres travelled

The distances that will be travelled as automation penetrates the vehicle fleet will depend naturally on the type of usage of these vehicles: public transport or private transport. It is argued that private automation will be associated with longer distances because with a lower value of travel time (Correia et al., 2019) the disutility of traveling will be lower for the same travel distance (Wadud et al., 2016).

That change of utility on the short term may mean longer routes but also more time spent on congestion as passengers will not feel their time inside the vehicle (Correia et al., 2015; de Almeida Correia and van Arem, 2016; Milakis et al., 2016). On the longer term a lower disutility of traveling (i.e. possibility to utilize the time in transit) may mean a willingness to move farther away from work locations (typically in the city center) which will then lead to longer commute distance trips which will then be difficult to avoid once the spatial structure of urbanized regions is allowed to change (Correia et al., 2016; Wadud et al., 2016).

Other researchers argue that there could be an inverse movement back to living in city centres as these become more attractive due to the reallocation of public space from parking to other more attractive uses such as wider sidewalks or parks (Hollestelle, 2017). What effect will dominate the other is still to be seen and again it depends on what technology will allow to do inside an AV as well as human preferences of traveling and living.

Regarding public transport, the risk is more focused on the empty kilometres that may be generated by shared vehicle systems (Martinez et al., 2014). Results in the literature point for the need of fewer vehicles to satisfy the same demand once vehicles become level 4 or level 5 and start to be incorporated in taxi and Uber-like systems (Fagnant et al., 2015; International Transport Forum, 2015), however the other side of the coin is the need to relocate such vehicles as they move to pick-up clients in other parts of the network (Jorge et al., 2014; Martínez et al., 2017). Current Uber systems are already creating more traffic congestion due to the added empty kilometres but also to the added demand of people who used to use public transport and who find it much more comfortable now to just request for a ride (Growth et al., 2017; Schaller, 2018). Arbib and Seba (2017) suggest that Vehicle Mileage Travelled (VMT) in the USA could increase by 50% as a result of automated mobility services.

3.4 Share of car & public transport

Mode choice depends on many factors including trip distance and travel time, trip motive, available transport alternatives and travel costs. It is complex to assess mode choice before new alternatives are introduced into the market, which is the case with automated vehicles. Many times what researchers have available are stated preference surveys whereby people state what they would do if they were before a certain situation. Several of these experiments have been done in recent years and they help understand the impact of connected and automated vehicles on the shares of car and public transport demand (Correia et al., 2019; Yap et al., 2015, 2016).

Vehicle automation may come in essentially two forms: private cars or public transport systems. Researchers and practitioners have been discussing the pros and cons of both uses of vehicle automation and certainly the future can be a mix of both uses. Regarding the latter there are already many pilot systems under operation in Europe and the United States with pod like buses (Alessandrini, 2017; Alessandrini et al., 2015). In the Netherlands a level 4 system running in its own segregate path, the Parkshuttle bus connection, has been in operation for two decades now.

In public transport usage of vehicle automation it is foreseen that with the cheaper operation costs (no drivers needed) and flexibility to operate the system (vehicles can be sent anywhere at any time to other areas of operation) it will be possible to offer a better quality of service to the population (Winter et al., 2018, 2016). This can be done with smaller vehicles (cars in car sharing systems) (Liang et al., 2018) or buses (in a more traditional public transport approach). These systems are expected to be used essentially in urbanized regions and one of the most useful usages will be as last/first mile transport. For long distance intercity transport, still high capacity public transport systems such as rail continue to be seen as the best option to transport many people in the most sustainable way. The role of robotaxis in connecting different cities thus using the motorway network is difficult to assess, as this will represent a management challenge: moving vehicles from one city to another may represent great vehicle stock imbalance, which will lead to a high price to be paid by the passengers. These robotaxis can be driven in any optimal way desired by their operators but there could also be the case of, if imposed by law, a specific behaviour being imposed by public authorities for a certain part of the network.

Increased uptake of automated vehicle sharing and ride sharing models, may reduce total vehicle ownership. MaaS is likely to play a key role in encouraging the shared ownership model of automated vehicles (Johnson & Rowland 2018). This is promoted by the lower price of shared mobility for the user. Buckley (2018) estimates that vehicle cost per mile or km will be less than half the current prices of ride-hailing services such as Uber and Lyft. Although Bosch et al. (2018) are not as optimistic for Switzerland, Wadud (2017) also suggest substantial reduction in the costs of providing mobility services on a life cycle basis. On the basis of costs of ownership and use, including the costs of time, Wadud and Mattiolli (2019) suggest that between 33% to 45% of current vehicle users will find automated mobility services to be the cheaper option in future, while the rest will find ownership to be more affordable.

A study for the Boston area (WEF 2018) predicts a clear shift to mobility-on-demand for both automated and traditional vehicles, which will account for nearly 30% of all trips in the Greater Boston area and 40% of trips within city limits in the future. Driving this shift are the cost-competitive nature of robo-taxis and robo-shuttles – especially on shorter trips – and the added convenience and comfort compared with mass transit. In suburban and other areas outside the city proper, that mobility-on-demand will mainly replace personal-car usage. In urban areas, it will replace the use of both personal cars and mass transit, to equal degrees. Shared automated vehicles will reduce the number of vehicles on the streets by 15% while the total number of miles travelled will increase by 16% (WEF 2018).

An increase in private vehicle modal share is also possible, as the option of travelling in an automated private vehicle becomes more attractive than using alternative public transport or walking/cycling options (Cavoli et al., 2017, Johnson & Rowland 2018). Automated vehicles even when shared can compete with public transport and active transport modes (walking and bicycling) leading to better individual mobility but less transport system efficiency (UITP 2017).

Private cars in the future may at some point in time be fully automated everywhere and in all conditions i.e. without any ODD limitations (= level 5 automation) and in that case, we are talking about vehicles that can become almost like private living rooms where people would be able to have leisure time or even work. This can shift demand toward private cars, if prices are competitive, with the difference that with an improved experience people are willing to stay longer in their vehicles which can add to the traffic congestion as an occupant does not have an incentive to change his/her behaviour. The driving behaviour of the vehicle can be controlled in terms of route and lower level control (trajectory) which can be beneficial to the road operators; however, it is not clear what type of control will be possible to centralize or to give to the vehicle itself. In a very futuristic scenario with only automated vehicles, the control over those vehicles could be perfectly centralized to achieve what is called the system optimal equilibrium whereby travel time/costs are minimized.

In summary, it is impossible to estimate yet the demand that both modes (private or public) will have. The demand is depending greatly on what the technology will allow the occupants to do in a car, the price of the vehicles, shared mobility market take-up (Nieuwenhuijsen et al., 2018) and whatever policies authorities will implement in the future to achieve desired outcome on the mobility system locally and on a national level (Milakis et al., 2016).

3.5 Travelling on peak hour (timing)

It is expected that autonomous cars increase the road capacity, possibly resulting in a higher traffic demand during peak hour without increase of travel time. On the other hand, it is expected that (work-related) activities performed during a trip in an autonomous vehicle might result in a better spread of peak travels (i.e., leaving at a different moment in time while working the same number of hours), and thereby reducing the number of trips performed during peak hour.

Nearly 50% of drivers intend to perform work-related activities such as phoning or mailing while driving a fully automated vehicle according to a large survey by Kyriakidis (2015). Contrary, a survey on the public opinion about self-driving vehicles by Schoettle (2014) showed that only 4.9% of the respondents would perform work-related activities during driving. Overall, it may be hard to imagine this situation when asked in the surveys, and additionally, the survey sample representativeness explains a lot in this case; in Kyriakidis study 5000 respondends were from 109 different countries, and is is hence expected that the sample wasn’t representative in any of those countries.

However, it is difficult to check whether the intention of drivers is identical to their actual behaviour due to the non-existence of autonomous vehicle on the highways. One might say that activities performed during a train trip are an indicator for activities that will be performed in an autonomous private vehicle. Therefore, Cyganski (2015) also asked for activities currently performed during train trips. Figure 8 shows that working while traveling by train only plays a minor role. This is explained by stating that both people do not want to spend their time working while traveling, but also that are various jobs, which cannot be executed while en route. In the same questionnaire, a question on benefits of automated vehicles was asked, showing that people merely want to perform leisure activities. 30% of the respondents indicated that they would (sometimes) perform work-related activities, identical to the activities performed in the train.

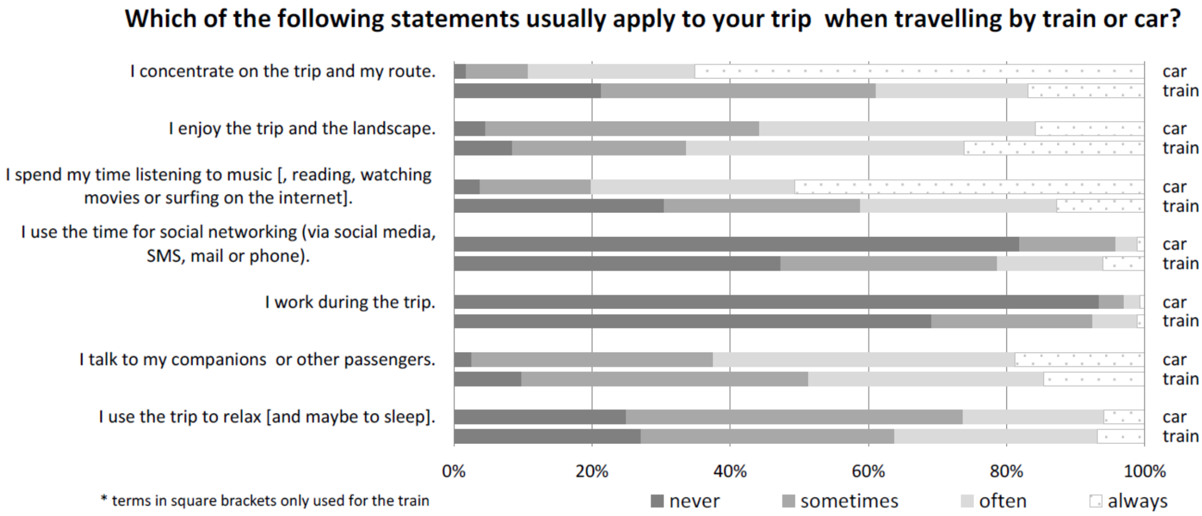

Figure 3. Usual time use when traveling by car (N=824) and train (N=1.000) (Cyganski, 2015)

Another comparison with a current existing travel mode was made by Wadud and Huda (2019): he showed that there exists a high correlation with intended activities in fully automated vehicles and current performed activities in chauffeur-driven cars. He also showed different behaviour for both the outbound (e.g., morning peak) and inbound (e.g., evening peak) travels. Whereas working is the most popular activities on the first, people like to relax during their return trip.

It can be concluded that the number of trips during peak hour will not decrease remarkably after the first introduction of the autonomous car. Some people will perform work-related activities, probably to start later or be home earlier. However, most will just use the time to 'switch off' and relax. Only the effect of increased capacity might result in a busier peak period in terms of number of vehicles, but this aspect remains unclear and will not appear with low penetration rates.

3.6 Travelling reliability

Travel reliability here is seen from a broader perspective since most often the term is associated to travel time reliability. This is for sure a very important component of reliability but not the only one. Reliability is considered to be associated with certainty in being able to do a trip at the expected travel time. Thus, it surely includes the travel time but also the existence or not of a certain transport system to serve transport needs.

Automated vehicles, if used as public transport, will bring the advantage that they will be able to react fast and act in a demand-responsive public transport systems reaching virtually any point of a city or country. This flexibility may increase the response of the transport system, therefore, providing a more reliable service to the clients (Winter et al., 2018b). When operating in scheduled based systems the difference to today's public transport service should not be very significant in that respect since today's transit services are quite optimized and the drivers can catch up very fast to maintain a proper schedule.

When looking at a generalized use of automated vehicles in the future (public and private) and the driving of such cars on the road, there will be an effect on the reliability of the travel times on the network as a result of the proven stability that they will have, especially if these vehicles are connected (Wang et al., 2017). That stability is essential to decrease the variance of travel times on the road, therefore, increasing their predictability. Not to be confused with travel time since this depends on traffic congestion and therefore on the total demand that will exist in the future. "Drivers care not only about the amount and value of time per trip, but also the value of reliability, that is how likely is it that a trip of uncertain travel time can be completed within some expected time costs of congestion" (Rubin, 2016).

One of the causes for travel time instability and variability are for sure the incidents and accidents that happen on the network (Kwon et al., 2011; Tu et al., 2008). Departing from a point where these incidents and accidents will decrease as a result of a lower probability of human error then we can expect that the reliability would be increasing in the future. If on the other hand, possibly only during a transition period, there are failures of the AVs under some conditions, for example extreme weather, there could be the case where the reliability would decrease during some time before it could increase taking advantage of the full capabilities of the CAVs.

3.7 Travelling comfort

Journey or travel comfort relates to a number of underlying factors, mental, emotional and physical. High mental and emotional comfort engenders a sense of mental well-being and thus is related to the desire to minimise uncertainty and stress. In the context of automated driving, such stress and anxiety can be linked to trust in system operation (Carsten and Martens, 2019). A contribution of road authorities to such comfort is related to the provision of high quality journeys on the network, free from incidents and with assured journey times. When environmental condition deteriorate or are about to deteriorate, then good prediction of future conditions and high-quality services in terms of e.g. ice-prevention, snow removal and incident management would help to mitigate journey stress. Here users of automated vehicles will benefit from road operations in the same way as users of conventional vehicles, but users of AVs may have higher expectations than conventional drivers, particularly if they are paying for services. There is a clear role for connectivity here, in terms of providing high quality information and hence reassurance to users of AVs.

Another aspect of comfort relates to physical well-being. One factor in many studies of travel mode choice is seat comfort (see e.g. Hagen and Bron, 2014). There is no reason to believe that automation would have a major effect on this aspect of comfort, although by freeing the driver from the necessity of being coupled to the vehicle controls, an ADS may somewhat reduce limb and back strain. On the other hand, there is every reason to believe that automation might affect another aspect of comfort (or rather discomfort), namely the potential for motion sickness. Passengers in a vehicle are more liable than a driver to experience motion sickness (Rolnick and Lubow, 1991), and engagement in screen-related tasks or in reading while being driven exacerbates motions sickness (Turner, 2010).

Motion sickness is related to the degree of horizontal and lateral acceleration of the vehicle (Turner and Griffin, 1999) and hence to vehicle speed and vehicle aggression in manoeuvring. Motion sickness can also pose a threat to the performance of the user when requested to take back vehicle control. Diels and Bos (2016) report that this does not necessarily have to refer to the extreme of a user vomiting at the time of a request or an emergency situation, but also to more subtle effects such as reduced situation awareness and increased response times.

Smooth driving will reduce the incidence motion sickness, and the designers of ADS can be expected to be aware of this linkage. One can anticipate, therefore, that AVs will tend to drive at longer following distances so as to permit less rapid deceleration when the preceding vehicles slow down, to negotiate sharp curves at lower speeds and to be less prone to undertake rapid manoeuvres such as abrupt lane changes. Such smoother driving may reduce incidents, but there might also be an impact in the reduction of capacity.

3.8 Accessibility

Automation can affect accessibility by altering its all four components (Geurs and van Wee 2004) – land use, transportation, temporal and individual – in different ways. Firstly, by reducing the wasted value of travel time, automation reduces the total costs of travelling by private cars, affecting the transportation component. As such, people could accepts jobs, shopping, leisure or residential locations farther from they are used to now. These have direct implications on land use in the long term. Automation could increase urban sprawl or even exurbanisation toward rural areas, subject to land use regulations – affecting the land use (Milakis et al. 2017). Increased demand, however, could increase congestion and thus have an adverse effect in accessibility, too.

Secondly, fully automated vehicles could perform some activities on their own, e.g. picking up shopping, or dropping off children at school. This allows overcoming the temporal and individual constraints (e.g. shop closing hours, competition between job and children's activities) to improve accessibility (Milakis et al. 2017).

Thirdly, on-demand mobility services are expected to become substantially cheaper in a driverless environment than they are now. As such, car-based mobility services are expected to become more affordable to users who cannot afford a car now. This also has large implications for access to job or leisure opportunities that would otherwise have been difficult to avail without owning a car. Automated dynamic ridesharing could also serve low-density regions where public transport like buses are not viable, further improving the accessibility. A shift to shared mobility could also increase urban density by removing the need for the parking infrastructure and have further land-use implications (Bagloee et al. 2016).

The limited modelling studies so far show substantial improvements in accessibility, the definition of which could vary between studies. The effects on accessibility could also be different depending on geography, current transport offering and socio-economic characteristics. Childress et al. (2015) report an increase in accessibility resulting from an owned automated vehicle future, in the Puget Sound region in the US. Kim et al. (2015) report a 50% increase in accessibility for the entire Atlanta region. Childress et al. (2015) report that accessibility was improved the most in low density urban and remote, rural areas. Meyer et al. (2017) also report an improvement in accessibility in their three scenarios of automation, with well-connected exurban and rural municipalities in Switzerland benefitting the most. These results therefore agree that low-density areas are likely to enjoy the largest improvement in accessibility. All of the accessibility benefits in these modelling exercises result from improving network capacities due to automation; as such, V2X connectivity is vital toward realizing these accessibility benefits.

Childress et al. (2015) and Meyer et al (2017) also include demand increases and still report improvements in accessibility, especially, as long as it does not adversely affect the network performance. Through expert elicitation, Milakis et al. (2018) highlights the uncertainties and elicit three viewpoints: a) accessibility impacts are uncertain due to induced demand nullifying reduced transport costs; b) accessibility will change due to two opposing changes in land use (densification of centres and suburbanization); and c) only a segment of the society could enjoy the benefits of automated vehicles, with significant social equity concerns.

4 Impacts of connected and automated driving on Driver Behaviour & Traffic flow

4.1 Driving speed & speed variability

In automated vehicles, the longitudinal driving behaviour is mainly determined by the ACC or CACC systems. Different manufacturers are developing such systems nowadays, each with its unique specifications (such as the operational design domain and time-headways). Different studies have reached contradicting conclusions regarding the impact of ACC on driving speeds, but rather consistent conclusions with respect to the speed variation. Some of these studies used field operational tests (FOT) (Kessler et al., 2012; Viti, Hoogendoorn, Alkim, & Bootsma, 2008), while others used driving simulators (Hoedemaeker & Brookhuis, 1998; Piccinini, Rodrigues, Leitão, & Simões, 2014), and simulation (Aria, Olstam, & Schwietering, 2016). These impacts were investigated at the individual vehicle level, as well as, at the network level. In the EuroFOT study (Kessler et al., 2012) the Adaptive Cruise Control (ACC) was evaluated in a bundle with the Forward Collision Warning (FCW). Data from passenger cars as well as trucks was gathered for a period of 6 months (three months of baseline and three months of treatment). Figure 4 summarizes the findings regarding the average speeds per road type for passenger cars and trucks separately:

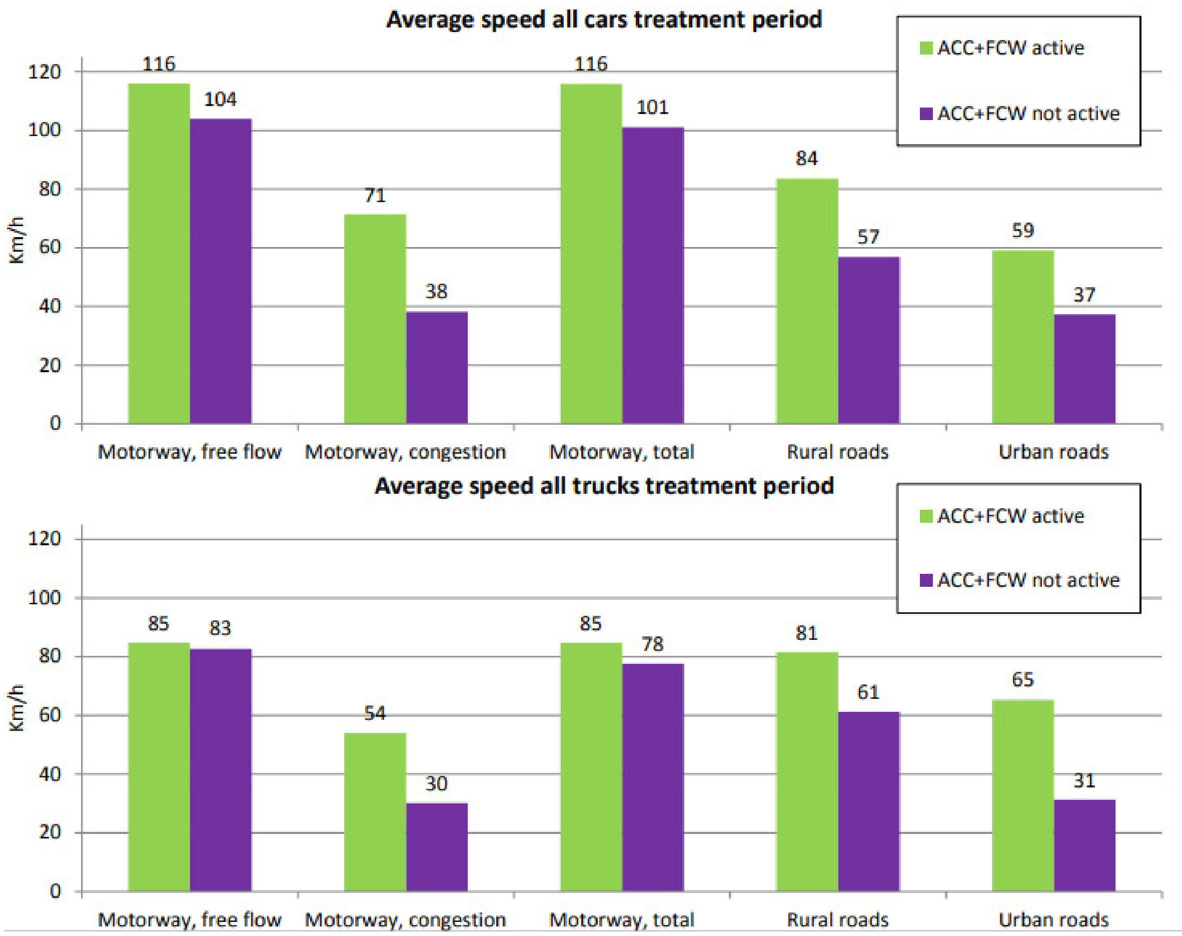

Figure 4. Average speeds per road type within treatment period for passenger cars (top) and trucks (bottom), (Kessler et al., 2012).

As shown in Figure 4 there is a significant increase in the average driving speeds on motorways when using the ACC in combination with FCW systems. A follow up simulation study found that the effect on network speed is similar in size to the effect found in the FOT and has a linear trend with higher penetration levels. The simulations were based on the driving behaviour and system usage observed in the FOT. The effect scales linear with the penetration of equipped vehicles in most situations.

Driving simulator studies (Piccinini et al., 2014; Stanton, Young, & McCaulder, 1997) found that the usage of ACC by both ACC users and regular drivers did not affect the driving speeds significantly compared to manual driving condition, contradicting the findings by other studies who used also the driving simulator (Hoedemaeker & Brookhuis, 1998).

Aria et al. (2016) used VISSIM to investigate two extreme scenarios, 100% conventional vehicles case versus 100% automated vehicles on a segment of an autobahn with discontinuities (on-ramps, off-ramps, and weaving sections). For that purpose, they have adjusted the driver behaviour parameters in the car following and lane changing model. The researchers found that the average travel speed on the autobahn segment in the p.m. peak enhanced from 82.42 km/h in the conventional vehicles scenario to 89.41 km/h in the automated vehicles scenario, which shows 8.48% growth in the average speed in peak hour. The results of standard deviation of speed determine that automated vehicle drive between the predefined ranges of speed, which show a less dispersion around the mean speed in accordance with the findings of previous studies (Viti et al., 2008).

4.2 Time headway

In automated vehicles, the time-headway is based on the ACC or CACC settings, which are never lower than the legally prescribed value. Therefore, it is expected that the time-headways will be larger than those adopted by human drivers who often drive with time-headways lower than the legal prescribed value. This has indeed been shown in the EuroFOT study (Kessler et al., 2012). An increase in the average time-headway of about 16% on motorways was found when using the ACC. Similar results were found in a naturalistic driving study with ACC-equipped vehicles in different traffic states on motorways. With ACC On, average spacing and headways were larger, whereas standard deviations were smaller (Schakel, Gorter, de Winter, & van Arem, 2017). Larger headways are expected to reduce traffic flow capacity, while the reduction in fluctuation of the headway, can reduce events of breakdown, which are inevitable with human driving, and eventually lead to an increase in capacity.

On the other hand, automation in combination with Vehicle-to-Vehicle (V2V) communication offers the possibility of platooning with shorter time headways between vehicles, which can increase the traffic capacity of lanes and thus traffic efficiency (Ntousakis, Nikolos, & Papageorgiou, 2015). Drivers' choices of following distances when driving a vehicle equipped with Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) depends on their level of comfort and acceptance (Nowakowski et al., 2011). It is expected that the CACC will give drivers an enhanced feeling of comfort compared to the ACC. The objective measurements in the study by Nowakowski et al. (2011) show that drivers of the CACC system selected vehicle-following gaps that were approximately half the length of the gaps they selected when driving the ACC system as presented in Figure 5. Furthermore, gender differences can be observed.

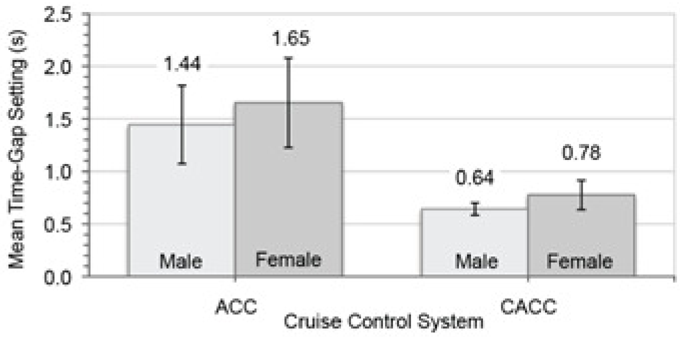

Figure 5. Overall Mean Time-Gap Settings (source: Nowakowski et al. (2011)).

Several driving simulator studies in the literature have found that when drivers of unequipped vehicles drive next to platoon of AVs, they tend to adapt their time headways and imitate the short time headways that AVs keep when driving in a platoon (Gouy, 2013; Gouy, Wiedemann, Stevens, Brunett, & Reed, 2014, (Yang, Farah, Schoenmakers, & Alkim, 2019). Drivers of unequipped vehicles drive with shorter time headways when driving next to equipped vehicles in a platoon maintaining shorter time headways, and sometimes these drivers spend more time under their 'critical' time headway threshold of 1.0 second.

Skottke, Debus, Wang, and Huestegge (2014) focused on the carryover effects of highly automated convoy driving on subsequent manual driving performance and compared their behaviour to a control group who performed only manual driving. The authors conducted a pre–post simulator design to measure the time headway and the standard deviation of the lateral position. They found that the time headway was reduced after leaving the automation mode, which is likely due to sensory and/or cognitive adaptation processes.

4.3 Capacity

Capacity of a road is highly related to the time headway. As shown in Section 4.2, users of ACC tend to keep a larger headway than manually driven vehicles. In accordance to this finding, Bierstedt et al. (FP Think Working Group, 2014) concluded that non-connected autonomous vehicles would indeed degrade highway capacity due to the safety-conscious programming of ACC equipped vehicles. Their simulation suggests that capacity benefits will only occur if 75% of the fleet mix consists of autonomous vehicles – leading to traffic flow benefits of 25-35%. Friedrich's (2016) findings are identical: capacity drops due to a larger time headway of ACC vehicles compared to manually driven. Although commonly a human reaction time of 1.8 seconds is assumed, empirical studies showed that headways of manually driven vehicles on highways are significantly shorter, especially at high traffic volumes (Wagner, 2014).

On the other hand, connectivity brings a lot of benefit. Headways decrease, resulting in an increase in capacity on highways. Shladover (2013) studied the impact of connected vehicles for different market penetration rates using microsimulation. The lane section had a speed limit of 105 km/h and a capacity of 2020 vehicles/hour without considering automated vehicles. They used time gaps as chosen by drivers during a field test with automated vehicles. An increasing market penetration of CACC leads to an increased road capacity – up to 3970 vehicles/hour/lane for a 100% CACC scenario. Combined with ACC vehicles, these only results in slight additional increases in capacity as can be seen in Figure 6.

	Percentage of CACC Vehicles								
Percentage of ACC	10%	20%	30%	40%	50%	60%	70%	80%	90%
10%	2065	2090	2170	2265	2389	2458	2662	2963	3389
20%	2065	2110	2179	2265	2378	2456	2671	2977	0
30%	2077	2127	2179	2269	2384	2487	2710	0	0
40%	2088	2128	2192	2273	2314	2522	0	0	0
50%	2095	2133	2188	2230	2365	0	0	0	0
60%	2101	2138	2136	2231	0	0	0	0	0
70%	2110	2084	2155	0	0	0	0	0	0
80%	2087	2101	0	0	0	0	0	0	0
90%	2068	0	0	0	0	0	0	0	0

Figure 6. Prediction of highway lane capacity (vehicles/hour) of ACC and CACC equipped vehicles using time gaps chosen by drivers in field test (Shladover, Su, & Lu, 2013)

If not only considering straight road sections, but also ramps and weaving sections, the introduction of connected automated driving might result in a decrease in capacity with small penetration rates (Rämä & Kuisma, 2018). This is due to the discontinuities where lane changes take place. Although homogeneous speeds of drivers result in fewer shockwaves, this results in a higher difficulty of performing lane changes. This might cause vehicles being stuck at merging sections, not able to get to the lane where they want to be. Only at higher penetration rates, communication between vehicles result in suitable gaps and an increased road capacity.

Atkins (2016) performed several microsimulation scenarios for testing the impact of autonomous vehicles on delays and congestion in a scenario including on-ramps, off-ramps and weaving sections. He applied several combinations of capability levels: L1 (no automation), L2 (driver remains in control, but vehicles have better throttle control and smoother acceleration behaviour), L3 (vehicle controls longitudinal and lateral behavior as defined by the user, e.g. assertive or cautious behaviour), and L4 (fully automated where the driver has not input and is not necessary). With a penetration rate of 25% autonomous vehicles (20% L2, 5% L3), this resulted in a slight increase in average delay. However, at a 100% scenario (40% L2, 20% L3, 20% L4), a decrease of delay of almost 35% was obtained. Davis (2004) is a bit more optimistic. At a level of 10% ACC vehicles, jams occurred in his simulation model, which consists of a single lane with an on-ramp. At 20%, all congestion was suppressed.

Another study on ACCs with a 25% penetration rate by Kesting et al. (2008) showed that a temporary reduction of the time gap setting to 0.75 seconds around an on-ramp bottleneck is able to fill the capacity gap and significantly reduce congestion compared to a 1.5-second headway.

Simulations including V2V communication were performed by Rios-Torres (2017). They assessed the impact of optimal coordination of CAVs by testing a 0% and 100% CAV scenario. They showed that the total travel time for low traffic flows remains the same – only a bit shorter in the 0% CAVs scenario due to neglecting of speed limits. However, for larger traffic flows the travel time rapidly increases for the baseline scenario. CAVs can contribute significantly to the wide variations in traffic flow and densities leading to congestion and unstable traffic, as can be seen in Figure 7.

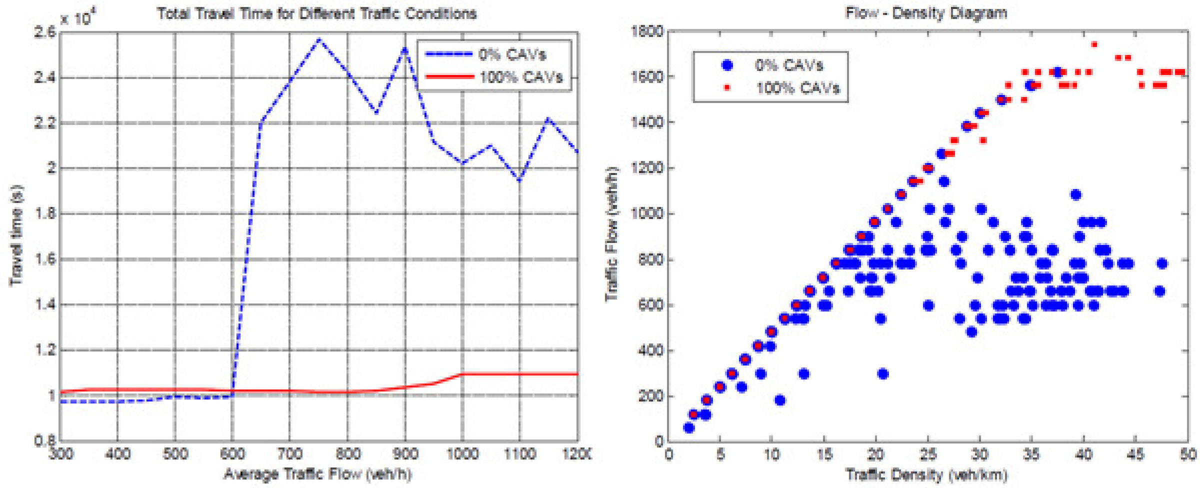

Figure 7. Time-flow and flow-density graphs for a 0% and 100% CAV penetration rate (Rios-Torres & Malikopoulos, 2017)

Makridis et al. (2018) showed that autonomous vehicles result in an increase of congestion due to the inability to predict movements of neighbouring vehicles during lane changes. However, connected autonomous vehicles outperform manual driven vehicles with high penetration rates. Especially during high demand, large decreases in congestion can be observed – identical to the finding of Rios-Torres (2017). With a low penetration rate, there's no vehicle to communicate with, falling back to a non-connected behaviour.

If connected and automated vehicles could utilize narrower lanes, this has potential to increase capacity, but only if all the vehicles are connected and automated. In this hypothetical 100% penetration rate scenario, the current 3+3 lane roads could be deployed to 4+4 lane roads, increasing the capacity accordingly. However, this is currently just a theoretical estimation, and would require all the vehicles on the road to be connected and automated.

4.4 Traffic stability

In the previous paragraph it was concluded that ACC equipped vehicles generally cause additional congestion, whereas CACC reduces the congestion. Likewise, ACC results in less stable traffic, CACC in more stable traffic.

Marsden (2001) performed microsimulation experiments with different ACC penetration rates (0 to 70%). The experiments showed that on a 3 km straight lane stretch, the average journey time increased by increasing number of vehicles equipped with ACC with a gap headway value of 1.5 seconds. Even with a 1.2 seconds gap, average travel times increased – albeit less. By extensively observing the simulation results, they concluded that most ACC equipped vehicles tend to drive on the 3rd lane, due to slow-driving HGV's on the 1st lane and a higher amount of lane changing vehicles on the 2nd lane. However, they noticed that the gap between ACC equipped vehicles forming platoons in lane 3 is large enough for vehicles from lane 2 to cut-in. As a result, the time gap becomes too small to handle by the ACC vehicles, and a manual takeover is required. The sharp deceleration to resume the driver's desired time gap results in a shockwave further downstream, with increasing congestion and decreasing stability. This simulation shows that the behaviour of automated vehicles in "emergency situations" (i.e., vehicles merging resulting in too small headways) highly influences the throughput of traffic. However, it is unsure whether drivers will turn on ACC after such an event, but probably not. This implies that ACC will have no impact on stability, since the systems will not be used in critical situations.

Stanek (2018) also performed microsimulation experiments for non-connected autonomous vehicles. However, these vehicles did not require manual take-overs at too low headway values. The default headway time gap of 0.9 seconds for manual driven cars (Wiedemann 99 Car Following model) was changed to 0.25. Likewise, this resulted in a decrease in total delay and increase in average speed with increasing penetration rates.

Milanes & Shladover (2014) implemented several intelligent driver models (IDM) on production vehicles. Their results indicate that consecutive strings of ACC vehicles are unstable, amplifying speed variations of preceding vehicles. On the other hand, CACC vehicles overcome these limitations, providing smooth and stable traffic.

4.5 Travel time

It is expected that with the introduction of connected and automated vehicles, travel times would reduce. This is because of the possibility of reduced time headway and the communication between vehicles, which increases traffic stability, and reduces shockwaves. This however, requires 100% penetration for the connected and automated vehicles without having the conventional vehicles in the same road or on a dedicated lane. For example, Aria et al. (2016) found that there is a reduction of about 9% in the average travel time in the scenario with 100% automated vehicles in comparison to the scenario with the 100% of conventional vehicles in the p.m. peak. Rios-Torres and Malikopoulos (2017) developed a microscopic simulation framework to explore the CAVs impact on travel time reduction in merging roadways. The authors found that 100% CAV penetration rate allowed for a significant reduction in travel time (up to 60%) in moderate and high traffic congestion situations. Talebpour, Mahmassani, and Elfar (2017) investigated the impact of dedicated lanes on travel time reliability. Three dedicated lanes strategies were evaluated: (a) mandatory use of the dedicated lane by highly automated vehicles, (b) optional use of the dedicated lane by highly automated vehicles; and (c) limiting highly automated vehicles to operate autonomously in the dedicated lane. The results revealed that the optional use of the dedicated lane by highly automated vehicles had positive effects in terms of travel time reliability.

5 Impacts of CAD on Traffic Safety

5.1 KPIs for Safety

As listed in chapter 2.3, the following key performance indicators were rated as most important ones in an international expert survey conducted by Trilateral impact assessment sub-group and reported by Innamaa & Kuisma (2018):

- Number of crashes (distinguishing property damage, and crashes with injuries and fatalities) in total and per 100 million km;
- Numbers of conflicts encountered where time-to-collision (TTC) is less than a pre-determined threshold /100 million km;
- Number of instances with hard braking (high deceleration) /1000 km.

The KPI work was continued in the CARTRE project. CARTRE (Rämä and Kuisma, 2018) selected fatalities and injuries as KPIs for further analyzing the safety impacts of automated driving.

5.2 Theoretical background for safety impacts

Overall, three aspects have been used to explain the traffic safety outcome (Nilsson, 2004; Elvik et. al. 2009):

- Exposure,
- Crash risk, and
- Consequence in a crash.

Out of the earlier (Chapter 2.2.) listed 9 impact mechanisms 5 first ones are related to crash risk (Kulmala, 2010). The following assumptions concerns these mechanisms:

Safety is assumed to increase when:

- speed decreases (power model), Nilsson (2004)
- standard deviation of speed decreases,
- speed violations decrease,
- number of jerks (sudden changes in longitudinal or lateral acceleration) decreases,
- very close following decreases,
- lateral position is more stable.

Additionally, the following are assumed to increase safety, too:

- signals are used correctly,
- vulnerable road users are given consideration,
- driver state is not deteriorated,
- focus of driver attention is allocated correctly.

Mechanisms 6 to 8 are related to exposure. Time spent on road has linear relationship with safety: when mileage increases, traffic safety decreases. In addition, the mode choice has impact on safety, since e.g. public transport is safer that driving or travelling in a passenger car. Moreover, the timing of the journey affects the safety, too. Peak-hour and nighttime driving are more dangerous than driving at other times. Different road types have also different crash risks: motorways are safer than two-lane rural roads etc. (Elvik et. al., 2009).

Kulmala's (2010) last mechanism 9 is related to the accident consequences. Overall, the consequences of the accidents are more severe when speed increases. Additionally, there is a relationship between the safety of a vehicle occupant, and the type of the vehicle as well as passive safety systems of the vehicle.

5.3 Earlier studies on safety impacts

5.3.1 CARTRE - a scenario based impact assessment

CARTRE (Rämä et. al., 2018) used scenario-based assessment for the impacts of automated driving. The scenarios used in the assessment were the following:

- short-term scenario
- long-term scenario, in which automation emerges parallel to shared mobility and the fleets are market operated
- long-term scenario 2, in which shared automated transport is authority driven
- long-term scenario 3, in which automated vehicles are mainly privately owned, and the shared mobility has not succeeded.

The evaluation work was done by three groups of experts. The experts evaluated impacts based on their background and expertise. They were asked to share their insight on the direction of change (increase/no change/decrease) and magnitude of change on a scale 1 - 5, where 1 = small change and 5 = large change. In addition, the certainty/uncertainty of the estimates was provided.

Three impact areas (driver behavior, energy and environment and network efficiency) were first analyzed for a single AD function. The following functions were included (Rämä et. al., 2018):

1. Highway autopilot including highway convoy
2. Urban & suburban pilot
3. Automated valet parking
4. Privately operated, automated personal rapid transit (PRT)/shuttles in mixed traffic
5. Publicly operated, automated buses and trams in mixed traffic.

It is important to notice, that in CARTRE, the ODD did not cover rural (two-lane) roads. This has huge impact on the potential effects, as very well demonstrated by Rösener et. al. (2018) (Figure 8). Even in Germany with an extensive motorway network, only 6% of the accidents take place on a motorway. Out of them, 47% happen in the situations, where L3 automation could help in preventing the crash. From this, one can calculate that the safety potential of L3 motorway chauffeur is up to 3% of all accidents in Germany.

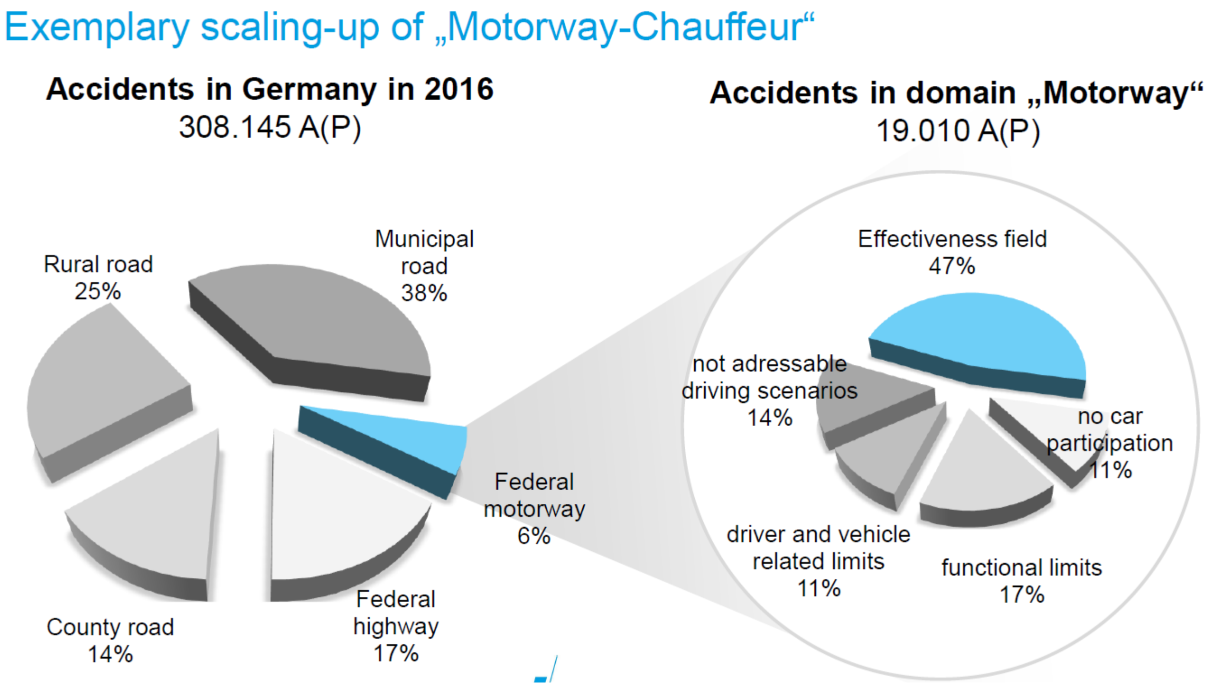

Figure 8. A German example of potential safety impacts of motorway chauffeur. (Rösener et. al., 2018)

In CARTRE (Rämä et. al., 2018) safety and public health impacts were grouped together. (Table 5).

Table 5. Estimated public health and safety impacts for the society by Rämä et. al. (2018).

KPI	Targeted direction of change	Scenario 1 ~2025: *Gradual extrapolation*	Scenario 2 ~2035: *Market-operated, shared*	Scenario 3 ~2035: *Authority-driven, shared*	Scenario 4 ~2035: *Private AVs*
		0 1 2 3 4 5	0 1 2 3 4 5	0 1 2 3 4 5	0 1 2 3 4 5
Use of active modes of transportation	Increase				
Number of injuries	Decrease				
Number of fatalities	Decrease				
Access to health services	Increase				
Access to recreation and other services	Increase				
Social isolation	Decrease	NO ESTIMATE	NO ESTIMATE	NO ESTIMATE	NO ESTIMATE

	CERTAINTY Low --> high				
Targeted change	1	2	3	4	5
Undesirable change	1	2	3	4	5
No change	1	2	3	4	5

To summarize (Table 5), total mileage travelled by active modes was not estimated to increase in any of the scenarios. In scenario 4 the comfort of automation and private ownership of automated vehicles would lead to a considerable reduction in use of active modes. The most positive impacts were assumed in scenario 3, where also the greatest decrease was estimated in the number of injuries and fatalities, due to automation. Thereby, the results highlighted the role of road authorities in maximizing the benefits of automated driving in road transport.

5.3.2 Safer roads with automated vehicles

OECD’s International Transport Forum (2018) reports the conclusions of the workshop “Safety and Security on the Road to Automated Transport: The Good, the Uncertain and the Necessary”, held in November 2017 in Paris. (OECD/ITF, 2018).

The report (OECD/ITF, 2018) introduces the Safe System approach for automated road transport, meaning that the traffic system should be designed in such a way that human fallibility does not result in death or serious injury. The safe system approach starts with the insight that human error should no longer be seen as the primary cause for the crashes. Crashes are seen as a consequence of many actors, and the transport system should be forgiving to human errors. The often-mentioned 90% reduction of crashes due to automation (removing human error) is criticized, and especially L3 (and L4) automation including the need for the driver to take over the control of the vehicle is considered as potential risk. In addition, the issue of shared responsibility is introduced as potential risk: shared responsibility between human and automation often makes decision making more complex. In addition, human error is not removed from the traffic system as long as there are humans in the system (pedestrians, cyclists, drivers of conventional vehicles). (OECD/ITF, 2018).

OECD/ITF (2018) also highlight that both the automated vehicles and the transport system needs to be safe. The minimum requirement should be that the transport system as at least as safe as today. Ideally, the system level safety should be improved with the introduction and deployment of automated vehicles. Automation has potential in removing such issues as impaired driving due to intoxication, fatigue, or just simply not concentrating on driving, but having secondary, non-driving related in-vehicle tasks, such as texting.

How much automation then will improve road safety depends on how safely automated driving functions can carry out the parts of the driving task they are designed for. Aiming for perfection in automated driving systems is important, but a Safe System should remain the fallback solution. A system built to safely absorb human error is also tolerant to machine errors (OECD/ITF, 2018).

One remaining question is why to automate human functions. According to Wickens et. al. (2003) and OECD/ITF (2018) there are the following potential motivations:

- When it is dangerous for humans to carry out a task (intoxication, fatigue…)
- When it is impossible for humans to carry out a task (e.g. accurate night-time sensing)
- When carrying out a task is difficult for humans (e.g. something needing very fast reaction times)
- Just for the sake of automation.

The current deployment of automated driving functions is motivated by all these different measures according to OECD/ITF (2018). The comparison of human and hw/sw performance in various aspects is summarized in table 6.

Table 6. Comparison of Human performance to AD performance according to OECD/ITF (2018) and Schoettle (2017).

Aspect	Human	Hardware/Software system
Speed	Relatively slow.	Fast.
Power output	Relatively weak, variable control.	High power, smooth and accurate control.
Consistency	Variable, fatigue plays a role, especially for highly repetitive and routine tasks.	Highly consistent and repeatable, especially for tasks requiring constant vigilance.
Information processing	Generally single channel.	Multichannel, simultaneous operations.
Memory	Best for recalling/understanding principles and strategies, with flexibility and creativity when needed, high long-term memory capacity.	Best for precise, formal information recall, and for information requiring restricted access, high short-term memory capacity, ability to erase information after use.
Reasoning	Inductive and handles ambiguity well, relatively easy to teach, slow but accurate results, with good error correction ability.	Deductive and does not handle ambiguity well, potentially difficult or slow to program, fast and accurate results, with poor error correction ability.
Sensing	Large, dynamic ranges for each sense, multifunction, able to apply judgement, especially to complex or ambiguous patterns.	Superior at measuring or quantifying signals, poor pattern recognition (especially for complex and/or ambiguous patterns), able to detect stimuli beyond human sensing abilities (e.g., infrared).
Perception	Better at handling high variability or alternative interpretations,3 vulnerable to effects of signal noise or clutter.	Worse at handling high variability or alternative interpretations,3 also vulnerable to effects of signal noise or clutter.

Safety considerations in automation levels L2-L4 have the core in the safe handover from automated systems to the human driver when the system cannot interpret its environment satisfactorily, or when the vehicle is simply approaching the end of its designed ODD. The following issues need to be taken into account when assessing the potential safety effects of automated driving (OECD/ITF, 2018; Noy et. al., 2018)

- Task allocation: which tasks are left to the humans, and which are handled by automation?
- De-skilling: Lack of practice or imperfect situational awareness leads to reduced skills and may hence cause delays for humans to carry out the driving tasks when required.
- Cognition: Lack of cognitive engagement in the driving task leads to lower levels of situational awareness, and hence longer reaction times if the automated driving function disengages.
- Control: Driving is a learned skill. Less time spent driving can lead to worsening skills in handling the vehicle.

Chan (2017) discusses the state-of-the-art of automated driving systems in his paper. The paper includes also predictions of the readiness of various systems by various OEMs. In addition, the paper summarises the main activities around the world related to the development of automated driving, at the time the paper was written. One point worth mentioning is the fact, that many predicted market entries have now been postponed slightly.

Chan (2017) also brings up the major difference between the "traditional" OEMs and the new players on the field of automated driving. Whereas the "old" players are deploying automation stepwise, and with the plan "Something everywhere", adding the driver support gradually, the "new" players are merely targeting at full automation in selected environments, so called "Everything somewhere". Chan (2017) summarizes many studies related to the safety impacts of automated driving, of which many are much less optimistic than the often-stated 90% of the accidents will be removed with the automation. One study often mentioned and referred to in this area is Sivak and Schoettle (2015) paper, which summarises the safety as follows:

- the expectation of zero fatalities with self-driving vehicles is not realistic
- It is not a foregone conclusion that a self-driving vehicle would ever perform more safely than an experienced, middle-aged driver
- During the transition period (human driven and self-driving vehicles sharing the road), safety might actually worsen, at least for the conventional vehicles.

In addition to all the above listed, it is worth noting, that connected and automated vehicles are assumed to comply with the traffic rules better than humans: no speeding, no intoxicated driving, no red-light running etc. and hence have potential to increase the safety by decreasing the number of accidents related to the non-compliance of traffic rules and regulations.

5.3.3 Implications of automated vehicles on transport planning and safety

Litman (2018) presented an extensive review of existing studies and literature on the autonomous vehicles and impacts on transport planning, including safety. The report summarized the findings of benefits and costs of autonomous vehicles, as well as impacts on transport planning issues.

In the introduction to his report, Litman (2018) states that the most optimistic predictions on the autonomous vehicle penetrations are made by the “people with financial interest in the industry”, and are often based on the technology adoption of consumer electronics. On the other hand, vehicle industry and research community are more conservative with their estimates.

The most commonly mentioned benefits of autonomous vehicles are according to Litman (2018) reduction of driver stress. In addition, the utilization of travel time for working, or even sleeping is a benefit. This may reduce the travel time unit cost. Autonomous vehicles can also provide independent mobility for non-drivers (people who cannot or are not willing to drive currently). Many potential not so positive impacts are also mentioned, such as increased stress with the new technology, reduction of the public transport usage, and increased congestion.

Litman (2018) also highlights the difference between the personal autonomous vehicles and shared vehicles or rides. The autonomous driving is often pictured as a mobile living room. This could be the case if one has his own autonomous vehicle. However, if sharing the ride (or vehicle), the closer comparison could be an elevator ride. Litman (2018) also discusses the advantages and disadvantages of personal vs. shared autonomous vehicles/rides (table 7)

Table 7. Advantages and disadvantages of personal versus shared autonomous vehicles (Litman, 2018).

	Advantages	Disadvantages	Appropriate Users
Personal autonomous vehicles - Motorists own or lease their own self-driving vehicles	High convenience. Available without delay. Items, such as equipment, tools and snacks, can be left in vehicles.	High costs. Does not allow users to choose different vehicles for different trips, such as cars for commuting or trucks for errands.	People who travel a lot, reside in sprawled areas, want a particular vehicle, or leave items in their vehicles.
Shared autonomous vehicles - Self-driving taxis transport individuals and groups to destinations.	Users can choose vehicles that best meet their needs. Door to door service.	Users must wait for vehicles. Limited service (no driver to help passengers carry luggage safely reach their door). Vehicles may be dirty.	Lower-annual-mileage users.
Shared autonomous rides - Self-driving vans (*micro-transit*) take passengers to or near destinations.	Lowest costs.	Least convenience, comfort and speed, particularly in sprawled areas.	Lower-income urban residents.

Litman (2018) also includes discussion of the penetration rate development by comparing the deployment to the previous vehicle innovations, such as automatic transmission. Based on those, his prediction is that the autonomous features would take two to three decades to be incorporated into middle- and lower-priced vehicle models.

For the traffic safety implications, Litman (2018) starts with the often stated, “autonomous vehicles could reduce crash rates by 90% due to elimination of human error”, but continues then with the additional risks the technology could introduce, such as

- Hardware and software failures,
- Malicious hacking,
- Increased risk taking (offsetting behavior/risk compensation),
- Platooning risks,
- Increased total vehicle travel,
- Additional risks to non-auto travelers,
- Reduced investment in conventional safety strategies.

In addition, Litman (2018) reminds that even if the autonomous vehicles would increase safety (per driver km), if they increased the driven kilometres, the benefit may be minimal (see also Nilsson, 2004). The summary of Litmans (2018) conclusions on benefits and costs is presented in Table 8.

Table 8. Summary of benefits and costs according to Litman (2018)

	Benefits	Costs/Problems
Internal (user Impacts)	*Reduced drivers' stress and increased productivity.* Motorists can rest, play and work while travelling. *Mobility for non-drivers.* More independent mobility for non-drivers can reduce motorists' chauffeuring burdens and transit subsidy needs. *Reduced paid driver costs.* Reduces costs for taxis and commercial transport drivers.	*Increased vehicle costs.* Requires additional vehicle equipment, services and fees. *Additional user risks.* Additional crashes caused by system failures, platooning, higher traffic speeds, additional risk-taking, and increased total vehicle travel. *Reduced security and privacy.* May be vulnerable to information abuse (hacking), and features such as location tracking and data sharing may reduce privacy.
External (Impacts on others)	*Increased safety.* May reduce crash risks and insurance costs. May reduce high-risk driving. *Increased road capacity and reduced costs.* More efficient vehicle traffic may reduce congestion and roadway costs. *Reduced parking costs.* Reduces demand for parking at destinations. *Reduced energy consumption and pollution.* May increase fuel efficiency and reduce emissions. *Supports vehicle sharing.* Could facilitate carsharing and ridesharing, reducing total vehicle ownership and travel, and associated costs.	*Additional risks.* May increase risks to other road users and may be used for criminal activities. *Increased traffic problems.* Increased vehicle travel may increase congestion, pollution and sprawl-related costs. *Social equity concerns.* May reduce affordable mobility options including walking, bicycling and transit services. *Reduced employment.* Jobs for drivers may decline. *Increased infrastructure costs.* May require higher roadway design and maintenance standards. *Reduced support for other solutions.* Optimistic predictions of autonomous driving may discourage other transport improvements and management strategies.

Litman (2018) also estimates that the safety benefits of autonomous vehicles is only seen when major share of vehicle travel is autonomous. According to him, this will take until 2040-2060's.

5.3.4 Simulation studies on safety effects of automated vehicles

Safety effects on intersections

Morando et. al. (2017 and 2018) studied safety impacts of automated vehicles by using VISSIM microsimulation and Surrogate Safety Assessment Model (SSAM) for two case studies: signalized intersection and a roundabout. They also varied penetration rate of automated vehicles in both cases. They assumed level 4 automation (full automation in NHTSA scale). In the parameter setting, the conservative values for gap acceptance etc. were selected due to expected OEMs willingness avoid liability due to aggressive AV behavior.

Morando et. al. (2017, 2018) used surrogate safety measures to assess safety impacts of AVs in the two above-mentioned environments. Time-to-collision (TTC) less or equal to 1.5 seconds was used as a threshold for potential conflicts if involving human driven vehicles (human driven/human driven or human driven/automated), and 1 second if between automated vehicles. Another surrogate measure used in the study was Post Encroachment Time (PET) (Post-encroachment time is conventionally defined as the time between the first road user leaving the common spatial zone (in a 2 road user encounter) and the second road user arriving at it.), and a threshold of 5 seconds was used for PET.

The case studies selected for the simulation and safety assessment included two different intersections; one signalized intersection and one roundabout. Both of the selected intersections were simulated models of existing intersections with the actually measured traffic, speed etc. available. The penetration rates of AVs were varied from 0% up to 100%, with the 25% steps (i.e. 0%, 25%, 50%, 75% and 100%). (Morando et. al, 2017 and 2018).

In the roundabout, the conflicts seemed to be increasing between baseline and 25% penetration rate, but then decreasing, being 29% to 64% less with the 100% penetration rate than in the baseline (0% AVs). This result was statistically significant, $p<0.05$). In the signalized intersection the conflicts decreased with the increased penetration rate, and the reduction of conflicts was 20% to 65% with the penetration rates between 50% and 100% (both statistically significant at $p<0.05$). The authors conclude that a high penetration rate might be required to deliver AV's anticipated safety effects. (Morando et. al. 2018).

Safety effects on motorways

Papadoulis et. al. (2019) studied the safety of connected and automated vehicles on motorways with the VISSIM microsimulation. They also used Surrogate Safety Assessment Model (SSAM) for the safety assessment. The penetration rate of CAVs was varied from 0% to 100% with the 25% intervals, as in Morando et. al. (2017 and 2018) studies. The simulation model included one motorway section (model of M1 between junctions 19 - 21, in UK) with 3 lanes to both directions. The total length of the modelled section was 44km, and it included on and off-ramps. Time to collision (TTC), and Post Encroachment Time (PET) were used as indicators for safety. The thresholds set to the indicators were 1.5 and 5 seconds, respectively.

Papadoulis et. al. (2019) found major reduction of conflicts even at low penetration rates. The reduction of conflicts was 12 - 47%, 50 - 80%, 82 - 92% and 90 - 94% for the 25%, 50%, 75% and 100% penetration rates respectively. The authors list a few limitations of their study. First of all, it only includes motorway section. Secondly, the model allowed very long convoys to be built, which might not be possible in the real world, since it would prohibit other vehicles to merge in or out of the motorway sections. Thirdly, the malfunction or other technical errors were limited out of the scope of this study. One issue outside the safety effect scope is also the result on travel times: the travel times in the studied sector increased due to decreased average speed on the section.

Discussion on the simulation as a tool to assess impacts of automated vehicles

The authors (Morando et. al, 2018) discuss the limitations of micro-simulations as a tool for assessing safety impacts of automated vehicles. The first issue for the future research they mention is the correspondence of modelled behavior to the real-world behavior. Due to the deployment phase of AVs currently, the real-world data is either missing or very limited. This will, of course change when the development progresses and allows more on-road testing. One particular issue to study in the real world is the interaction between human drivers and automated vehicles. In addition, the car following model in the current simulation tool (VISSIM) may not be fully compatible with the connected and automated vehicles. Morando et. al. (2018) also mention that new surrogate safety measures may be needed especially for AVs due to their different (to human) behavior. They also remind the readers that the study included only two intersections, and hence the overall conclusions of the safety improvements to the larger network level cannot be directly drawn from these results. (Morando et. al. 2018).

When considering Papadoulis et. al. (2019) results, it is important to keep in mind that those are purely for motorway (3+3 lane) environment, and the automation is assumed to cover also merging. Hence, one should not read the results as they would indicate the same magnitude safety effect on the other type of roads (being typically worse in traffic safety than motorways), and is slightly contradictory with the current ODD for AVs, which excludes on- and off-ramps. Most of the safety benefits in Papadoulis et. al. (2019) were found in the merging areas. Hence, one needs to take these positive results as indicative, and take into account that they cannot be directly up scaled to the transport system as such.

Trubia et. al. (2017) also presented a review of the road safety implications, presented both a list of relevant studies, and proposed how to edit the Wiedemann 99 car following parameters in VISSIM to simulated automated vehicles. These may be useful when further plan the simulations for selected MANTRA use cases.

In general, road crashes tend to occur due to driver errors – either in perception, judgement or action. This will likely also apply to automated vehicles with the automated driving system as the driver. In order for the simulation software to be able to simulate crashes or even near-crashes, the driver error making would need to be a key part of the simulation system.

6 User acceptance and use of connected and automated vehicles

User acceptance and hence use of automated vehicles is important when estimating the impacts. User acceptance can guide the adoption or rejection of systems and must therefore be examined in detail to understand what is acceptable and what is not, and for what kind of reasons (Rämä and Kuisma, 2018). CARTRE selected the following user acceptance related KPIs for further impact analysis work (Table 9).

Overall, user acceptance and use of automation in various situations have great impacts on the realization of the intended benefits of automation (table 10). Currently, user have positive expectations towards automation, but also many concerns (see e.g. Schoettle and Sivak, 2014, Penttinen et. al, 2019).

Table 9. KPIs for user acceptance according to CARTRE-project (Rämä and Kuisma, 2018).

Name of KPI	Definition of KPI (unit)	Targeted direction of change from societal perspective
Use of automated driving functions	Share of kms driven within the ODD when the driver decides to use automation	Increase
Requirement of attention and concentration (for driving)	Whether the driver has to be attentive to driving or not, and to what extent (varies with SAE level).	Decrease
General feeling/acceptance of general public	The public considers that AD is reliable, safe, and useful and might be used for the purpose it is intended to.	Increase
Trust (Connected and Automated Driving, CAD, users)	Experienced trust (Likert scale: e.g. I do not agree at all – I fully agree in 5 steps)	Increase
Perception of reliability	Experienced reliability (Likert scale)	Increase
Perceived usefulness	Experienced usefulness (Likert scale)	Increase
Perceived comfort	Experienced reliability (Likert scale)	Increase
Feeling of safety (from the perspective of vehicle users)	Subjective safety (Likert scale)	Increase
Feeling of control of the overall situation (from the perspective of vehicle users)	a) Feeling of being able to control the vehicle at any time b) Feeling of control over the vehicle while the system is driving (Likert scale or share of time when feeling able to have control)	a) Increase b) Decrease due to delegation of responsibility to AV
Intended use	Will the drivers think they would use the AD systems more and more often?	Increase

Table 10. CARTRE-project example of calculating the system penetrations (and use) in actual traffic for selected ADFs.

Deployment / system penetration in ~2035									
Application	Targeted vehicle type (vehicle population)	A = % of targeted vehicles AD equipped	Definition ODD	% vehicle kms represented by targeted ODD	% vehicle kms driven by target vehicle population in ODD	% vehicle kms of targeted ODD which can be used by target population (free of system limitations/ constraints)	% usage within ODD where there are no limitations for target population	% of all vehicle kms driven by AD equipped vehicles where system can be used and is used	% of all vehicle kms driven by AD equipped vehicles where system can be used and is used, limited to the ODD
Label		A		B	C	D	E	F	G
Calculation						Assumption		A x B x C x D x E	A x C x D x E
Highway Autopilot /cars	All cars	50%	Motorway - Interurban and urban	16.9%	79.3%	80%	80%	4.29%	25%
Urban & Suburban Pilot (USP)	All cars	25%	Urban Spacious	13.9%	86.4%	80%	20%	0.48%	3%
Automated Valet Parking (AVP)	All cars	60%	Parking lots (not represented in the veh-kms)	0.0%	0.0%	80%	90%	0.00%	0%
Highly Automated Vehicles on Dedicated Lanes/roads/areas			Not analysed						
(Organized) Highway pilot Truck Platooning			Not analysed						
Private operated, Automated Personal Rapid Transit (PRT)/Shuttles in Mixed Traffic	All taxis/commercial ridesharing services (e.g. Uber)	40 %	Urban - compact and spacious	27.8%	4.3%	80 %	100 %	0.38 %	1 %
Public operated, Automated buses (and trams) in Mixed Traffic	PT buses	40 %	Urban - compact and spacious	27.8%	1.5%	80 %	100 %	0.13 %	0 %

7 Impacts of connected and automated driving on Energy & Environment

7.1 Energy

Automation and connectivity of vehicles can have large effects on the energy and carbon footprints of how we travel in future. While early researchers have focused on the potential for reducing energy and carbon footprint, suggesting as high as a 90% reduction in greenhouse gas emissions (Greenblatt and Saxena 2015), careful review shows that most of that reduction arise, not from automation, but rather from electrification. Recent studies rather point to uncertain energy and carbon effects of automation (Wadud et al. 2016, Taiebat et al. 2018, Chen et al. 2019) and often warn against potential unintended consequences.

Wadud and Anable (2016) adapted Milakis et al.'s (2016) ripple approach to understand the energy and carbon impacts of vehicles automation. The ripple diagram in Figure 9 presents qualitatively the first, second and higher order impacts of automation. What this shows is that energy and carbon impacts of vehicle automation are not first order effects, but happens through other direct effects of automation.

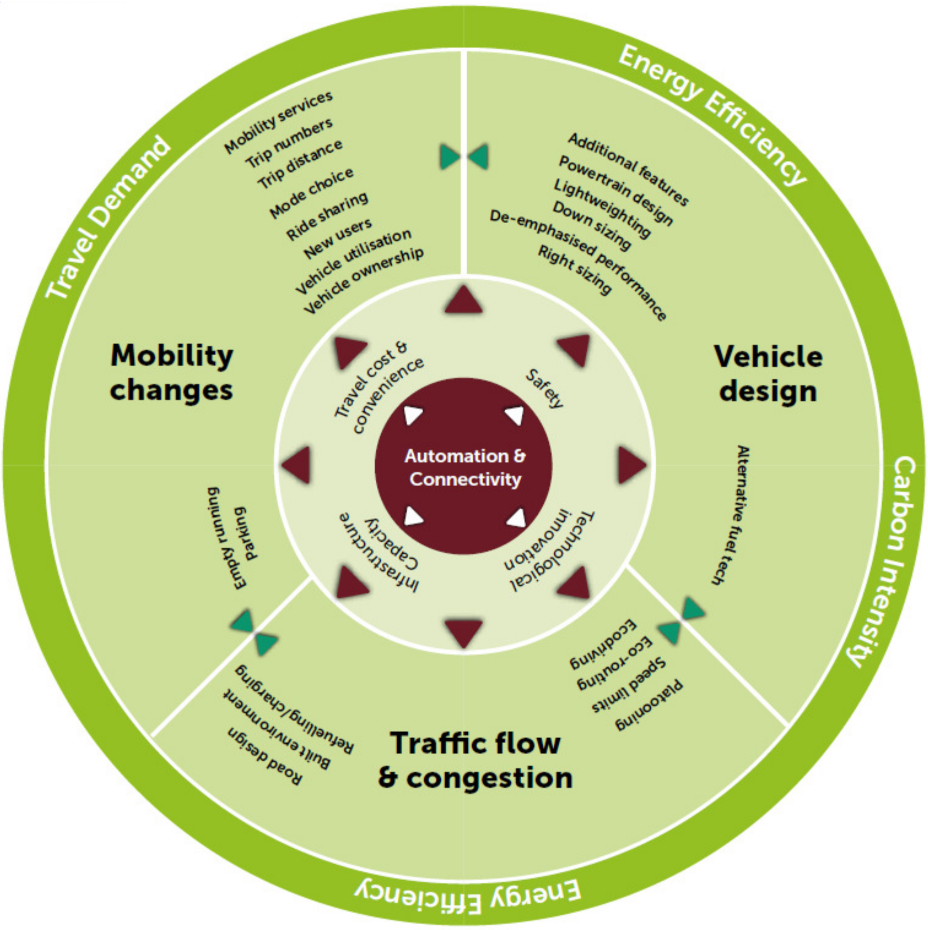

Figure 9. Energy and carbon ripple effects of vehicle automation (source Wadud and Anable 2016)

Wadud et al. (2016) and Brown et al. (2014) suggest a decomposition framework in order to quantify and bound the potential energy and carbon effects. They use the carbon decomposition framework in Eq. 5.1 to highlight that investigating only energy efficiency effects, which is often the focus of energy engineering, misses the wider picture – especially the potential effects of radical changes in mobility and travel demand.

Carbon emissions = Travel demand × Energy intensity of travel × Carbon intensity of energy

Wadud et al. (2016) quantified several of the pathways to energy effects and suggest the following:

- Traffic flow can be streamlined and optimized for fuel consumption with automated vehicles connected to the network;
- On motorways, automated vehicles can drive very close to each other, creating platoons, thus reducing aerodynamic drag at high speed and fuel consumption;
- The automated vehicles can be programmed to run on an eco-driving mode (driving practices that can reduce fuel consumption);
- At very high level of penetration, automated vehicles can be light-weighted as crash risks fall dramatically (currently, nearly 90% of traffic fatalities are attributed to human errors);
- Lower engine performance requirements for automated driving (decreases consumption).
- Right-sizing of vehicles made possible by self-driving shared-cars (decreases consumption);
- Higher speed limits resulting from increased safety (increases consumption);

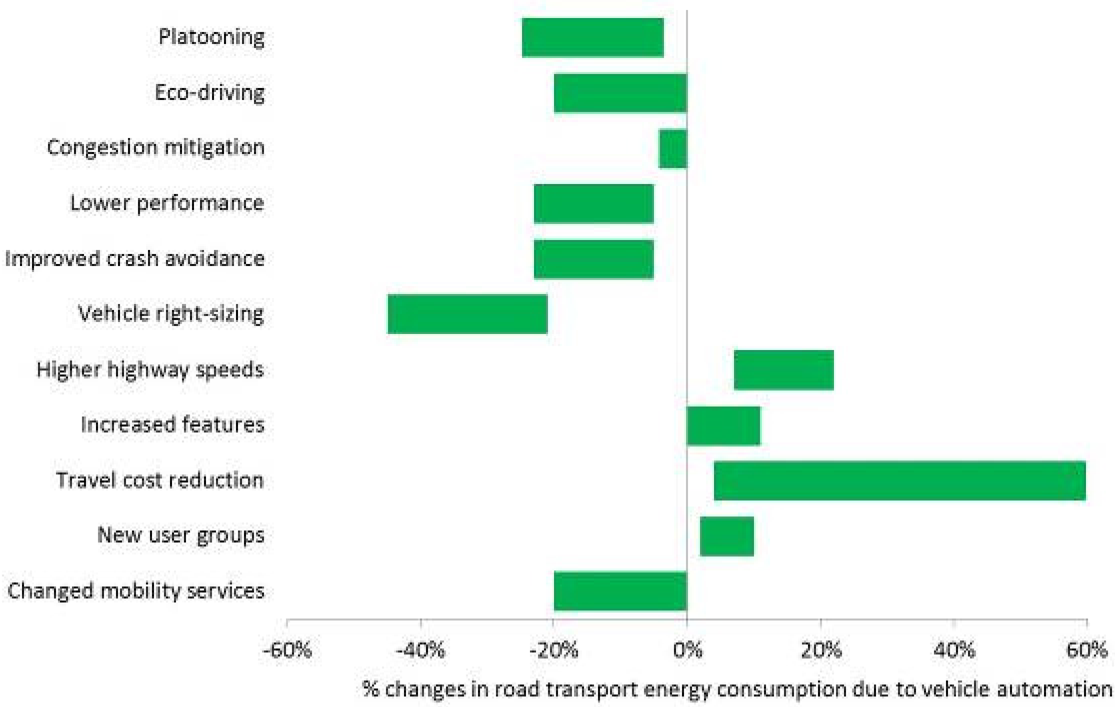

Figure 10. Potential impact of vehicle automation on energy demand through various mechanisms (source Wadud et al. 2016)

All of these mechanisms improve 'fuel efficiency' of individual vehicles, except for potential increase in fuel consumption due to higher speed. Right sizing of vehicles (matching trip type to vehicle type) is also dependent on a shift away from ownership to sharing, which is a large uncertainty, as discussed earlier in section 2. Figure 10 presents the results of the bounding exercise for energy effects of vehicle automation in the US.

One area that has not received much attention in this literature is the additional energy consumption in vehicles due to the computational requirements. Gawron (2018) suggests an increase in life cycle energy use of 3% to 20% due to increased weight from ICT equipment and associated computing and data transfer. This could also nullify some of the energy efficiency gains in Figure 10. Of course, when the development and deployment of automation happens gradually, the computing capacity increases remarkably during this time, too. Hence, this may not be such an issue in the future.

Studies reviewed earlier in section 2 agree with Wadud et al. (2016) suggestion that travel demand could increase substantially due to vehicle automation, which could nullify any gains in energy efficiency. Indeed Wadud et al. (2016) and Auld et al. (2017) report very similar results on potential increases in energy demand due to changes in travel demand, despite quite different modelling strategy and geographic coverage. Recent studies (Chen and Kockelman 2016) also suggested that travel demand due to increases in empty running in an automated mobility regime might be larger than that in Figure 15 (changed mobility services). Especially Arbib and Seba (2018) show a large transition away from ownership to automated mobility service could still increase Vehicle Mileage Travelled by 50% in the US.

Fulton et al. (2017) uses a global scale model and suggest that the combined reduction in energy use due automation, electrification and sharing can be as high as 70% in the passenger travel sector. Naturally, this relies on strong assumptions of all the mechanisms discussed earlier to be aligned toward the same direction. Overall, Chen et al. (2019) suggest a net reduction of 45% in the optimistic scenario or a net increase of 30% in the pessimistic scenario for the light duty fleet in the USA, revealing the uncertainty in energy impacts, which appear more plausible.

While most of these studies focus on passenger transport, there is little on freight transport (Taiebat et al. 2018). Only Wadud et al. (2016) suggest potential net reduction (combination of energy efficiency and travel demand) of 10% to increase of 40% in freight energy consumption in the US due to vehicle automation under different scenarios. Further research in this area is necessary to ascertain the potential impacts.

7.2 Carbon

As seen from the Eq. 5.1 above, the effects of automation and connectivity on carbon emissions are also related to travel demand and energy efficiency, which has been discussed above and is relevant here, too. On top of it, the important question is whether automation can encourage a transition to electrification or other alternate-low carbon fuel sources, which could reduce carbon intensity of the energy sources and thus overall carbon emissions. Automation has some important synergies with low carbon transition of the personal road transport sector (Wadud et al. 2016):

- One of the largest barriers in energy transition is whether to build the supply infrastructure first (which is expensive) or to encourage demand (which is difficult if there is a lack of supply infrastructure). Automated vehicles could refuel in an unattended mode on their own when they are not being used, thus circumventing the initial inconvenience of refueling from a scarce alternate fuel station.
- Most low-carbon fuels have low volumetric energy density and high storage costs, resulting in a lower operating range. Of course, if autonomous vehicles could refuel/recharge themselves, this barrier will decrease.

- In an automated on-demand mobility environment, the vehicles are utilized intensively compared to owned vehicles. As such, the high capital costs of alternate fuel vehicles could be recouped via this higher utilization. Recent estimates for electric automated mobility services indeed show low per-mile costs of automated on demand mobility services (Wadud and Mattioli 2019).

While all of the above factors are applicable for electric automated vehicles, automation and electrification have a few more synergies, such as (Anair 2017):

- Automated vehicles use electric power for on-board computing and sensors, and electrification for traction and computing requirements appear a natural choice.
- Automation can assist electrification through battery operation and recharging management – both in an owned or mobility on demand regime.

Authors such as Greenblat and Saxena (2015) and Fulton et al. (2017) suggest a potential reduction of carbon emissions of up to 80% to 90% due to automation, electrification and sharing. However, these are very optimistic scenarios and are not a direct result of automation, rather a combination of different factors – all working together in the same direction. Especially, there is often an assumption that all automated vehicles will be electric – however, absent strong policies toward electrification, this is not guaranteed as an automated conventional vehicle could still be financially more attractive compared to an automated electric vehicle, but this depends on many factors, such as purchasing cost, energy cost, and the availability of charging in the area the vehicle is operating.

In summary, there are still large uncertainties in the quantification of net energy and carbon effects of vehicle automation and connectivity. While substantial reduction is possible, it is not a direct consequence of automation, but rather due to vehicle operations and design or transport system optimisation, that can be facilitated by automation and connectivity.

- Some of the reductions in energy demand could be brought about by a higher degree of connectivity, even at a lower level of automation than self-driving cars.
- For fully automated vehicles, there is a substantial risk of increased travel and energy demand, even in an on-demand automated mobility future.
- While electrification has some synergies with automation, policies need to be there in order to ensure that automated vehicles are electric, in order benefit the most from this technology.

7.3 Noise

The noise level of a road section depends on the following traffic properties (in addition to road properties): vehicle volume, share of heavy vehicles, share of motorcycles, average speed. However, there is a lack of studies on the effects of automated vehicles on noise pollution. The primary effects can comprise the following:

- Automation will affect travel demand (Vehicle Mileage Travelled, trip pattern, etc.), which could either increase (empty trips) or reduce (automated ride sharing) noise pollution.
- Automated vehicles, if accompanied by electrification, could substantially reduce noise, especially in the urban, low speed environment, where engine noise governs.
- Automated vehicles will likely not accelerate and decelerate as much as human driven vehicles, and thus reduce noise pollution.

8 Discussion

This report presents an overview of the impacts of connected and automated driving on mobility and travel behaviour, driving behaviour and traffic flow, traffic safety and energy and environment. The review is based on the available literature and ongoing EU and national projects in the relevant area.

It is important to keep in mind that even if the search for the literature and studies is extensive, it only gives an overview of the situation as of today. Most of the impact estimates are based on either expert evaluation or traffic simulation or make their assumptions based on the available studies on driver assistance systems. It is of utmost important to continue following the studies in this area, to complement the results when on-road testing of automation and data received from those tests is available in large scale. In addition, one area, which remains open, and which will definitely develop over time, is the interaction between automated vehicles and other road users.

Moreover, even the models for estimating impacts, e.g. traffic microsimulation models, still need adjustment and parameters for automated vehicles. The current behavior, e.g. car following behavior, is mostly based on the behaviour of human drivers. In addition, it is important to notice, that even the behavior of human drivers might change when interacting with automated vehicles. The development of the technology also have great impact on the area and conditions where automation can be used (ODD), and hence can have impacts in.

One can anticipate, that AVs in mixed traffic will tend to drive at longer following distances so as to permit less rapid deceleration when the preceding vehicles slow down, to negotiate sharp curves at lower speeds and to be less prone to undertake rapid manoeuvres such as abrupt lane changes compared to human drivers in the same situations. Such smoother driving may reduce incidents, but there might also be an impact in traffic throughput, i.e. decreased capacity.

Another issue closely related to capacity, is that automated vehicles even when shared can compete with public transport and active transport modes (walking and bicycling) leading to better individual mobility but less transport system efficiency.

The earlier presented nine impact mechanisms (e.g. Kulmala, 2010) need to be kept in mind when considering the variety of impacts of connected and automated driving not only to traffic safety, but also to other impact areas. Additionally, the ripple effect (Milakis et. al. 2017) and the impact paths created by the Trilateral Impact Assessment group (Innamaa and Kuisma, 2018) reminds the reader of the variety of impacts the introduction and deployment of automation may have on the transport system.

The variety of studies reviewed for this paper give an overview of the expected impacts of the deployment of connected and automated driving. As the reader can see when going through the various impact areas, the expectations of the magnitude of the impacts vary a lot. Where someone is expecting the traffic safety to be improved by 90%, the others are much more conservative and present only one-digit estimates. The same applies for other impact areas. When assessing safety, the additional risks the technology could introduce, needs to be taken into account. Moreover, as long as there is mixed traffic, i.e. not all the vehicles are fully automated, the conventional safety strategies are still needed.

As many of the studies summarized in this deliverable also, remind: automation is not the only megatrend that affects the road transport in the oncoming years. Shared mobility is one issue, which may have great impact on how people select to move around. In addition, electrification will certainly have an impact on CO2 emissions, and maybe even on travelling patterns.

The content of this deliverable will be presented and discussed with CEDR in a mini-workshop in September 2019. Based on that, the further work on modelling and simulation in WP3 will be planned in details. The outcomes of this WP will contribute to the further work in MANTRA where the consequences of automation to infrastructure and road operators' core businesses will be elaborated.

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